**Technical assessment for**

**Smart Thermostats**

Sector: Buildings

Agency Level: Household

Keywords: Smart Grid, Energy Efficiency, Space Heating, Space Cooling, Learning Thermostat, Communicating Thermostat, Wi-Fi Thermostat

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# Acronyms and Symbols Used

* AC - Air Conditioning
* BMS - Building Management Systems
* BYO - Bring Your Own
* BYOT - Bring Your Own Thermostat
* BYOTs - Bring Your Own Things
* CRE - Commercial Real Estate
* DER - Distributed Energy Resources
* DLC - Direct Load Control
* DM - Demand Management
* DR - Demand Response
* DRMS - Distributed Resource Management Systems
* DSM - Demand Side Management
* EIA - Energy Information Administration
* EV - Electric Vehicles
* HEM - Home Energy Management
* HVAC - Heating, Ventilation, and Air Conditioning
* IoT - Internet of Things
* M&V - Measurement and Verification
* OEM - Original Equipment Manufacturer
* PCT - Programmable, Communicating Thermostats
* PDS - Project Drawdown Scenario
* PLMA - Peak Load Management Alliance
* REV - Revising the Energy Vision
* REF - Reference (Scenario)
* RHR - Rush Hour Rewards
* ROI - Return on Investment
* ST - Smart Thermostat
* TAM - Total Addressable Market

# Executive Summary

Globally, the buildings sector is the largest end-use sector, accounting for over 36% of global energy usage and as much as 39% of energy-related CO2e emissions. Thus, the global building sector needs innovative technologies and approaches to reduce energy consumption while ensuring building operations are not affected. Thermostats are a technology that have historically been used in residential buildings of the developed world to reduce energy consumption. In recent years, thermostats are evolving to become part of the smart home ecosystem - multiple Internet of things (IoT) devices that communicate with each other to increase the ease of everyday activities. Smart thermostats are currently the first home smart technology to really enter in the mainstream market .

A “smart thermostat” connects to Wi-Fi networks and learns from user behavior to optimize energy settings, saving energy while providing benefits in improved comfort and convenience. These thermostats currently make up roughly 4.1 percent of the market globally, primarily in the US, Europe, and Asia Pacific. Smart thermostats are largely absent elsewhere.

Smart thermostats offer the potential to reduce home heating and cooling needs by 10 to 15 percent, and coupled with demand response programs and analytic capabilities savings of up to 40% have been reported. Hence, the climate and financial savings of scaling up this solution are significant. The benefits that smart thermostats provide are substantial enough that it is likely that they will become a replacement technology for mechanical or programmable thermostats in developed economies. Growth could be further driven with government, and utility demand response programs such as bring your own thermostat (BYOT) .

The adoption prognostication model is based on comparing scenarios for future smart thermostat adoption. The Project Drawdown Scenarios (PDS) are built upon market research report estimates for the future adoption of smart thermostats and uses wealth indicators to project growth. The reference (REF) growth scenario for smart thermostats, fixes the future adoption to its current percentage share of the total market, 4.1 percent.. The “*Drawdown*” scenario, which is aimed at achieving drawdown, projects 1.6 billion households could have installed a smart thermostat by 2050.

The climate and financial impacts for this accelerated adoption of smart thermostats are significant. Based on a model developed at Project Drawdown, the “*Drawdown”* scenario avoids a total of 5.9 gigatons of CO2-equivalent greenhouse gas emissions. The marginal capital cost of PDS adoption compared to the REF scenario is $173 billion, but the PDS scenario saves $1,454 billion in operating costs . Based on the financial impacts alone, it is clear that global adoption of smart thermostats is economically viable and will provide a significant return on investment. Rapid adoption will also, however, contribute to global emissions reductions.

# Literature Review

Globally, the buildings sector is one of the largest end-use sectors, accounting for 30% of global final energy usage. Including building construction increases this to 36%. These two together account for 39% of energy-related CO2 emissions (UN Environment & IEA, 2017). Thus, the global building sector needs innovative technologies and approaches to reduce energy consumption while ensuring building operations are not affected. Breaking down the building sector by energy end-use gives us an idea of where the potentials lie. Space heating consumed 32% of final building energy in 2014. The other top uses are cooking energy (22%), water heating (19%), appliances and equipment (16%), and lighting (6%) (IEA, 2017). Clearly there are many opportunities across the building sector for energy efficiency. Space and water heating energy is affected by windows, walls and heat source, cooking energy is affected by source and cooking technology, appliance energy by appliance efficiency and use, and lighting is affected by light technology and use.

In the last five years, the term “Smart”, as used in “Smart Cities”, “Smart Grid” and “Smart buildings”, has been used to define solutions that reach beyond the idea of simply ‘automation’. The term “Smart Energy” or “Smart Energy Systems” represents a broader view of building energy and strategies for its optimal use. (Lund et al. 2017). Smart cities have the potential to make a major contribution to the reduction of the impacts of climate change. (Norman 2018). Areas of impact include: the obvious mobility, buildings, and energy, but also water and governance. The next evolution of the smart city is its application of its concepts to the confined physical space of commercial building environments (Minoli et al. 2017)

**Smart Buildings (SB)**: Also commonly known as “intelligent buildings”, can be thought of as an ensemble of systems that integrate: information and communications technologies (ICT), human feedback and preferences, and the building’s physical infrastructure systems (Abrol, Mehmani, Kerman, Meinrenken, & Culligan, 2018). SB allow building managers to be equipped and incentivized to respond to real-time market and weather conditions by taking advantage of advances in ICT (Rocha et al., 2015, p. 203). “Smart buildings are flexibly connected and interacting with the energy system, being able to produce, store and/or consume energy efficiently” (BPIE, 2017).

**Smart Energy Buildings (SEB)**: These buildings include an advanced, high-performance building automation systems and Control System (BAS) coupled with technical building management (TBM), to dramatically reduce building energy consumption while improving building operations and the indoor environment (Roth, Westphalen, Feng, Llana, & Quartararo, 2005). They use a range of sensors throughout the building to measure temperature, CO2, airflow, occupancy, and daylight levels, and they integrate these sensors with a central system connected to an array of actuators that control the functioning of individual building systems as shown in Figure 1.1.

**Smart Home**: residence[s] “equipped with a high-tech network, linking sensors and domestic devices, appliances, and features that can be remotely monitored, accessed or controlled, and provide services that respond to the needs of [their] inhabitants. (Balta-et al., 2013)” in (Hargreaves, Wilson, & Hauxwell-Baldwin, 2018) pg.127. Smart Home systems increase the ease of everyday activities by communicating with each other and over the internet. They can be considered Internet of things (IoT) devices (Amirthalingam, Peko, & Sundaram, 2017).

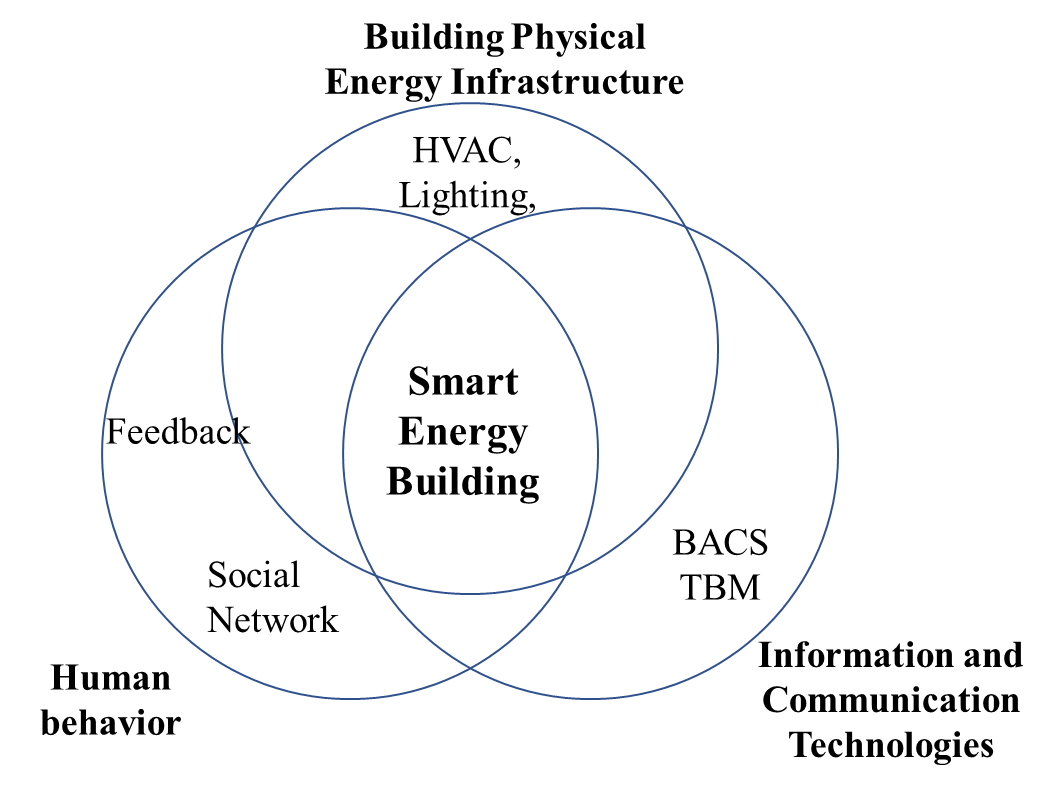


Figure 1.1 Smart Energy Buildings as an integrated system of systems as per Abrol et al. 2018

Within the realm of SEB are Home Energy Management (HEM) systems. These are networked devices that can provide information on home energy use via the internet. HEM also can adjust energy settings. Due to decades of development, they appear ready for mainstream adoption (Snell, 2016). HEM devices available in the market offer great variability, for instance a recent article identified 308 HEM products available in the US Market in 2015-2016 (Pritoni, Ford, Karlin, & Sanguinetti, 2018). Controller HEM products include remote access smart plugs, remote access smart thermostats, and systems that can automatically stop appliance use during peak hours (Kamel Ehsan & Memari Ali M., 2019). Smart thermostats and smart appliances can collect and communicate end-use consumption data to the customer or to a third party, which already decentralizes the collection of energy consumption data from the utility electric meter (Potter, Stuart, & Cappers, 2018). Thus, HEM devices typically fall into the following overarching product categories: Smart thermostats; smart plugs, smart appliances, connected light bulb and in-home display from which smart thermostats have been the first to really flourish in the mainstream market (Snell, 2016).

## State of Smart Thermostats

Buildings are complex systems, and they involve a large number of individual components, each with highly technical systems and operating procedures. There are a number of terms that are frequently used when discussing smart devices such as smart thermostats. The literature demonstrates little consensus on these definitions between energy authorities, academia, and industry groups. However, this report uses the following definition from Snell (2016):

***Smart Thermostat***: generally refers to a device that is able to run software that uses temperature setbacks during expected unoccupied periods; features external communications that may include internet connectivity, mobile app access, and data reporting; and can respond to inputs such as occupancy or customer preferences (Snell, 2016). A related technology is *communicating thermostats* which also have the ability to communicate bi-directionally. Both may have web portals and mobile apps that provide insight into household energy consumption, however smart thermostats also optimize HVAC settings for efficient heating and cooling performance by data gathering and analytics (Potter et al., 2018).

A thermostat is an important tool for regulating household temperature. Thermostats give the household occupant agency over temperature settings so that energy consumption for heating and cooling can be adjusted to ensure comfort while also limiting consumption for these purposes when the household is unoccupied.

According to the US Environmental Protection Agency (EPA), 49 percent of households do not have anyone home during the day, but in the winter, only 42 percent turn the heat down, and only 46 percent turn the heat down when they are sleeping (EPA, 2016). Given that in many households’ thermostats are not diligently adjusted by the occupant, there exists much potential for a more effective and efficient thermostat to reduce thermal energy-related GHG emissions by only heating and cooling buildings when, where, and to the extent needed.

### An Overview of Smart Thermostats

There are four broad categories of thermostats on the market. For the purposes of this report, the first three of these are considered the “conventional” thermostat technology. The earliest model was introduced in the 1950s and is set manually to one temperature and adjusted as needed. The second type, called a “clock setback thermostat”, was introduced in the 1970s. These two types of thermostats can be programmed to a particular schedule, enabling owners to choose the temperature settings they want for a given time period during any day of the week. The third type of conventional thermostat is a touchscreen programmable thermostat, a more precise and functional version of a clock setback thermostat, that was introduced in the 2000s.

The newest model for thermostats, which in this report is sometimes referred to as the “solution” thermostat, is the “smart thermostat”. Several other names have been given to these types of thermostats, including “programmable communicating thermostats”; “Communicating thermostats” (PLMA, 2018) or “Wi-Fi” thermostats and, in some cases, “Learning thermostats,” but in this report, these are all considered part of the “solution” technology and are collectively called “smart” thermostats. Smart thermostats are distinctly different than conventional thermostat technologies because they have two-way communication capabilities enabled over a Wi-Fi network that allow for more efficient and effective temperature sensing and control functions than conventional thermostats (Navigant, 2016).

Smart thermostats were first available on the market in the late 2000s, when in the fourth quarter of 2011, Nest Labs introduced their 1st-generation model. Nest invested heavily in consumer marketing- an unusual approach for the thermostat and utility demand response (DR) markets. With pervasive home Wi-Fi networks and smart phones, consumers were very attracted to the technology (PLMA, 2018)

Some of the better-known vendors of smart thermostat technologies include Nest Labs, manufacturer of the Nest Learning Thermostat, Honeywell, manufacturer of the Lyric Round™ Wi-Fi Thermostat, and Ecobee, manufacturer of the Ecobee series of Wi-Fi thermostats.

Smart thermostats are different from conventional thermostats, including programmable thermostats, in that they do not require programming. Instead, they “learn” the behaviors of their users and adjust settings accordingly in order to maximize energy savings while maintaining occupant comfort. Smart thermostats are designed to be used with a Wi-Fi connection because one of their important features is the ability to communicate remotely with the occupant through a Wi-Fi-enabled device, such as a smart phone. Using these remote-control features, smart thermostat owners can remotely adjust the temperature of their homes, can program their thermostats to stop heating or cooling when the occupant is not home, and can even connect with smart phone GPS features so that the smart thermostat can adjust the temperature accordingly based on when the occupant leaves the home or is nearing return. Most smart thermostats also have an occupancy sensor, and this enables the thermostat to determine whether anyone is at home, so it can adjust the temperature accordingly.

Smart thermostats are used to get insight in domestic energy usage and can contribute to more economic energy usage in a number of ways. These devices can control the heating system while saving money for instance by keeping the heating system off when nobody is detected at home, or by educating consumers about their energy consumption to influence their behavior (van der Ham, Klein, Tabatabaei, Thilakarathne, & Treur, 2016). Advanced thermostats can also enable hydraulic balancing - substantially optimizing the heating system, a task that can save energy performed in the past by plumbers using calculation sheets to compute the settings of the radiators balancing knobs based on parameters like room size, radiator size and valve type (Muth, 2017).

For many of the features mentioned previously, smart thermostats require a Wi-Fi connection, but this does not mean that they fail to heat or cool the home if a broadband connection goes down or if they are not installed in a Wi-Fi-enabled home. However, most of the reported savings estimates for space heating and cooling in households with a smart thermostat assume that these products are being used with a Wi-Fi network.

While the three smart thermostat manufacturers mentioned above are the market leaders in terms of product ratings and number of products sold, there is a large and growing market for smart thermostat vendors. Some of these include Hive, Netatmo, Emerson, Allure Energy, Blue Line Innovations, Carrier, Climote, Computime, Control4, GridPoint, Schneider Electric, XFINITY, and Trane.

### Conventional Thermostats and Energy Savings

Conventional or programmable thermostats can accrue savings because users can program them to have what are called “setbacks” (a higher temperature threshold before the air conditioning kicks in or a lower temperature threshold before the heat turns on) during certain periods. According to Muth, Conventional thermostats can already maintain good internal comfort in homes that have good insulation (newer, and retrofitted older homes). There is therefore a minimal effect of night setback for room temperature under general circumstances, though for long absences from home there is benefit (Muth, 2017).

A widely reported estimate is that programmable thermostats can save anywhere from 10 to 30 percent on space heating and cooling needs (Malinick et al., 2012).In practice however, these savings are rarely achieved (Muth, 2017). The EPA found evidence that there might be a significant discrepancy between predicted and actual savings for programmable thermostats. Their findings included a range of factors that could be driving down actual energy savings. First, many households (30 percent or more) with programmable thermostats may be unable, unwilling, or reluctant to use default programs or to create custom programs. Second, many households (about 50 percent) set their thermostats manually, which reduces the savings potential from a programmable thermostat. Third, the automatic program feature that programmable thermostats have is not necessarily any more conservative than manually adjusting the thermostat or setting it back when the household is not occupied. And finally, many consumers believe they will not save energy from setting back their thermostats except for during long periods of time, so they are less inclined to go through the trouble of setting back their thermostats in the first place (EPA, n.d.).

In evaluating the effectiveness of the second type of conventional thermostats—programmable thermostats—it is often assumed that older thermostats are operated under constant settings, while new programmable thermostats are programmed. Studies found, however, that two-thirds of customers already practiced energy conservation behaviors by manually setting back their thermostats during non-operating hours, essentially running their mechanical thermostats in the same way programmable thermostats are intended to be used, thus reducing or eliminating the potential for energy savings from programmable thermostats (Meier, 2012). In addition, programmable thermostats can be “complicated and difficult for users to understand, leading to errors in operation and wasted energy” (Meier, 2012), p.g.1.

Programmable thermostats can reduce energy consumption when used correctly, but because of technical and conceptual barriers to correct use, their full potential for savings is often missed. The failure of programmable thermostats to deliver on their anticipated energy savings led the EPA to suspend labeling programmable thermostats as ENERGY STAR® devices in 2009 due to the fact that savings still depend on user behaviors (Malinick et al., 2012). Rather than promoting programmable thermostats through ENERGY STAR® certification, the EPA transitioned to an educational program for customers, explaining, “installing a programmable thermostat, in itself, does not *de facto* result in energy savings. Rather, the manner in which the customer uses the programmable thermostat—or their behavior—actually drives the potential for savings” ((Malinick et al., 2012), p. 7-163).

The failure of programmable thermostats to deliver expected energy savings was one of the primary reasons the smart thermostat market began to grow. Because programmable thermostats relied in large part on occupant behavior, these savings were not being realized when occupants failed to use their programmable thermostats as intended. Smart thermostats were designed to address this important gap for energy savings by reducing the reliance of the thermostat on specific occupancy behavior, instead using complex learning algorithms to automatically adjust temperatures in order to achieve savings.

### Smart Thermostats and Energy Savings

Recently, reports on the effectiveness of energy efficiency using thermostats have soared. Most of these reports are based on pilot programs that compare savings between households with smart thermostats and those without them, however several peer reviewed articles and research studies show that using systems with control capabilities such as smart thermostats can save up to 30% of energy-related costs and those with advanced data-processing can achieve up to 40% (Kamel Ehsan & Memari Ali M., 2019). In reality however, the 30% for energy savings as promised by smart thermostats market leaders is rarely achieved (Muth, 2017).

This section will briefly discuss some of the recent reports on smart thermostat savings, as these are critical for calculating the financial and climate impacts of adoption in the model.

A recent review by Ford et al., summarize the results of North American studies done by several utilities that have piloted smart thermostats during the period 2013-2017. Most of the studies show positive energy savings with ranges between -5% and +13% for heating and cooling and from 10% and 25% of cooling (Ford, Pritoni, Sanguinetti, & Karlin, 2017).

The different studies developed by the different utility companies exploring the impact of their pilot programs, are not comparable since these differ in different methodological choices. Other two independent studies, conducted by Apex Analytics with the Energy Trust of Oregon and by Vectren Energy in Indiana, showed space heating and cooling-related electricity reductions from 12 to 13.9 percent and space heating-related natural gas reductions of 12.5 percent, respectively (Apex Analytics, LLC, 2014); (Aarish & Jones, 2016). Ford et al. argues that these technologies can deliver greater savings with additional software to add intelligent learning or enable participation in demand response events, such as Ecofactor’s Proactive Energy Efficiency Service that saves 10-15% more energy than programmable communicating thermostats or Nest’s Rush Hour Rewards that has helped achieve a 55% reduction in energy use during peak times, (Ford et al., 2017).

Most of the recent studies on savings estimates for smart thermostats were co-developed by industry members and independent bodies, often consultancies or energy utilities. Using system dynamics analysis, Ariza demonstrated that smart thermostats, in the business as usual case, can save around 60 TWh/year of electricity (equivalent to the continuous production of around three 2500MW coal plants) by 2025. If programs such as BYOT, where part of the thermostat is subsidized, were going to be popularized, this number could almost double (Ariza, 2016). A white paper produced by Nest Labs in February 2015 presents an analysis of three studies of Nest Learning Thermostat energy savings, two of which were independently funded, designed, and evaluated, and one of which was performed by Nest (Nest Labs, 2015). These three studies compared utility bills of customers with smart thermostats before and after installation of the Nest Learning Thermostat. Unlike several other studies that estimate savings based on the assumption that the occupant was previously using a thermostat with a constant set point, in effect assuming a constant baseline, the Nest study empirically measured customers’ pre-smart thermostat behaviors using a platform called MyEnergy and then assessed actual savings for customers based on their energy usage after they installed a smart thermostat.[[1]](#footnote-1) The results from the study led by Nest showed 11 percent reductions in gas heating and 15.5 percent reductions in electric HVAC use for households with a single Nest Learning Thermostat (Nest Labs, 2015). Other studies conducted in the past several years show a range of savings from 8 to 26 percent for natural gas heating and 13 to 20 percent for electric heating and cooling (Johnson, Reynolds, & Perussi, 2013; Urban and Roth, 2014; Nest Labs, 2012).

Advanced thermostats can also enable hydraulic balancing substantially optimizing the heating system, a task that has been empirically demonstrated to save energy between 10 and 30 percent (Muth, 2017). According to Muth, for many years, hydraulic balancing has been considered a key optimization for different heating systems, since unbalanced heating systems require higher flow temperatures and stronger pump pressures than necessary. Hydronic balancing is also required when parameters change, such as a home’s insulation is improved, e.g. by installing new windows (Muth, 2017) and performed in the past by plumbers using calculation sheets to compute the settings of the radiator’s balancing knobs based on room size, radiator size and valve type.

Most of these studies are “observational” in nature, meaning they are not randomized control trials and thus may be susceptible to sources of bias. In the Nest Labs study, for instance, customers who had installed a Nest Learning Thermostat and also used the MyEnergy platform to track their energy use are clearly more interested than the average consumer in energy savings. However, as Nest writes, these more energy-conscious customers probably observed lower energy savings than average Nest customers or even average thermostat users because they were previously using relatively efficient thermostat settings (Nest Labs, 2015).

Other sources of bias exist, including weather extremes or energy price changes (or a whole host of energy-behavior influencing factors that will not be elaborated here[[2]](#footnote-2)), and in some studies these are taken into account while in others they are not controlled for to the same extent. Still, these estimates for savings are necessary to calculate the benefits of smart thermostat adoption in the model, and they are at this point the best estimates available for determining the impact of smart thermostat technologies.

It is important to note that even smart thermostats depend on occupant behavior to achieve savings, in part because savings calculations require a before-and-after comparison (or consideration of how the occupant would otherwise have behaved). If smart thermostat savings estimates assume that previous household occupants operated mechanical thermostats with only constant settings, then the actual savings will disappoint because most individuals who purchase a smart thermostat, especially in the early-adopter phase, were likely already using their conventional thermostat efficiently. Instead of making explicit assumptions about occupant behavior in order to calculate smart thermostat performance, this report instead relies on reported data from the industry and from independent studies. Model limitations will be discussed more fully in *Section 2.8*.

According to Ford et al., evidence for energy savings associated with HEMS control capabilities is growing, especially for smart thermostats, but it is still very sparse and much remains to be investigated on the net energy impact of smart home technologies with HEM capabilities. This is so for technical potential and realistic potential considering consumer behavior (Ford et al., 2017).

## Adoption Path

### Current Adoption

Early adoption of smart thermostats has been primarily based in the US with some growth in Europe as well. According to market research group Berg Insight, the number of homes with a smart thermostat globally was 3.2 million in 2014—of which 2.5 million were in the US and 0.7 million in the EU—and reached 5.8 million in 2015 (Berg Insight, 2016a). More recent data suggest that the adoption has grown to 37 million homes in 2018 (22 million in US and Canada, 14.5 million in the EU). There are several reasons why adoption has primarily been based in these regions. First there is a relatively large existing stock of conventional thermostats in these regions (EIA, 2009), so there exist more opportunities for current thermostat owners to replace their old technologies with smart thermostats. Second, there is also a large residential building stock in these regions that has both central heating and/or cooling in addition to broadband Internet access, which are two drivers of adoption. Third, early reports of savings from smart thermostat installation have been promising, which can help justify the upfront cost of purchasing a smart thermostat. Nest, for instance, suggests that households that install a smart thermostat can save, on average, $131 to $145 per year on thermal energy costs, which means the thermostat can pay for itself[[3]](#footnote-3) in less than two years (Nest Labs, 2015). Finally, regulations in some parts of the US, such as the state of California, have helped grow the smart thermostat market by mandating the use of energy management devices that are enabled for two-way, automated use (St. John, 2014). In other parts of the US, utilities have provided rebates and other incentive programs to customers who purchase a smart thermostat. In North America and Europe, the smart thermostats market is growing rapidly. In other parts of the world, smart thermostats remain a relatively untapped market, although adoption could increase in the future as more homes get access to broadband Internet and the costs for smart thermostats fall.

### Trends to Accelerate Adoption

The adoption of Smart Thermostats will be accelerated by several trends; the following trends are presented in decreasing level of relevance.

#### The Rise of Smart Buildings and the Home IoT

The first trend that will increase the adoption of smart thermostats is the growing demand for smart building systems, and smart homes in particular. Consumer Internet of Things (IoT) devices have drawn the most attention, but according to a research report from the Deloitte Center for Financial Services, “it is enterprise-level adoption of the technology that will likely have the bigger impact on [the Commercial Real Estate (CRE)] industry” (Kejriwal & Mahajan, 2016). The report argues that the CRE industry is positioned to implement IoT technologies within commercial BMS in order to enhance both building performance and user experience. In 2018, the IoT market was generating $200 billion in revenue, a number expected to triple in the next 10 years (Downes, 2018).

The growth of other “smart” devices and the increasing prominence of the “smart home” concept, which will aid in the growth of the smart thermostat market by integrating these with other growing “Internet of Things” markets. This trend will likely increase the awareness and perceived usefulness of smart thermostats, thereby helping to accelerate adoption.

#### Increasing Cost of Energy

Consumers in Western Europe and California, for example, face higher electricity and gas prices than in some other regions, and adoption has been rapid in both. Because the upfront costs of smart thermostats are an obstacle for many households, as energy prices increase, the increased savings from smart thermostat installation may encourage adoption in markets that have not yet seen much growth. Additionally, macroeconomic trends both regionally and globally will likely play a role in the future adoption of smart thermostats. In fact, the model takes into account macroeconomic trends for the purpose of modeling both the total addressable market for smart thermostats as well as smart thermostat adoption.

#### Increasing Value of Data Collected by Smart Thermostats as Part of The Home IoT

As most devices connected to the IoT, HEM devices such as smart thermostats can collectively gather relevant data on home energy management and occupant behavior that in turn can generate important benefits. For instance, Muth argues that more than energy usage adjustments, smart thermostats can enable hydraulic balance, a task that can save between 10 to 30% energy and that is rarely performed by home owners (Muth, 2017). In this study, hydraulic balancing is performed using an algorithm that monitors the actual balance and adjusts inputs to achieve an adequate balance. The required data are gathered from smart home devices with the capability to run the software. (Muth, 2017).

#### The Rise of Smart Thermostats for Demand Response in Bring Your Own Thermostat and Bring Your Own Things Programs

For many years, utilities have been administering thermostat-based programs to face demand response (DR)[[4]](#footnote-4) events- also known as peak rates events. However, in the last couple of years these programs have shifted to the “bring your own” model in which consumers began to independently purchase their own smart thermostats capable of receiving DR control signals (PLMA, 2018).

Efforts among energy companies to deploy smart thermostats among their residential customers for the purposes of better managing demand-side energy consumption, thus reducing energy-related GHG emissions are increasing and thus the awareness of and willingness to manage personal energy consumption in the residential market. Innovative marketing efforts among technology companies to truly “disrupt” the thermostat market may spur rapid growth.[[5]](#footnote-5) In 2016, there were only about 50,000 homeowners enrolled in bring your own thermostat (BYOT) programs in the US, nevertheless, there was high expectation that smart thermostats can impact energy efficiency and change the residential DR landscape (Ariza, 2016). DR contribute to reduction in energy-related costs for building occupants rather than energy savings (Kamel Ehsan & Memari Ali M., 2019). Ford et al. argue that adding smart thermostat technologies to intelligent learning software can deliver greater savings. EcoFactor claims that their service saves 10-15% more energy than programmable communicating thermostats, and Nest claims that their portal has helped achieve a 55% reduction in energy use during peak times (Ford et al., 2017).

#### Increasing Integration of Smart Thermostats in DER Portfolios

The proliferation of distributed energy resource (DER) programs is a dominant topic among executives at electric utilities according to PLMA. DER[[6]](#footnote-6) is driven by technology evolution, environmental regulations and customer choice. These are inevitably pushing the electricity industry toward a more distributed system such as direct install DR assets, solar, energy storage and electric vehicles (EVs). 84 percent of utilities predict that DER will also increase as part of their overall fuel mix (PLMA, 2018).

Increasing Interest In Home Security

According to Bugeja et al, the smart home market is anticipated to double in the US with family safety being the greatest motivator (Bugeja, Jacobsson, & Davidsson, 2016).

#### Aging Global Population

The application of smart thermostats in assisting an ever-increasing elder population is commonly discussed in the literature. Machine to machine applications such as home IoT will help seniors age in their own homes (Downes, 2018). Demiris et al. identified environmental sensors for comfort and energy efficiency (e.g., smart thermostats) as the smart technology that offers aids of various types for elder groups (Demiris & Hensel, 2008).

Older thermostats are more likely to be replaced when newer options provide more convenience, such as the ability to change temperatures and improve occupant comfort. Global smart thermostat adoption might occur in several different ways based on regional economic differences. This will likely be the case in the US, Europe, and, to a growing extent, in Asia Pacific. Market saturation of smart thermostats and declining prices will likely cause most households to replace older manual thermostats with smart thermostats, especially when older versions reach the end of their lifetimes.

#### Middle Class Growth

Increases in the middle class and economic growth will likely be the primary drivers for smart thermostat adoption in regions such as Latin America, Sub-Saharan Africa, and Eastern Europe as these will enable homes that previously would not be suited for a smart thermostat to have the characteristics necessary for adoption. Especially because of the projected growth in energy demand in these regions (Ürge-Vorsatz et al., 2015), smart thermostats may play an increasing role in regional and national energy efficiency plans. These developments could prime the smart thermostat market for significant growth in regions that have yet to see much activity.

### Barriers to Adoption

There are also several market inhibitors that could prevent or stall the growth of smart thermostats, and these include the following.

#### Consumer Confusion About Technology and Benefits

Navigant reported in 2014 that “the general public may not be perceptive of how regional climate and energy market differences will yield different levels of savings from the same device and platform. This is a potential source for customer dissatisfaction, poor publicity, and churn” (Navigant Research, 2014). Recent studies examining the real-world acceptance of IoT systems such as smart thermostats show that accuracy and customer interface and mismatch with customer expectation decreased adoption (Malik et al., 2018) Furthermore, consumer surveys over the last few years, reveal slower-than-expected adoption of IoT solutions due to stories of hacked baby monitors and connected toys, video cameras taken over by botnets and fitness trackers revealing the locations of secured military installations, have generated skepticism that IoT applications are indeed ready for mass markets (Downes, 2018). Recent reviews on the state of the art of smart home technologies further indicate that smart home blurs the role of the user and its boundaries, for instance, it is still arguable if it is the user who uses an electricity system, or vice versa or if an appliance- such as a smart thermostat -is there for the person who bought it or for the remote operator that switches it on and off in accordance with system conditions? (Darby, 2018). According to several studies, one solution to system complexity is to manufacture devices that are ready for automation and pre-programmed with default settings such as smart thermostats with temperature and/or schedule pre-sets, or default options (Sintov & Schultz, 2017).

#### Lack of Clear User Value Proposition

Hoffman and Novak argue that for consumer IoT adoption to expand beyond the niche segments of technologically sophisticated upscale consumers marketers must do a better job of understanding the actual value of smart products. Smart speakers like the Amazon Echo and the Google Home are now in 20% of homes with Wi-Fi in the United States. However, many consumers are struggling to find the value in replacing their current light bulbs, switches and monitoring devices with more expensive versions (Hoffman & Novak, 2018).

#### Achieving Full Value is Challenging

ST’s require more capabilities to analyze household energetics and achieve their full efficiency potential. According to Van de Ham et al., giving the thermostats the intelligence needed- by both monitoring devices and providing analysis methods for interpreting the data- may provide the basis for comparison with other users and tailored advice about measures to reduce energy usage (van der Ham et al., 2016). Kamel & Memari (2019) indicate studies showing that using smart thermostats can save up to 30% of energy-related costs and that systems with advanced data-processing capabilities can save 40%. Advanced data-processing capabilities include the ability to perform more complicated operations on the data acquired from sensors by using different tools, such as optimization, simulation, Building Information Modeling (BIM), and Artificial Neural Networks learning (Kamel & Memari, 2019).

### Adoption Potential

More than 20 billion IoT devices will be connected by 2020 (Gartner, 2017) and this will include a mass adoption of smart thermostats. In North America, by 2021, more than half of all homes will become smart homes (Berg Insight, 2017) while in 2019 it is expected that 25 million homes install a smart thermostat (Statista, 2016) in (Dorai, Houshmand, & Baggili, 2018).

According to a recent industry report by the Peak Load Management Alliance (PLMA) by 2027, smart thermostats will become the norm for North American customers due to the attractive customer benefits, BYOT and DER programs and connections among all these which can compound the attractiveness and growth. They expect that products and features will continue to improve and attract new customer segments and that technology integration and marketing will reduce the barriers to adoption, further accelerating market penetration (PLMA, 2018).

Several different market research groups have released projections for smart thermostat adoption over the next five to ten years. A 2014 report from Navigant Research predicted that 32 million smart thermostats would be installed worldwide by 2020, with shipments expected to reach nearly 20 million by 2023 (Navigant Research, 2014). Navigant also predicted that the smart thermostat market could be worth nearly $1.4 billion in annual revenue by 2020 and $2.3 billion in 2023, though this includes not only smart thermostat devices but also associated software and services.[[7]](#footnote-7) Navigant sees favorable conditions in terms of demographics, climate, policy, and broadband penetration in certain parts of the Asia Pacific region, so it projects future adoption in this region along with the US and EU, but other regions, including Latin America and the Middle East and Africa, have yet to see the emergence of a smart thermostat market.

Berg Insight forecasts that 46.2 million homes in North America and 44.9 million homes in Europe will be smart by 2020, and by 2020 it expects that the total number of households with a smart system in Europe and North America to be 91 million (Berg Insight, 2016b). The sixth edition of the same report forecasted that between 2017 and 2022, the number of households that adopt smart home systems was forecasted to grow at a compound annual growth rate (CAGR) of 23.1 percent in North America, resulting in 63.0 million smart homes. It also expected growth at a compound annual growth rate (CAGR) of 30.2 percent in Europe resulting in 84.0 million smart homes by 2022. This sums to a total of 147 million homes smart by 2022 in Europe and North America (Berg Insight, 2018). Several additional market research groups, including Grand View Research and IoT Analytics also project total numbers of households with a smart thermostat, but these projections are similar to the reports from Navigant and Berg Insight.

## Advantages and Disadvantages of Smart Thermostats

### Similar Solutions

The HEM market is evolving rapidly in the last years, since many different types of wireless-enabled “smart” products keep emerging. Snell identified the following technologies within the HEM market: smart appliances, thermostats, and plugs, connected lightbulbs, and home energy-use displays (EUDs) (Snell, 2016). All of these devices represent specific functions within the realm of HEM, however when effectively combined they collectively have the potential to provide relevant, granular, and actionable energy-use information to prompt behavioral energy savings, directly reduce energy consumption. A comparison of some of these technologies is made in Table 1.1.

### Arguments for Adoption

Smart thermostats represent an alternative to conventional thermostats and enhance the Total Cost of home Ownership (TCO) by reducing energy consumption and enhancing indoor air quality. Although in theory programmable thermostats can offer similar energy savings benefits to smart thermostats, in practice they may not reduce energy consumption and can even lead to increases. Because smart thermostats are designed with the intent of avoiding this particular energy efficiency pitfall, instead learning user behavior and providing a much more intuitive means of managing household thermal energy demand, they offer a more efficient way to heat and cool a home.

Consequentially, the primary advantage of smart thermostat adoption is the reduction in energy consumption for thermal purposes, which leads to household savings and reduced GHG emissions. Given the volatility of electricity and fuel prices, as well as the need for the residential building sector to significantly reduce its consumption in order to reduce emissions, the sustained reductions that smart thermostats can provide are an important advantage of the technology. It has been shown that homes with technologies that enable an automatic reduction in electricity use have achieved the highest energy savings (Newsham & Bowker, 2010).

In addition to reducing emissions from thermal energy demand, smart thermostats provide some cascading benefits such as improved occupant comfort. It has been found that the strongest influencing factor on the long-term thermal comfort is the indoor set point temperature (more impactful than thermal mass, setback temperature, and air exchange rate) (Schieweck et al., 2018). Surveys of Nest customers have shown that 66 percent of participants in smart thermostat pilot programs report feeling more comfortable after installing a Nest Learning Thermostat (Nest Labs, 2015). Other benefits, such as improved ability to manage home energy demand and enhanced feedback on energy behaviors, which suggests ways to increase energy conservation, are reasons that smart thermostats are undergoing a wave of such popularity among residential customers in recent years.

### Additional Burdens

There are some other less publicized issues surrounding Smart Thermostat adoption. These are discussed below.

#### Household Needs are High

Smart thermostats require several household characteristics that conventional thermostats do not, and this ties smart thermostat adoption to other trends that may in some places inhibit adoption. This is especially the case in developing countries, which are faced with similar if not more serious problems related to energy management in the residential sector. Smart thermostat adoption has not yet occurred in many developing regions, and this could prove to be a significant disadvantage of the technology unless efforts are undertaken to deploy smart thermostats (or the other infrastructural components necessary to enable them) in markets where there has not been much adoption. The high upfront cost of smart thermostats will present another challenge for increasing adoption in these regions.

Privacy Concerns on Smart Thermostats Data Usage

As smart thermostats are becoming more connected and begin to share large amounts of data with other devices in the realm of the IoT, many questions about homeowner’s privacy regarding external entities who storage, track, analyze and regulate this data are starting to arise (Bugeja et al., 2016). The rush to market by developers of consumer IoT products and services has been accompanied by shortcuts in design, particularly in information security, usability and branding (Downes, 2018). A recent study found that smart home IoT users are unaware of privacy risks from inference algorithms operating on data from non-audio/visual devices (Zheng, Apthorpe, Chetty, & Feamster, 2018).

#### Split Incentives and Building Ownership

A disadvantage that has not been discussed but is common to both smart thermostats and other energy efficiency technologies, caused by the lack of knowledge necessary to make decisions or upgrades. In the EU, around 70 percent of the population lives in privately owned residential buildings, but owners often do not invest in cost-efficient renovations because they lack the knowledge necessary to make informed decisions or face split incentives (in the case of multi-apartment buildings) (European Commission, 2016) . Split incentives are especially an issue in privately owned rental buildings where owners have little incentive to invest in energy efficiency upgrades when the tenant pays the energy bill. In public owned buildings, such as social housing, the shortage of funds is the biggest barrier to investments in energy efficiency.

Table 1.1 Technology Comparison

|  | **Installation Costs** | **Operations & Maintenance Costs** | **Ability to Save Energy** |
| --- | --- | --- | --- |
| Programable Thermostats | Low | Low | High |
| Smart Thermostats | Low | Low | High |
| Smart Plugs | Medium | Low | High |
| Home energy-use displays (EUDs) | Low | Medium | Medium |

# Methodology

## Introduction

Project Drawdown’s models are developed in Microsoft Excel using standard templates that allow easier integration since integration is critical to the bottom-up approach used. The template used for this solution was the Reduction and Replacement Solutions (RRS) which accounts for reductions in energy consumption and emissions generation for a solution relative to a conventional technology. These technologies are assumed to compete in markets to supply the final functional demand which is exogenous to the model, but may be shared across several solution models. The adoption and markets are therefore defined in terms of functional units, and for investment costing, adoptions are also converted to implementation units. The adoptions of both conventional and solution were projected for each of several scenarios from 2020 to 2060 (from a base year of 2014) and the comparison of these scenarios (for the 2020-2050 segment[[8]](#footnote-8)) is what constituted the results.

The model constructed projects the adoption of smart thermostats globally over 30+ years and calculates the climate and financial impacts of household smart thermostat adoption during this period. The implementation unit is the same as the functional unit to provide most the flexibility in adoption measurement, in this case *million households*. The agency perspective used is that of building owners or households, who are assumed to be the key decision makers on installing smart thermostats. In order to determine the costs and benefits of rapid smart thermostat adoption, both a set of Project Drawdown Scenarios (PDS) and a Reference (REF) global adoption pathway for smart thermostats are developed.

The model thus projects the total financial costs and benefits of optimistically plausible adoption cases for smart thermostats, as well as the contribution this adoption can make to annual and cumulative emissions reduction.

This section discusses the methodology for constructing global TAM and adoption scenarios for the residential smart thermostat market and explains how the total costs and savings as well as the emissions reduction potential of PDS adoption have been calculated. It explains the critical assumptions necessary for modeling adoption of this technology globally and concludes with a discussion of model limitations and areas needing further development.

## Data Sources

Data for the model come from a variety of sources, including from peer-reviewed publications and from institutional and market research reports. For many of the variable inputs, a meta-analysis of existing literature is conducted to create low, high, and mean estimates. For each variable, a sensitivity analysis is developed of, on average, seven data points reported in the literature and in some cases as many as 20. This allows us to calculate robust and reliable inputs for the financial and climate analyses that represent both optimistic and conservative estimates for the future costs and benefits of adopting this solution.

### TAM and Adoption Data

In constructing the TAM for smart thermostats, several demographic indicators are used that enable creation of customized prognostications for functional demand for this solution. As described in the next section, TAM for smart thermostats is based on several variables, including population, number of households, percentages of households globally with Internet access, and wealth indicators, namely GDP/capita (PPP). Projections for population and total number of households globally are obtained from the United Nations (2011), and ICT indicators are obtained from the International Telecommunication Union (ITU) World Telecommunication/ICT Indicators database (ITU, 2016).

Adoption data is based primarily on recent market research reports from groups such as Berg Insight (2016), Bloomberg (Stubbe, 2018), and others. Because of limitations to the availability of adoption data, especially given that most of the market research projections for smart thermostat adoption do not extend beyond 2025, custom adoption scenarios were generated.

### Financial Analysis Data

Recent cost data for a variety of smart thermostat products available on the market, including those which comprise the majority of the existing market,[[9]](#footnote-9) were obtained directly from industry vendors, while cost data for conventional thermostats, including both mechanical (non-programmable) and programmable thermostats, were obtained from online retailers. Cost data comes from sources referencing markets primarily in North America and Europe, and while this represents a limitation to the model and cost projections, most adoption is projected to take place in these markets, which is why these sources are used.

Operating costs, which are assumed in the model to be the total household expenditure on space heating and cooling, are calculated using data for average energy consumption per household for these activities in both the PDS and REF scenarios. Given that household energy consumption for space heating and cooling varies significantly around the world, the methodology creates a weighted average value for space heating and cooling consumption in the countries and regions in which the majority of adoption is prognosticated. The sources used for space heating and cooling estimates are US EIA’s 2009 Residential Energy Consumption Survey (RECS) (2009), the European Commission *Institute for Energy and Transport*’s 2012 report (Pardo et al., 2012), and an analysis of the 2012 China Residential Energy Consumption Survey (C-RECS) (Wei et al., 2016).

In order to calculate operating costs from household thermal energy consumption, the model uses a global weighted average residential electricity price based on historical price data from several countries normalized to 2014 USD. For fuel prices, the model uses an average price based on historical natural gas spot prices from 2007-2018 several countries from the IEA Energy Prices (2016, 2019) publications.

Several additional variables were necessary for calculating the capital and operating costs for smart thermostat adoption. These variables include lifetime capacity and learning rates for both conventional and smart thermostats, as well as estimates for the percentage share of the existing conventional thermostat market between programmable and non-programmable or mechanical thermostats. Several lifetime estimates for both programmable and non-programmable thermostats were obtained from the International Association of Certified Home Inspectors (InterNACHI, n.d.) and two environmental and engineering consultancies (CLEAResult, 2015; GDS Associates, Inc, 2007). The methodology for calculating learning rates for smart thermostats is explained in the next section, and the primary data sources for this calculation are from a meta-analysis of several different residential energy demand technologies conducted by Weiss, Junginger, Patel, & Blok (2010). Finally, data for the percentage breakdown between programmable and non-programmable thermostats was obtained from EIA (2009).

### Climate Analysis Data

The climate analysis contained in the smart thermostat model uses many of the same variables and data sources that are contained in the financial analysis, including the values for annual electricity and fuel consumption for space heating and cooling. In order to calculate key results, such as maximum annual emissions reductions and total emissions reductions, as well as the rate of change in approximate PPM CO2-eq, the model uses reported emissions factors for both electricity and fuel. Emissions factors for electricity generation are derived from the projected energy generation mix and direct/indirect emissions factors by generation type taken from the IPCC AR5 Model Database, AMPERE3-MESSAGE Base and 450 scenarios. Fuel emissions factors are calculated using the methodology recommended in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Volume 2, Annex 1.

## Total Addressable Market

The first step is to model a global total addressable market (TAM) for number of households that could purchase and install a smart thermostat. Adoption of smart thermostats depends on the total functional demand for smart thermostats or TAM. Because the REF scenario is defined as a fixed percentage of TAM, as determined by the percentage of adoption in the model’s base year, it is necessary to calculate the total market size for households that could install a smart thermostat. There were several ways to calculate TAM in this model. One of these ways, common to several energy demand model analyses,[[10]](#footnote-10) is to model the global and regional increase in residential building space (in m2) and use energy consumption estimates based on global and regional values for consumption per m2 of residential floor space. Modeling the total market for smart thermostats using this approach presented several problems. First, estimates for adoption of smart thermostats are not projected in this unit, so it would have been difficult to get reliable estimates for number of smart thermostats installed per m2 of residential building space. Second, as was discussed previously, the climate and financial benefits of smart thermostat adoption rely on reductions in thermal energy consumption at the household level, and these reductions can only be realistically expected if a smart thermostat is being used as intended, meaning with an internet connection so as to enable many of the features of smart thermostats that lead to savings. The difficulties of projecting the number of smart thermostats per m2 of residential building space with Internet connectivity were too complex, so instead TAM is defined as the number of households (in millions) with Internet access at home, while acknowledging that some utilities actually have other ways of connecting to homes without internet, via their own networks.

The presence of central heating and cooling equipment and the existing market for programmable and mechanical thermostats are other factors that will determine the total market size for smart thermostats, and while these are not used as the specific unit of analysis for TAM, they do inform the estimates of the total market size for smart thermostats. For instance, in the US, 85 percent of households have central heating equipment and a central thermostat, and 60 percent have central cooling equipment (EIA, 2009)In the EU, central heating equipment in individual countries varies significantly as, for example, countries such as Portugal and Spain have very low percentages of residential buildings with central heating, but northern countries, such as most Scandinavian countries and the UK, have central heating in more than 90 percent of the residential building stock (Boverket, 2005, p. 40). On average in the early 2000s, close to 70 percent of residential buildings in the EU had central heating.

Data on rates of household Internet access were obtained from the International Telecommunications Union (ITU), which is the UN’s specialized agency for ICTs, and these rates were often found to be lower than the rates for central heating and cooling in the regions where most adoption of smart thermostats will take place, so this is why it was decided to use Internet access rather than central heating and cooling estimates to define the TAM (ITU, 2016). This decision may result in a more conservative estimate for the total market size, but because adoption of smart thermostats over the period of analysis is much less than the TAM, this decision will not impact the climate and financial analyses of PDS adoption in a significant way.

Using reported estimates for the total number of households globally from the UN Centre for Human Settlements report (2001) and estimates for percentage of households globally with Internet access at home from the ITU (2016), the total number of Internet-connected households from 2005-2016 is calculated. Data for projected rates of global Internet connectivity were not available beyond 2016, so in order to prognosticate TAM for the full period of analysis, a customized approach that calculates TAM based on projected values for global GDP/capita from the AMPERE3-MESSAGE model is used.

In order to model TAM beyond 2016, a logarithmic regression model is used, which estimates the relationship between total number of households with Internet access and global GDP/capita values. TAM is calculated using Equation 1:

|  |  |
| --- | --- |
|  | Equation 1 |

where:

* is the total number of households (millions) with Internet access at home in year .
* *xi* is the global GDP/capita at year *i*.
* is the coefficient calculated using the logarithmic regression model.
* is a constant.

Using this equation along with historical global GDP/capita values and calculated values for number of Internet-connected households, future adoption as a function of economic growth (in GDP/capita) is projected. The analysis uses three different GDP/capita scenarios from AMPERE3-MESSAGE (Base, 550, and 450 scenarios) to generate three separate TAM prognostications. Figure 2.1 shows the correlation and resulting logarithmic curve between household Internet connectivity and GDP/capita (using the AMPERE3 – Base Scenario).

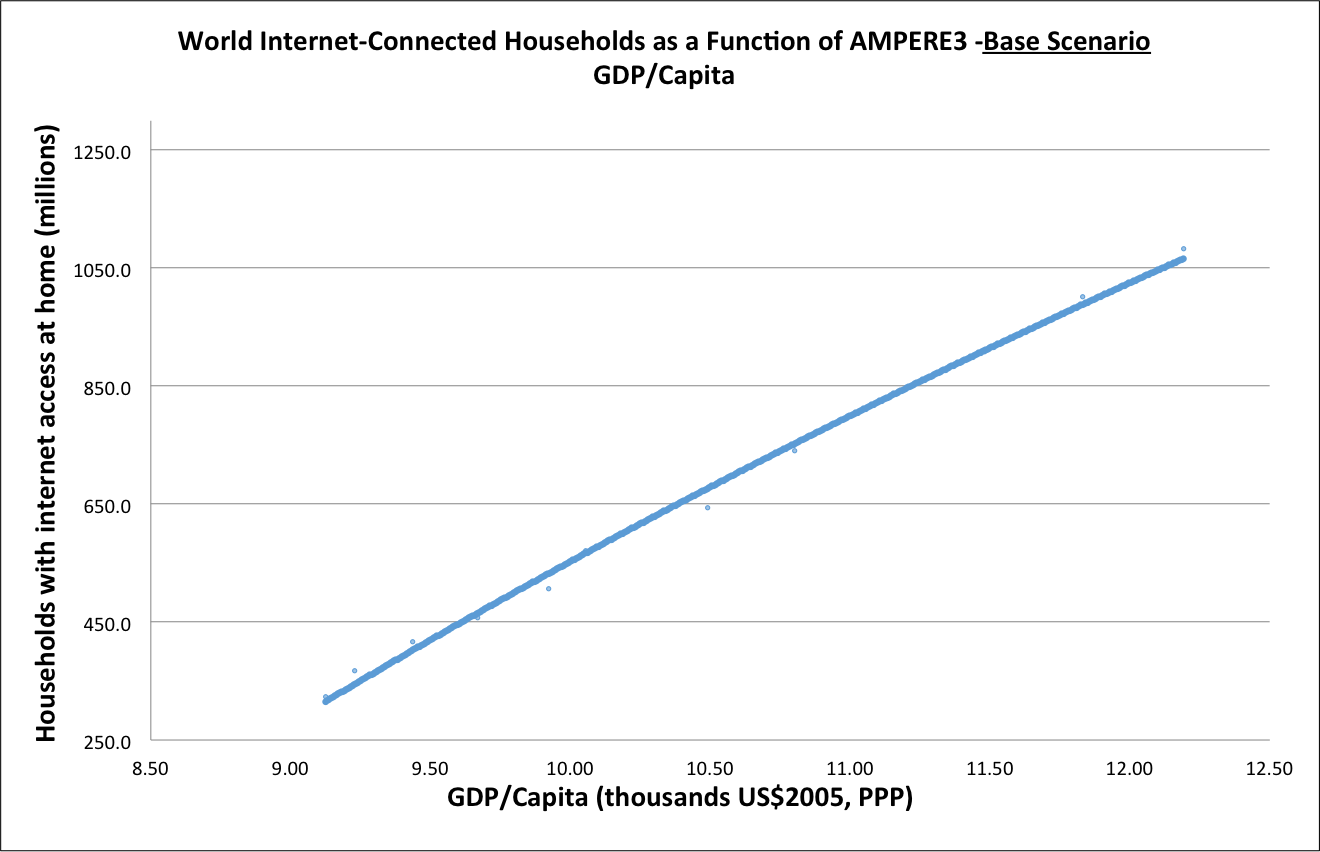


Figure 2.1 Logarithmic regression to calculate correlation between TAM and global GDP/capita

using the AMPERE3 Base Scenario. R2 = 0.99548

Using the three TAM scenarios generated with the AMPERE3-MESSAGE Base, 550, and 450 projections for GDP/capita, a global TAM forecast over the modeling period is calculated, selecting a “low growth” curve for global TAM. It is estimated in all scenarios that by 2050, around 2.5 billion households will have the equipment necessary to achieve energy savings by installing a smart thermostat. This represents over 60 percent of the global stock of households, based on projections of total households from the UN (2001). Data for regional analysis of TAM was available, but given that adoption data was not (see *Section 2.2*), this model does not construct regional TAM forecasts in this analysis.

## Adoption Scenarios

The rate of adoption of smart thermostats will determine the magnitude of both their climate and financial impacts. The adoption rate will also influence the cost of smart thermostats, as an increase in market demand for new technologies tends to lead to competition, new market entrants, and a decline in costs over time. Because smart thermostats are a relatively new technology, very few forecasts for adoption are reported in the literature. Market research reports provide some estimates for smart thermostat adoption, but these are not always reliable sources and do not project further than the next 10-15 years. For this reason, a customized approach to modeling adoption of smart thermostats was undertaken, both for the purpose of generating several different adoption scenarios as well as projecting beyond the next 10-15 years. In this report, adoption is defined as the total number of households (in millions) with a smart thermostat installed.[[11]](#footnote-11)

Two different types of adoption scenarios were developed: a Reference (REF) Case which was considered the baseline, where not much changes in the world, and a set of Project Drawdown Scenarios (PDS) with varying levels of ambitious adoption of the solution. Published results show the comparison of one PDS to the REF, and therefore focus on the change to the world relative to a baseline.

### Reference Case / Current Adoption

In order to determine the costs and benefits of rapid smart thermostat adoption, both a set of Project Drawdown Scenarios (PDS) and Reference (REF) global adoption pathway for smart thermostats are developed. The second step is to create a REF scenario by assuming future adoption of smart thermostats remains fixed at the current base-year (2014) percentage of TAM, which in this model is set at 4 percent., or about 37 million households that have installed a smart thermostat.

### Project Drawdown Scenarios

The next step is to construct the PDS scenario, drawing on existing adoption projections for smart thermostats over the next five years and extrapolating future adoption. The model contains both financial and climate analyses in order to determine the global impacts of adoption in the PDS scenario compared to the REF scenario. PDS adoption in this model uses polynomial or Bass diffusion model curves to project the growth of the smart thermostat market over the modeling period using historical estimates from various sources

#### Plausible Scenario

The Drawdown Scenario extends the near term projections of Berg Insight (Berg Insight, 2016a,b) to the full analysis period using a 2nd- degree polynomial curve fit. The *Smart Homes and Home Automation – 4th Edition* report projects that 51.1 million smart thermostats will be installed by 2020, and using these values, interpolation and extrapolation was used to calculate adoption for missing years.

A 2nd-degree polynomial regression model is used, which estimates the relationship between smart thermostat adoption and year. Adoption is calculated using Equation 2:

|  |  |
| --- | --- |
|  | Equation 2 |

where:

* is the total number of households with a smart thermostat installed in year .
* *xi* is the year *i*.
* - are coefficients calculated using polynomial regression.

Using this equation along allows us to project future adoption. The analysis assumes that the majority of adoption will take place in North America, Europe, and Asia Pacific, as was previously discussed in *Section 2.2*.

#### Drawdown Scenario

The Drawdown Scenario extends the near term projections of Bloomberg (Stubbe, 2018) to the full analysis period using a 2nd degree polynomial curve fit.

#### Optimum Scenario

The Optimum Scenario uses a Bass Diffusion S-Curve with Innovation Constant of 0.001678 and Imitation Constant of 0.2465. Model parameters were taken from literature with adjustments that correspond to Cellphone diffusion in Western Europe.

## Inputs

### Climate Inputs

In order to calculate the climate impacts of smart thermostat adoption in the PDS scenario, the total reduction in both electricity and fuel consumption for thermal energy uses per millions of households using smart thermostats is calculated. These energy consumption variables are discussed in the Technical Inputs section. Emissions factors for grid electricity and fuel are applied to calculate maximum annual emissions reduction, total emissions reduction, and the GHG concentration reduction equivalent. Emissions reductions are calculated using Equation 3:

|  |  |
| --- | --- |
|  | Equation 3 |

where:

* is the CO2-eq emissions reduction associated with the reduction in annual thermal energy consumption in the PDS scenario (when compared to the REF).
* is the reduction in electricity consumption for space heating and cooling in the PDS scenarios.
* is the emissions factor (in *t*CO2-eq per TWh) of grid electricity globally for each year of emissions reduction (values decline annually). These values are derived from the AMPERE-3 MESSAGE model. See values in Table 2.1.
* is the reduction in fuel consumption for space heating in the PDS scenario.
* is the fuel emissions factor for natural gas. This value is derived from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Volume 2, Annex 1. See values in Table 2.1.

Table 2.1 Climate Inputs

|  | **Units** | **Project Drawdown Data Set Range** | **Model Input** | **Data Points (#)** | **Sources (#)** |
| --- | --- | --- | --- | --- | --- |
| Global average REF Grid Emissions Factor | g CO2e/kWh | 503-593 | Depends on year. Starts at High Input in 2020 declines to Low Input in 2050 to represent the decarbonization of the grid in the reference. | 12 each year | 4 |
| Combined REF Space Heating & Cooling Fuel Emissions Factor | t CO2e/TJ of fuel | N/A | 87.04 | 8 including individual fuel emissions factors and shares | 1 |

Note: Project Drawdown data set range is defined by the low and high boundaries which are respectively 1 standard deviation below and above the mean of the collected data points[[12]](#footnote-12).

### Financial Inputs

In the PDS scenario for global smart thermostat adoption, both the capital costs and the operating costs in each year of analysis are modelled. The capital cost represents the total financial costs to a household for purchasing and installing a smart thermostat instead of a conventional thermostat. The model assumes smart thermostat installation does not add any additional cost, as many smart thermostats can be installed without professional assistance, and for those that do require professional assistance, the installation cost is assumed to be embedded in the total cost of the smart thermostat. Annual operating costs in both the REF and PDS scenarios are assumed to be the costs to the household for space heating and cooling. The model calculates annual operating costs by using the equations for energy savings discussed above, applying a total expenditure per TWh (in the case of electricity) and TJ (in the case of natural gas) to calculate annual savings (many energy consumption inputs are in the Technical Inputs section). Equation 4, Equation 5 and Equation 6 are used in the financial analysis:

|  |  |
| --- | --- |
|  | Equation 4 |

|  |  |
| --- | --- |
|  | Equation 5 |

|  |  |
| --- | --- |
|  | Equation 6 |

where:

* is the net spending avoided on space heating and cooling-related energy expenses by replacing conventional thermostats with smart thermostats.
* & are the total capital costs for purchasing conventional or smart thermostats to meet functional demand in the REF or PDS scenarios, respectively.
* are the total costs to households for space heating and cooling-related energy expenses with either a conventional thermostat (REF) or smart thermostat (PDS).
* is the consumption of electricity for space heating in the REF scenario.
* is the consumption of electricity for space cooling in the REF scenario.
* is the consumption of fuel for space heating in the REF scenario.
* is the consumption of electricity for space heating in the PDS scenario, which is calculated by applying an energy efficiency factor.
* is the consumption of electricity for space cooling in the PDS scenario, which is calculated by applying an energy efficiency factor.
* is the consumption of fuel for space heating in the PDS scenario, which is calculated by applying a fuel efficiency factor for space heating.
* is the global weighted average price for residential electricity. Values are in Table 2.2 and Table 2.3.
* is the global weighted average price for natural gas. Values are in Table 2.2 and Table 2.3.

The total capital cost for conventional thermostats, both programmable and non-programmable, is a weighted average of retail cost estimates for these types of thermostats, weighted by the share of each in the total US market.[[13]](#footnote-13) The total capital cost for smart thermostats is an average of 11 different smart thermostat models, retailing for between $125.00 and $350.00.

Given the relative infancy of the technology, historical prices could not be used to calculate a learning rate for smart thermostats. Instead, a sensitivity analysis of several different learning rate estimates for modular air conditioners was undertaken to determine an appropriate learning rate for smart thermostats. This particular energy demand technology was chosen because of the similarities it shares with thermostats—they are both used for temperature regulation in the home; they are both modular; and they have relatively comparable total costs.

Table 2.2andTable 2.3show the model inputs used to calculate the financial costs and savings annually for smart thermostat adoption. Because there are widely varying estimates for total reductions in space heating and cooling-related energy consumption for households with smart thermostats, a conservative approach was taken when selecting efficiency factors in order not to overestimate the total annual savings per household.

Table 2.2 Financial Inputs for Conventional Technologies

|  | **Units** | **Project Drawdown Data Set Range** | **Model Input** | **Data Points (#)** | **Sources (#)** |
| --- | --- | --- | --- | --- | --- |
| First costs (Conventional) | *US$2014/ household* | $19.75 – $57.10 | $38.42 | 17 | 1 |
| Variable Operation and Maintenance Costs (Conventional) | *US$2014/ household/year* | $739 | $739 | 1 | (based on other inputs) |

Table 2.3 Financial Inputs for Solution

|  | **Units** | **Project Drawdown Data Set Range** | **Model Input** | **Data Points (#)** | **Sources (#)** |
| --- | --- | --- | --- | --- | --- |
| First costs (Solution) | *US$2014/ household* | $96.00-$267.99 | $181.99 | 18 | 13 |
| Fixed Operation and Maintenance Costs (Solution) | *US$2014/ household/year* | $660 - $672 | (depends on scenario) | 1 | (based on other inputs) |
| Learning Rate Factor (Solution) | % | 8-18% | 13% | 6 | 5 (based on Data for Air conditioning systems) |

### Technical Inputs

#### Energy Consumption

As was mentioned previously, it is challenging to account for the vast range of thermal energy consumption totals across different regions, as levels of consumption are directly related to variable factors, such as climate conditions, household characteristics and occupant behavior, technology and material availability, regional economic trends, and cultural elements, among others (IEA, 2016). In addition, the type of fuel used for space heating and cooling can vary significantly across countries. For instance, while electricity only accounts for around 10 percent of total energy consumed for space heating in the US (EIA, 2009), it makes up on average over 40 percent of total space heating-related energy consumption in the EU-27. Globally however, it’s still 10% (IEA, 2017).

In order to analyze the climate and financial impacts of smart thermostat adoption globally it was necessary to create weighted average values for electricity and fuel consumption from space heating and cooling. Because smart thermostat adoption is projected to take place primarily in three regional markets, those being North America, Europe, and Asia Pacific (Navigant Research, 2016), average electricity is used and fuel consumption values for these three regions and then weight these by the total share of households in each in 2014. Taking a bottom-up approach to calculating average energy consumption in these regions by estimating country totals for space heating and cooling was considered too complex for global-level analysis (in addition to the fact that data limitations in many countries prohibited reliable estimates for space heating and cooling), so instead, the model uses the US, EU-27, and Urban China as proxies for these three regions, primarily because reliable data was available and because these three represent a large share of the total number of households that will likely adopt smart thermostats over the period of analysis.

The model considers two primary fuel types for space heating and one for space cooling. For space heating, both electricity and natural gas are included, and for space cooling just electricity is considered. The authors acknowledge the limitations of this approach, given that other fuels, including propane, liquid petroleum gas (LPG), fuel oil, and kerosene, represent a significant proportion of energy used for space heating in many regions, but the decision to only include electricity and natural gas was made primarily to simplify the calculations necessary to model both climate and financial impacts of PDS adoption at a global scale. The rationale for this decision is elaborated in *Section 2.6*, and the limitations inherent in this approach are discussed in *Section 2.8*.

As electricity is used for both space heating and cooling, it was necessary to calculate average annual household electricity consumption for space heating and cooling separately in the US, EU-27, and Urban China. For each of these countries and regions, Equation 7 is used to determine the reductions in electricity consumption for space heating and cooling:

|  |  |
| --- | --- |
|  | Equation 7 |

where:

* is the reduction in electricity consumption for space heating and cooling in the PDS scenarios compared to the REF.
* is the consumption of electricity for space heating in the REF scenario.
* is the consumption of electricity for space cooling in the REF scenario.
* is the efficiency factor (or percentage reduction in consumption) for space cooling and heating in a household with a smart thermostat.

To calculate the reduction in fuel consumption for space heating, in this case reduction in consumption of natural gas, the Equation 8 is used:

|  |  |
| --- | --- |
|  | Equation 8 |

where:

* is the reduction in fuel consumption for space heating in the PDS scenario
* is the consumption of fuel for space heating in the REF scenario.
* is the fuel efficiency factor (or percentage reduction in consumption) for space heating for a household with a smart thermostat.

Using these equations, the total consumption of both electricity and fuel for space heating and cooling in the REF and PDS scenarios are calculated. With these values, estimated reductions in CO2-eq emissions globally over the modeling timeframe are projected. Table 2.4 below lists the model’s inputs for space cooling and heating consumption from both electricity and natural gas by country/region. Using the total numbers of households for each in 2014, a weighted average for each energy consumption value is used in the climate and financial analyses. The result is shown in Table 2.5.

Table 2.4 Climate and financial model inputs: consumption of energy for space heating and cooling.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Region** | **Space Cooling (TWh/million households)\*** | **Space Heating – Electric (TWh/million households** | **Space Heating – Natural Gas (TJ/million households)†** | **Number of households in 2014 (millions)** |
| USA | 1.64 | 1.05 | 35,487.40 | 114.80 |
| EU | 0.12 | 3.95 | 18,834.50 | 212.51 |
| China (urban) | 0.23 | 0.09 | 22,039.32 | 205.00 |

\* All space cooling is assumed to be electric.  
† All non-electric space heating is assumed to be from natural gas.  
Sources: EIA, 2009; Pardo et al., 2012; Wei et al., 2015.

#### Lifetime

The number of years of use was estimated as a simple average of the data collected. The data summary is shown in Table 2.5 and Table 2.6.

Table 2.5 Technical Inputs - Conventional Technologies

|  | **Units** | **Project Drawdown Data Set Range** | **Model Input** | **Data Points (#)** | **Sources (#)** |
| --- | --- | --- | --- | --- | --- |
| Lifetime Capacity | *years* | 6.2-41.3 | 23.75 | 2 | 2 |
| Electricity Consumed in Household with Conventional System – Space Heating | *TWh/ million Households* | 0.03-3.99 | 1.84 | 3 | 3 |
| Electricity Consumed in Household with Conventional System – Space Cooling | *TWh/ million Households* | 0.05-1.23 | 0.49 | 3 | 3 |
| Fuel Consumed in Household with Conventional System | *TJ/ million Households* | 15,870-31,448 | 23,659 | 3 | 3 |

Table 2.6 Technical Inputs - Solution

|  | **Units** | **Project Drawdown Data Set Range** | **Model Input** | **Data Points (#)** | **Sources (#)** |
| --- | --- | --- | --- | --- | --- |
| Lifetime Capacity | *years* | 10 | 10 | 1 | 1 |
| Electricity Efficiency Factor of Smart Thermostats | *percent* | 12.1-29.7 | (depends on scenario) | 6 | 5 |
| Fuel Efficiency Factor of Smart Thermostats | *percent* | 10.1-21.5 | (depends on scenario) | 7 | 5 |

## Assumptions

Six overarching assumptions have been made for Project Drawdown models to enable the development and integration of individual model solutions. These are that infrastructure required for solution is available and in-place, policies required are already in-place, no carbon price is modeled, all costs accrue at the level of agency modeled (household for Smart Thermostats), improvements in technology are not modeled, and that first costs may change according to learning. Full details of core assumptions and methodology will be available at [www.drawdown.org](http://www.drawdown.org). Beyond these core assumptions, there are other important assumptions made for the modeling of this specific solution. These are detailed below.

1. The TAM for smart thermostats is assumed to be the total number of households (millions) with broadband Internet access at home. While the presence of HVAC systems and Internet access are both necessary for achieving the household energy savings used in the analysis, rates of home Internet access are lower than rates for home central heating and cooling systems in the areas where the majority of adoption is projected (Boverket, 2005; EIA, 2009; Wei et al., 2016).
2. Adoption is assumed to be the total number of households (millions) with one smart thermostat. While some households do in fact have more than one smart thermostat, energy savings estimates based on reported values for single-smart thermostat homes are used and assume that variations in energy savings in households with more than one smart thermostat will be negligible (Nest Labs, 2015).
3. All energy consumed for space cooling purposes is assumed to be electric. While there are trace energy sources other than electricity used for space cooling in some residential markets, electricity is the energy source used for 94 percent of space cooling globally (IEA, 2017).
4. All non-electric (fuel) energy consumed for space heating purposes is assumed to be from natural gas. While other fuels such as distillate fuel oil, propane, LPG, and kerosene are also used for space heating purposes, the model assumes all of these fuels have the same price and emissions factor as natural gas. This assumption is made to simplify analysis of climate and financial impacts.[[14]](#footnote-14)
5. The amount of energy consumed as well as the breakdown of energy sources for both space heating and cooling are assumed constant annually.
6. Both electricity and natural gas prices are assumed constant in the model. This assumption is made due to the complexity of modeling variable energy costs globally during the period of analysis.
7. The first cost (or capital cost) of both conventional and smart thermostats assumes that the price of installation is either zero or is embedded in the cost of the product. In the US, the Nest Learning Thermostat can be installed by the purchaser in half an hour (Nest, 2016).
8. The learning rate for smart thermostats is equal to the mean estimate for modular air conditioner learning rates across several different studies (Weiss, Junginger, Patel, & Blok, 2010).
9. Indirect emissions for neither conventional nor smart thermostats are calculated or considered in this analysis. This assumption is made due to the lack of reliable data about the lifecycle emissions from thermostat manufacturing as well as the fact that indirect emissions vary considerably between regions.
10. The operating cost is defined as the cost to the household for energy consumed for space heating and cooling. In other words, the prices paid by households per TWh of electricity and TJ of natural gas represent the total costs and savings generated for smart thermostats.

## Integration

The complete Project Drawdown integration documentation (will be available at [www.drawdown.org](http://www.drawdown.org)) details how all solution models in each sector are integrated, and how sectors are integrated to form a complete system. Those general notes are excluded from this document but should be referenced for a complete understanding of the integration process. Only key elements of the integration process that are needed to understand how this solution fits into the entire system are described here.

Each solution in the Buildings and Cities Sector was modeled individually, and then integration was performed to ensure consistency across the sector and with the other sectors. These solutions require an integration analysis to avoid double counting, as they primarily relate to either reducing demand for space heating and cooling (for residential and/or commercial buildings), commercial lighting, cooking, or water heating. The integration process therefore was addressed through sequential adjustments to the efficiencies of the solutions in a prioritized sequence for each of space heating and cooling, lighting, cooking, and water heating (performed in four separate sequence chains). The prioritized sequence is fixed for all scenarios and is described in the Drawdown Building Sector Integration documentation.

For each solution in an integration sequence, the estimated impact of previous solutions on the emissions savings of the current solution is estimated and a reduction factor is applied. The factor is only applied to emissions and energy savings attributed to adoptions that overlap with previous solutions[[15]](#footnote-15), and for this adoptions are generally assumed independent. Solutions that start each integration sequence are therefore unaffected (unless they are affected by solutions in other sequences), and solutions that apply to different buildings (say commercial and residential) do not affect each other. The method of estimating overlap is based on the percent adoption of the higher priority solution applied to the area adopted in the lower priority solution. For the efficiency factor of this overlapping area only, the reduction factor is applied, it is scaled and used to update the results in the lower priority solution model.

The Smart Thermostats solution (of the space heating and cooling sequence) is assumed to interact with only other previous solutions that are modeled on Residential buildings: Insulation, Cool Roof, Green Roof, and HPS Glass. The adoptions of these solutions are converted to residential floor area and in any single year, each is assumed to overlap with Smart Thermostats in accordance with its adoption (assumed uniform and independent). The adoption overlap is the maximum overlap calculated from any one of those solutions in each year. The average overlap over 2020-2050 (81% - 96% depending on the scenario) is multiplied by the reduction factor assumed and then this result is used to adjust (reduce) the efficiency factors of the electricity and fuel for Smart Thermostats. Results in this report reflect the results of the modeling and integration process.

In addition to building sector integration, there was an integration process across the grid and electricity efficiency solutions (buildings, transport, materials etc.) which adjusted for the double counting. Double counting of emissions reduction was a factor of using the reference grid emissions factors for electricity-based solutions. As grid solutions (Utility-scale Solar PV and others) are adopted, the grid gets cleaner and the impact of efficiency solutions is reduced (where they reduce electricity demand) or increased (where they increase electricity demand[[16]](#footnote-16)). Grid solutions are adjusted to remove the double counting as described in the Project Drawdown integration documentation.

## Limitations/Further Development

Smart thermostats are a relatively new technology, and there remain a number of uncertainties around estimates for energy savings, market size and future growth, and the total global market for smart thermostats. This report attempts to model the adoption of smart thermostats and to calculate the climate and financial benefits of optimistically plausible adoptions. A number of assumptions are made in order to simplify the calculations needed to model global adoption, and while it is acknowledged that in many cases these assumptions do not reflect reality, they are necessary to make for the purposes of estimating the contribution smart thermostats can make to global emissions reductions. This section briefly explains some of the primary limitations to the modeling methodology and areas needing further development.

### TAM and Adoption

Both TAM and Adoption in the model are customized projections based on a number of factors, including numbers of households, rates of broadband Internet access, and projected global values for GDP/capita. Given that many of these variables are estimates in themselves, it is truly difficult to accurately project the total global market for smart thermostats. In addition, given that most of the adoption estimates for smart thermostats come from market research groups rather than industry-trusted agencies such as the IEA or EIA, there are limitations to how accurately adoption can be projected.

The analysis does not undertake regional-level modeling for TAM or Adoption but rather assumes that the majority of adoption will take place in the US, EU-27, and Asia Pacific (using urban China as a proxy). That these three markets will represent the global smart thermostat market over the modeling period is also assumed. These assumptions may affect the accuracy of projecting adoption in countries or regions that have not shown adoption historically, but that is not to say that these could not become emerging markets in the latter half of the modeling period. This is a possibility, especially as Internet access and centralized HVAC systems become ubiquitous in regional residential housing sectors.

### Climate and Financial Analyses

A significant limitation to the model is the consideration of only electricity and natural gas as the fuels used for space heating. While these do, in most countries, represent the majority of energy sources used for space heating, it is simply inaccurate to state that only electricity and natural gas are used for space heating. As explained above, this assumption was made in order to calculate energy savings and emissions reductions using a simple weighted average price for natural gas and electricity as well as a standard emissions factor for natural gas. In further iterations of this model, the ability to model the several different fuel types used is desirable, each with separate prices and fuel emissions factors. As it stands, this is certainly an important limitation to the model and one in need of further development.

Additionally, the analysis relies on the important assumption that energy consumption for space heating and cooling at the household level will remain constant throughout the period of analysis, but this is not likely to be the case. There is available data from modeled scenarios for different energy efficiency pathways (GBPN, & Central European University, 2012) that assume different rates of adoption for energy efficiency technologies, and the model could be refined by including some of these estimates for potential reductions in total energy consumption.

Finally, the model is forced to rely on available estimates from recent studies and reports about the projected energy savings from smart thermostat installation, but these reports (especially those from the smart thermostat industry) very clearly state that these are observations of smart thermostat performance rather than guaranteed savings. In the future, it is likely that more data on smart thermostat performance will be available, and the model could be updated with a more robust methodology for projecting total energy savings from adoption.

### Other Areas of Improvement

Two other areas where the analysis can be improved are in assessing the potential energy savings and related emissions reductions in the whole building sector rather than just the residential sector and including more detailed lifecycle analysis data in the model for the purposes of calculating indirect emissions and disposal costs of smart thermostats.

Regarding the former, it is true that the residential sector has seen the most adoption of smart thermostats thus far and will likely lead adoption globally for the foreseeable future, but there are also likely significant savings in the commercial sector that are not accounted for in this model. These may effective be captured in the Building Automation Systems modeling which provides a similar service to the commercial sector.

Regarding the latter, lifecycle analyses were not included because of data limitations, but if these are available in the future, they should be included.

# Results

Using the approach explained in the Methodology section, PDS scenarios are constructed in which smart thermostat adoption will increase from around 3.2 million households in 2014. The key results are shown below and discussed in the Discussion section.

## Adoption

Below are shown the world adoptions of the solution in some key years of analysis in functional units and percent for the three Project Drawdown scenarios.

Table 3.1 World Adoption of the Solution

| **Solution** | **Units** | **Base Year (2014)** | **World Adoption by 2050** | | |
| --- | --- | --- | --- | --- | --- |
| **Plausible** | **Drawdown** | **Optimum** |
| Smart Thermostat | *million households* | 37 | 1,453.4 | 1,589.21 | 2,499.93 |
| *(% market)* | 4.1 | 57.9 | 63.3 | 99.5 |

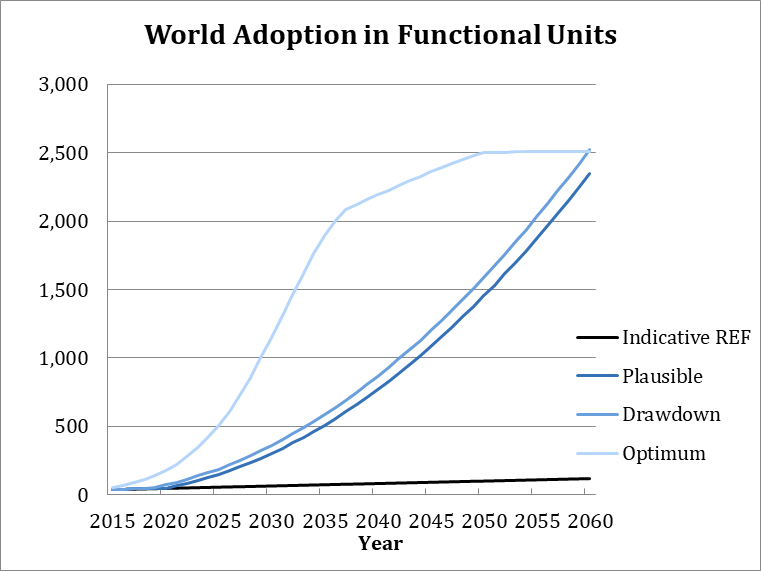


Figure 3.1 World Annual Adoption 2020-2050

## Climate Impacts

Below are the emissions results of the analysis for each scenario which include total emissions reduction, atmospheric concentration changes, and sequestration where relevant. For a detailed explanation of each result, please see the glossary (Section 6).

Due to the reduction of both electricity and fuel used for space heating and cooling, the climate impacts of PDS smart thermostat adoption are significant. From 2020-2050, as the rate of adoption grows, the emissions reduced also accelerate. Reductions in energy used for thermal purposes also produce significant savings for the global stock of households adopting smart thermostats compared to those using conventional thermostats. Table 3.2 presents the climate and financial results from the PDS scenarios.

Table 3.2 Climate Impacts

| **Scenario** | **Maximum Annual Emissions Reduction** | **Total Emissions Reduction** | **Emissions Reduction in 2030** | **Emissions Reduction in 2050** |
| --- | --- | --- | --- | --- |
| *(Gt CO2-eq/yr.)* | *Gt CO2-eq/yr. (2020-2050)* | (Gt CO2-eq/year) | *(Gt CO2-eq/year)* |
| ***Plausible*** | 0.46 | 5.56 | 0.08 | 0.46 |
| ***Drawdown*** | 0.46 | 5.87 | 0.10 | 0.46 |
| ***Optimum*** | 0.71 | 14.06 | 0.34 | 0.71 |

The solution was integrated with all other Project Drawdown solutions and may have different emissions results from the models. This is due to adjustments caused by interactions among solutions that limit full adoption (such as by feedstock or demand limits) or that limit the full benefit of some solutions (such as reduced individual solution impact when technologies are combined).

Table 3.3 Impacts on Atmospheric Concentrations of CO2-eq

| **Scenario** | **GHG Concentration Change in 2050** | **GHG Concentration Rate of Change in 2050** |
| --- | --- | --- |
| *PPM CO2-eq (2050)* | *PPM CO2-eq change from 2049-2050* |
| **Plausible** | 0.49 | 0.04 |
| **Drawdown** | 0.51 | 0.04 |
| **Optimum** | 1.17 | 0.05 |

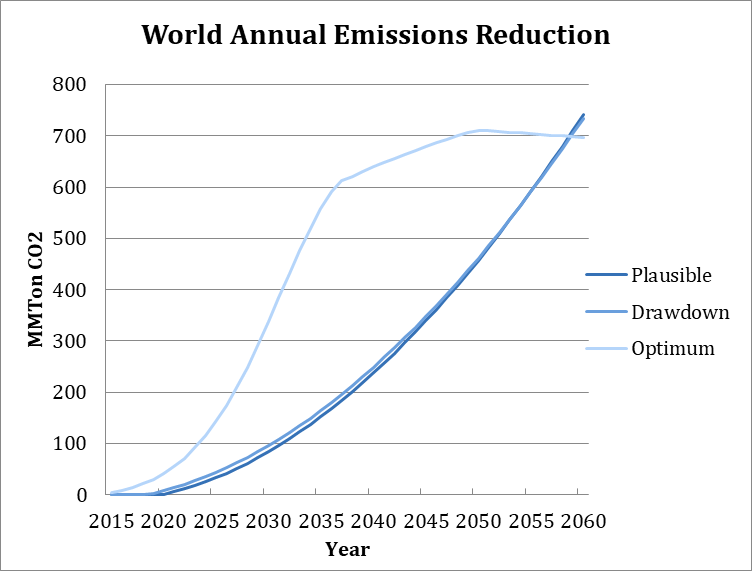


Figure 3.2 World AnnualGreenhouse Gas Emissions Reduction

## Financial Impacts

Below are the financial results of the analysis for each scenario. For a detailed explanation of each result, please see the glossary.

Table 3.4 Financial Impacts

| **Scenario** | **Cumulative First Cost** | **Marginal First Cost** | **Net Operating Savings** | **Lifetime Operating Savings** | **Lifetime Cashflow Savings NPV (of All Implementation Units)** |
| --- | --- | --- | --- | --- | --- |
| *2015-2050 Billion USD* | *2015-2050 Billion USD* | *2020-2050 Billion USD* | *2020-2050 Billion USD* | *Billion USD* |
| **Plausible** | 234.64 | 156.56 | 1,267.22 | 1,785.27 | 488.91 |
| **Drawdown** | 258.57 | 173.90 | 1,454.35 | 2,034.67 | 568.63 |
| **Optimum** | 503.58 | 371.53 | 3,624.59 | 4,492.81 | 1,421.98 |

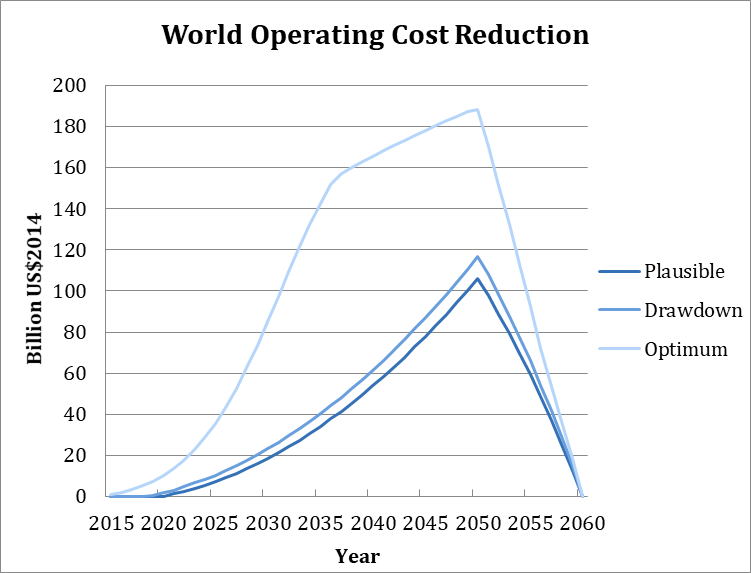


Figure 3.3 Net Profit Margin /Operating Costs Over Time

Figure 3.3 illustrates the savings in operating costs across the three scenarios. The drop off at the end of the periods illustrate that the only implementation units up to 2050 are included, and their savings decline as their lifetimes end.

# Discussion

The results show that not only is global smart thermostat adoption a way to reduce cumulative global emissions, but it is also a cost-effective means of doing so, resulting in an NPV of between $488 billion and $1,422 billion, which is a significant return on investment. The model estimates an annual savings of $72 per household that adopts a smart thermostat, but this represents a conservative estimate based on low energy savings for space heating and cooling and is also weighted based on consumption in three regions, including China, which has significantly lower energy consumption totals per household. As was mentioned previously, Nest estimates annual savings of around $150 per household, so our results are a much more conservative estimate. Still, even using a $72 annual savings estimate, the breakeven point for a smart thermostat investment in the analysis is under 2 years, which is very competitive with other energy efficiency and energy supply technologies.

By 2018, Smart thermostats accounted for 4.1 percent of the market of households globally. They offer substantial financial and energy savings while also providing a number of additional benefits to households and the grid system as a whole. Smart thermostats will likely gain an increasing share of the total thermostat market in the coming years since the technology presents an attractive alternative to traditional or programmable thermostats. Adoption rates can be accelerated through government support and through the entrance of new market players, which will likely further reduce the price. Current adoption is concentrated in the US and Europe, and future growth is projected to occur primarily in the US, Europe, and Asia Pacific.

Smart thermostats are an improvement over mechanical and programmable thermostats in that they are easy to install and use, adapt to user behaviors, and can give the occupant an enhanced ability to manage heating and cooling in the home. Pilot programs have shown significant energy savings for smart thermostat owners as well as improved thermal comfort in homes. They therefore represent a no-compromise solution that offers environmental, financial, and personal benefits. A Nest Labs customer survey found that 89 percent of customers were satisfied with their Nest Learning Thermostat, and in many cases, customers report that they would decide to purchase a smart thermostat at its current cost even if it did not result in significant energy savings because of the convenience it offers for managing home energy use (Nest Labs, 2015).

As the market grows globally and competition drives down the prices for smart thermostats, there will likely come a point in the future where any new homeowner looking for a thermostat will choose to purchase a smart thermostat because it makes sense financially to do so. The reductions in energy consumption and the improved convenience and agency for home thermal energy management will simply be add-on benefits of this decision. Thus, smart thermostats are an important technology that, when adopted rapidly, can lead to significant emissions reductions and financial savings. For these reasons, smart thermostats represent an important solution for *Drawdown*.

## Limitations

A major limitation of this technology is the requirement to share personal data. Data privacy is growing as topic of concern as many services are redesigned as web-based services that require sharing personal data with unknown entities that store data anywhere in the world. This is normally in exchange for lower costs and more functionality. While some initiatives such as the European Union’s General Data Protection Regulation (GDPR), are helping the world find a balance between individual privacy and service functionality, there is still much to be done and this concern is far from fully resolved. Smart Thermostat adoption could suffer from a resistance to share data, but at the same time, this could become an opportunity for some companies to provide functional local-only smart thermostats that do not communicate outside of the control of the user, or only does so with end-to-end encryption, a service that is already growing in popularity with some communication services.

## Benchmarks

In Table 4.1 are shown some selected results from another modeling effort with Drawdown results for comparison. The table aims to highlight the key differences and similarities between other studies and the work of Project Drawdown. Note that in the case of the IEA work, a multitude of technologies and approaches were assumed in the scenarios, and it was not possible to separate the expected impact of Smart Thermostats. It’s important to note that although IEA’s average energy reduction from technologies was above that of Drawdown’s most aggressive scenario, the emissions were similar. This suggests that IEA’s model takes into account the emissions of the grid being lowered over time. This was not directly captured in the single Drawdown model, as grid integration was done across the entire system of Drawdown solutions as described in the Integration section of this report. The emissions reduction is double counted in the efficiency solutions (such as Smart Thermostats), and the grid technology solutions (such as Solar PV), and the value of the double count is removed from the grid solutions.

Table 4.1 Benchmarks

| **Metric** | **IEA (2017)** | **Project Drawdown Plausible Scenario** | **Project Drawdown Optimum Scenario** |
| --- | --- | --- | --- |
| Description of Assumptions and Methodology | Difference between the Reference Technology Scenario (RTS) and the Beyond 2Degree (B2DS) Scenario. | Adoption Grows to 58% of Market - See Methodology Section | Adoption Grows to 100% of Market - See Methodology Section |
| Region | World | World | World |
| Building Use | Residential | Residential | Residential |
| Energy End Use | Space Heating, Space Cooling | Space Heating, Cooling | Space Heating, Cooling |
| Solution Technologies Included | All Building Space Heating and Cooling Efficiency Technologies | Smart Thermostats | Smart Thermostats |
| Comparator Technologies | N/A | Mechanical Thermostats | Mechanical Thermostats |
| Market Share in 2050 (%) | N/A | 58% | 100% |
| Energy Savings Potential | Average of 11 EJ/ year 2014-2060 | 1.7 EJ/ year average | 4.2 EJ/ year average |
| Emissions Reduction Potential | 404 Mt CO2/ year | 185 Mt CO2/ year average | 469 Mt CO2/ year average |

\* Note that ***OECD90*** is a Drawdown region defined as the OECD Countries as in 1990

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# Glossary

**Adoption Scenario** – the predicted annual adoption over the period 2015 to 2060, which is usually measured in **Functional Units**. A range of scenarios is programmed in the model, but the user may enter her own. Note that the assumption behind most scenarios is one of growth. If for instance a solution is one of reduced heating energy usage due to better insulation, then the solution adoption is translated into an increase in use of insulation. There are two types of adoption scenarios in use: **Reference (REF)** where global adoption remains mostly constant, and **Project Drawdown Scenarios (PDS)** which illustrate high growth of the solution.

**Approximate PPM Equivalent** – the reduction in atmospheric concentration of CO2 (in **PPM**) that is expected to result if the **PDS Scenario** occurs. This assumes a discrete avoided pulse model based on the Bern Carbon Cycle model.

**Average Abatement Cost** – the ratio of the present value of the solution (**Net** **Operating Savings** minus **Marginal First Costs**) and the **Total Emissions Reduction**. This is a single value for each solution for each **PDS Scenario**, and is used to build the characteristic “*Marginal Abatement Cost*” curves when Average Abatement Cost values for each solution are ordered and graphed.

**Average Annual Use** – the average number of functional units that a single implementation unit typically provides in one year. This is usually a weighted average for all users according to the data available. For instance, total number of passenger-km driven by a hybrid vehicle in a year depends on country and typical number of occupants. Global weighted averages are used for this input. This is used to estimate the **Replacement Time**.

**Cumulative First Cost** – the total **First Cost** of solution **Implementation Units** purchased in the **PDS Scenario** in the analysis period. The number of solution implementation units that are available to provide emissions reduction during the analysis period is dependent on the units installed prior to the analysis period, and hence all implementation units installed after the base year are included in the cumulative first costing (that is 2015-2050).

**Direct Emissions** – emissions caused by the operation of the solution, which are typically caused over the lifetime of the solution. They should be entered into the model normalized per functional unit.

**Discount Rate**- the interest rate used in discounted cash flow (DCF) analysis to determine the present value of future cash flows. The discount rate in DCF analysis takes into account not just the time value of money, but also the risk or uncertainty of future cash flows; the greater the uncertainty of future cash flows, the higher the discount rate. Most importantly, the greater the discount rate, the more the future savings are devalued (which impacts the financial but not the climate impacts of the solution).

**Emissions** **Factor**– the average normalized emissions resulting from consumption of a unit of electricity across the global grid. Typical units are kg CO2e/kWh.

**First Cost**- the investment cost per **Implementation Unit** which is essentially the full cost of establishing or implementing the solution. This value, measured in 2014$US, is only accurate to the extent that the cost-based analysis is accurate. The financial model assumes that the first cost is made entirely in the first year of establishment and none thereafter (that is, no amortization is included). Thus, both the first cost and operating cost are factored in the financial model for the first year of implementation, all years thereafter simply reflect the operating cost until replacement of the solution at its end of life.

**Functional Unit** – a measurement unit that represents the value, provided to the world, of the function that the solution performs. This depends on the solution. Therefore, LED Lighting provides petalumen-hours of light, Biomass provides tera-watt-hours of electricity and high-speed rail provides billions of passenger-km of mobility.

**Grid Emissions** – emissions caused by use of the electricity grid in supplying power to any operation associated with a solution. They should be in the units described below each variable entry cell. Drawdown models assume that the global electric grid, even in a Reference Scenario, is slowly getting cleaner, and that emissions factors fall over time resulting in lower grid emissions for the same electricity demand.

**Implementation Unit** – a measurement unit that represents how the solution practice or technology will be installed/setup and priced. The implementation unit depends on the solution. For instance, implementing electric vehicles (EV) is measured according to the number of actual EV’s in use, and adoption of Onshore Wind power is measured according to the total terawatts (TW) of capacity installed worldwide.

**Indirect Emissions** – emissions caused by the production or delivery or setup or establishment of the solution in a specified area. These are NOT caused by day to day operations or growth over time, but they should be entered into the model normalized on a per functional unit or per implementation unit basis.

**Learning Rate/Learning Curve** - Learning curves (sometimes called experience curves) are used to analyze a well-known and easily observed phenomenon: humans become increasingly efficient with experience. The first time a product is manufactured, or a service provided, costs are high, work is inefficient, quality is marginal, and time is wasted. As experienced is acquired, costs decline, efficiency and quality improve, and waste is reduced. The model has a tool for calculating how costs change due to learning. A 2% learning rate means that the cost of producing a *good* drops by 2% every time total production doubles.

**Lifetime Capacity** – this is the total average functional units that one implementation unit of the solution or conventional technology or practice can provide before replacement is needed. All technologies have an average lifetime usage potential, even considering regular maintenance. This is used to estimate the **Replacement Time**. and has a direct impact on the cost to install/acquire technologies/practices over time. E.g. solar panels generate, on average, a limited amount of electricity (in TWh) per installed capacity (in TW) before a new solar panel must be purchased. Electric vehicles can travel a limited number of passenger kilometers over its lifetime before needing to be replaced.

**Lifetime Operating Savings**–the operating cost in the PDS versus the REF scenarios over the lifetime of the implementation units purchased during the model period regardless of when their useful life ends.

**Lifetime Cashflow NPV**-the present value (PV) of the net cash flows (PDS versus REF) in each year of the model period (2015-2060). The net cash flows include net operating costs and first costs. There are two results in the model: Lifetime Cashflow NPV for a Single **Implementation Unit**, which refers to the installation of one **Implementation Unit**, and Lifetime Cashflow NPV of All Units, which refers to all **Implementation Units** installed in a particular scenario. These calculations are also available using profit inputs instead of operating costs.

**Marginal First Cost** – the difference between the **First Cost** of all units (solution and conventional) installed in the **PDS Scenario** and the **First Cost** of all units installed in the **REF Scenario** during the analysis period. No discounting is performed. The number of solution implementation units that are available to provide emissions reduction during the analysis period is dependent on the units installed prior to the analysis period, and hence all implementation units installed after the base year are included in the cumulative first costing (that is 2015-2050).

**Net Annual Functional Units (NAFU)** – the adoption in the PDS minus the adoption in the REF in each year of analysis. In the model, this represents the additional annual functional demand captured either by the solution in the **PDS Scenario** or the conventional in the **REF Scenario**.

**Net Annual Implementation Units (NAIU)** – the number of **Implementation Units** of the solution that are needed in the PDS to supply the **Net Annual Functional Units (NAFU).** This equals the adoption in the PDS minus the adoption in the REF in each year of analysis divided by the average annual use.

**Net Operating Savings** – The undiscounted difference between the operating cost of all units (solution and conventional) in the **PDS Scenario** minus that of all units in the **REF Scenario**.

**Operating Costs** – the average cost to ensure operation of an activity (conventional or solution) which is measured in 2014$US/**Functional Unit**. This is needed to estimate how much it would cost to achieve the adoption projected when compared to the **REF Case**. Note that this excludes **First Costs** for implementing the solution.

**Payback Period** – the number of years required to pay all the **First Costs** of the solution using **Net Operating Savings**. There are four specific metrics each with one of **Marginal First Costs** or **First Costs** of the solution only combined with either discounted or non-discounted values. All four are in the model. Additionally, the four outputs are calculated using the increased profit estimation instead of **Net Operating Savings**.

**PDS/ Project Drawdown Scenario** – this is the high growth scenario for adoption of the solution

**PPB/ Parts per Billion** – a measure of concentration for atmospheric gases. 10 million PPB = 1%.

**PPM/ Parts per Million** – a measure of concentration for atmospheric gases. 10 thousand PPM = 1%.

**REF/ Reference Scenario** – this is the low growth scenario for adoption of the solution against which all **PDS scenarios** are compared.

**Regrets solution** has a positive impact on overall carbon emissions being therefore considered in some scenarios; however, the social and environmental costs could be harmful and high.

**Replacement Time**- the length of time in years, from installation/acquisition/setup of the solution through usage until a new installation/acquisition/setup is required to replace the earlier one. This is calculated as the ratio of **Lifetime Capacity** and the **Average Annual Use**.

**TAM/ Total Addressable Market** – represents the total potential market of functional demand provided by the technologies and practices under investigation, adjusting for estimated economic and population growth. For this solutions sector, it represents world and regional total addressable markets for electricity generation technologies in which the solutions are considered.

**Total Emissions Reduction** – the sum of grid, fuel, indirect, and other direct emissions reductions over the analysis period. The emissions reduction of each of these is the difference between the emissions that would have resulted in the **REF Scenario** (from both solution and conventional) and the emissions that would result in the **PDS Scenario**. These may also be considered as “emissions avoided” as they may have occurred in the REF Scenario, but not in the PDS Scenario.

**Transition solutions** are considered till better technologies and less impactful are more cost effective and mature.

**TWh/ Terawatt-hour** – A unit of energy equal to 1 billion kilowatt-hours

1. Nest’s study uses larger samples and industry standard practices as defined by the US Department of Energy Uniform Methods Project (DOE 2013) in order to account for energy variations related to weather, occupancy patterns, and home/equipment modifications. For more information, see Nest Labs (2015). [↑](#footnote-ref-1)
2. For a comprehensive report on using a data-driven framework for comparing residential thermostat performance, see Urban and Roth (2014). [↑](#footnote-ref-2)
3. A Nest Learning Thermostat 3rd-gen retailed for $249.00 at Nest.com in 2014. [↑](#footnote-ref-3)
4. Demand Response (DR): a mechanism through which an end-use’s load profile is changed (by the user, a third party, or a utility) in response to system needs. The benefit to the end-user is often financial compensation (e.g., payments or a different rate structure). For example, programs that utilize control technologies, such as smart thermostats, direct load control switches, plug load controls, or automated demand response (ADR) technologies, and/or behavior-based DR programs. The majority of DR programs offered target heating and cooling measures, however, several utilities offer custom rebates to commercial customers that install other measures that are enabled with ADR and agree to participate in DR programs. Offerings can also include behavior-based programs (Potter, Stuart, & Cappers, 2018). [↑](#footnote-ref-4)
5. In January 2014, Google’s parent company Alphabet acquired Nest for US$3.2 billion, after which *The Guardian* noted, “given that Google is often a technology trendsetter, the move will likely accelerate the development of smart home technologies” (La Monica, 2014). [↑](#footnote-ref-5)
6. Distributed Generation (DG): programs that incentivize customer adoption of DG technologies, such as photovoltaics, fuel cells, combined heat power, small wind turbines (Potter et al., 2018). [↑](#footnote-ref-6)
7. Estimates for the total breakdown in market value between smart thermostats and associated software and services were not available. [↑](#footnote-ref-7)
8. For most results, only the differences between scenarios, summed over 2020-2050 were presented, but for the net first cost, the position was taken that to achieve the adoptions in 2020, growth must first happen from 2015 to 2020, and that growth comes at a cost which should be accounted for, hence net first cost results represent the period 2015-2050. [↑](#footnote-ref-8)
9. Honeywell, Nest, and Ecobee are quoted as market leaders in North America while several others, including Hive and Netatmo, along with the former three are leaders in Europe (IoT Analytics, 2015). [↑](#footnote-ref-9)
10. See GBPN, & Central European University. (2012); Ürge-Vorsatz et al. (2015) [↑](#footnote-ref-10)
11. See Total Addressable Market Section (2.3) for an explanation of this assumption. [↑](#footnote-ref-11)
12. In some cases, the low boundary is negative for a variable that can only be positive, and in these cases the lowest collected data point is used as the “low” boundary. [↑](#footnote-ref-12)
13. Data for other regions was not available. [↑](#footnote-ref-13)
14. Globally, natural gas accounted for over 62 percent of fuel consumption for space heating in 2014 (IEA, 2017). [↑](#footnote-ref-14)
15. This can be interpreted as a single building with multiple efficiency technologies. [↑](#footnote-ref-15)
16. Some solutions such as Electric Vehicles and High-Speed Rail increase the demand for electricity and reduce the demand for fuel. [↑](#footnote-ref-16)