A Framework for Analyzing Widespread Grid Intervening Technologies: A Case Study of Heat Pump-Integrated Thermal Energy Storage Systems in Buildings

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ABSTRACT

Heating and cooling demands of buildings require an immense amount of energy from the electric grid. Extreme temperatures or other weather events may stress the grid further by increasing the heating or cooling demands of buildings to maintain a livable indoor environment. When spread across the grid, this increase in energy demand requires grid operators to increase energy supply, often by using so-called peaker power plants. These plants are generally combustion turbines burning either natural gas or diesel fuel. As such, the emissions associated with these plants are higher than most baseload grid energy generation emissions. A building's peak energy demand from the grid may be reduced by employing energy storage systems that activate during these periods of high building energy demand to replace or supplement energy from the grid. Heating and cooling can benefit from thermal energy storage (TES). TES integrated into a heat pump (HP) system may reduce a building's peak energy demands during extreme temperature conditions. When deployed on a large-scale, the cumulative effect of HP-TES may reduce grid demand during critical times and abate the need for peaker power plants. This study establishes a framework around which the effect on grid emissions (CO_2, NO_x, and SO_x) of intervening technologies, such as TES, may be examined on a large scale. As a case study, residential HP-TES is analyzed for select households in the Southern US.

Keywords: *thermal energy storage, heat pump, residential buildings, emissions, intervening technologies*

1. INTRODUCTION

Energy storage has been deemed a critical component for the complete transition to a renewable energy-based energy grid (Gallo *et al.*, 2016). As such, energy storage is a rapidly advancing field of study with a large body of work dedicated to thermal energy storage (TES) systems. Generally, TES systems operate by storing and releasing heat in a narrow temperature range. Near-ambient temperature TES systems are well-suited for applications where low-grade heat is the primary end use: refrigeration, domestic hot water, and indoor building thermal conditioning.

Residential buildings occupy a large share of the US national energy consumption, upwards of 22% (*Monthly Energy Review*, 2021). Much of this energy consumption is spent on thermally conditioning the indoor spaces. This work presents a framework for analyzing the scaled impacts of residential heat pump-integrated TES (HP-TES) systems for indoor thermal space conditioning. As a case study, this framework is used to conjecture on the effect of grid-level

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emissions produced within the Southern Company Balancing Authority territory in 2018 attributed to a hypothetical widespread adoption of residential HP-TES for select residential building types.

Figure 1 illustrates the operating principle of such HP-TES systems for both heating and cooling. An HP-TES system acts as an intervention technology on building energy demand during peak hours by providing a more efficient HP operation to thermally condition the indoor space. TES provides an isothermal source or sink for the HP to couple. In doing so, the HP-TES may be acting with a more favorable temperature gradient to thermally condition the indoor space than if the HP is coupled to the ambient. During this discharging mode, the HP may use less electrical energy than the conventional HP system. This relative reduction in energy may be timed to coincide with the daily extreme ambient temperature, the peak hours. Much like an electrical battery, the TES needs to be recharged. This is done by coupling the HP to the TES and the ambient, ideally by choosing the time in which the ambient temperature is most favorable for the TES recharging, the off-peak hours. By taking advantage of naturally occurring diurnal ambient temperature changes, HP-TES systems may shift building energy consumption from peak hours to off-peak.

In this current work, the same TES system is used for both indoor heating and cooling applications. For this model, the TES temperature is chosen as 20°C. It is assumed that no temperature gradients exist within the TES, and it is well-oversized such that its capacity to condition the building in any 24-hour period is never deplete. Charging is still necessary to return the TES to a full state of charge.

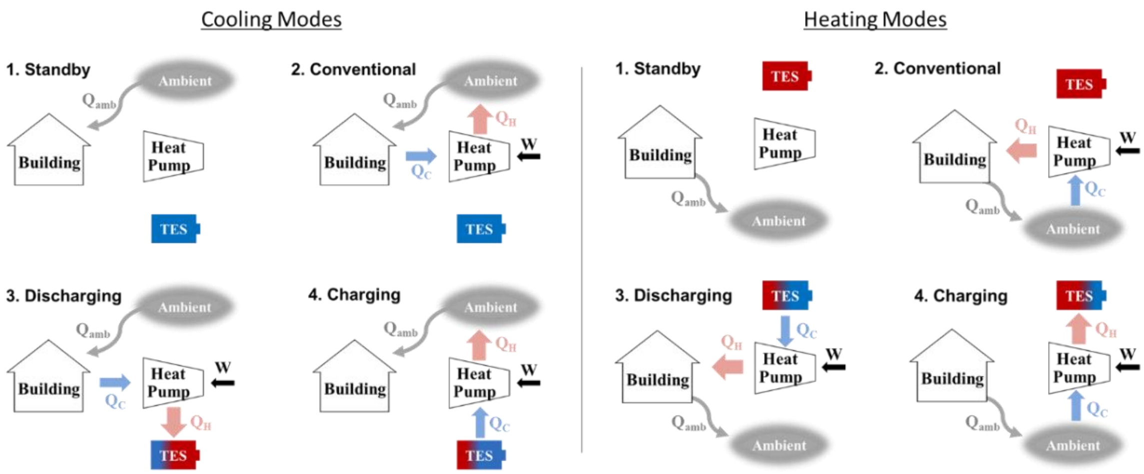

Figure 1. Operating modes of HP-TES system for heating and cooling

This present work builds a framework to analyze large-scale impacts of HP-TES systems but may be generalized for other intervening technologies. This framework is loosely based on the analysis done by Siler-Evans *et al.* (2012) as a method of determining marginal technologies and emissions. Compared to that work, this framework is more localized and specific; evaluating emissions of a single year and region, and speculating the impact a specific intervening technology may have. There are other tools to estimate emissions impacts, such as the Environmental Protection Agency (EPA) AVoided Emissions and geneRation Tool (AVERT) and some consumer-facing products.

The framework developed here is employed in a cast study evaluating the widespread effect that HP-TES systems may have on grid energy generation and emissions if these systems replaced conventional HP & air conditioning units in select residential homes within the Southern Company (SOCO) Balancing Authority (BA) territory in 2018. This paper outlines the framework in the context of the case study: discussing how the building model, the HP model, TES model, and the emissions model coalesce to estimate the large-scale effects of HP-TES systems.

2. MODEL OVERVIEW

2.1 Case Study Scope

This case study is limited to select residential households in the 2018 SOCO BA territory. However, the framework built will enable future examination of other building types, sizes, regions, times, generation portfolios, and what-if scenarios for TES and other intervening technologies. The results discussed herein are not widely applicable to other regions, HP-TES systems generally, or other energy storage technologies; care must be taken to understand the assumptions that led to the presented results.

The overall framework is composed of several component-level models that coalesce into one unified model. Each component-level model is discussed in Sections 2.3 – 2.5. The methodology for scaling the component-level models across the entire region is discussed in Section 2.6.

2.2 Weather Data

The weather data was collected from National Oceanic and Atmospheric Administration (NOAA) Local Climatological Data (LCD) Stations located within the territory of interest. This data provides hourly data presented in METeorological Aerodrome Reports (METAR) FM-15 or FM-16 format, historically reported for aviation purposes. The data includes dry bulb temperature, relative humidity, wind speed, any overhead sky conditions including cloud altitude. For the simplicity of this case study analysis, only dry bulb temperature is considered. Future versions of this model may correlate sky conditions and time of day and year to solar irradiance on a building or seek to find historical data on geospatial solar irradiance. This model does not consider relative humidity, though this is important for dehumidification purposes. These are outside the scope of this current report.

The NOAA LCD data was collected for 119 weather stations across SOCO BA territory in 2018. However, only a subset of 13 locations is used in this current analysis, and the data are extrapolated and scaled across the entire territory. Future versions of this model may apply more advanced regression and interpolation between weather stations to better characterize the effects of weather to the energy usage of households throughout the territory. Figure 2 shows the map of selected weather stations with the whole territory outlined.

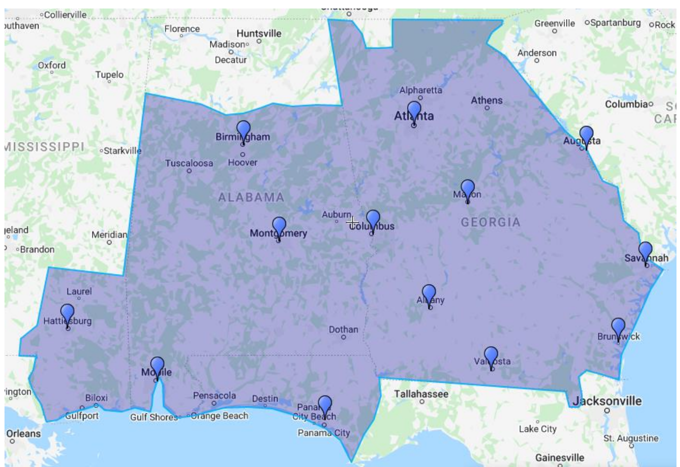

Figure 2. Map of selected weather stations with 2018 SOCO BA territory outlined

Alternatively, Typical Meteorological Year (TMY) data from the National Renewable Energy Lab (NREL) was considered. However, historical weather of the same year as power plant generation was deemed necessary for this framework; a correlation exists between local weather conditions and energy demand, and this was not captured properly with TMY data.

2.3 Vapor Compression Heat Pump and Thermostat Model

An R410A vapor compression heat pump (VCHP) model was written in MATLAB using open source CoolProp refrigerant data (Bell *et al.*, 2014). The condenser and evaporator temperatures were selectively tied to the indoor building, outdoor ambient, or TES temperatures. By assuming constant approach temperatures, superheating, and subcooling, the model iteratively solved for the heat removed from the evaporator side and pumped to the condenser side. The VCHP model includes a compressor operating with a constant volumetric displacement rate which was sized to provide approximately 4 refrigeration tons of cooling.

Figure 3 shows an example operation of the HP-TES model for a single day (Jan 12, 2018) as it switches between different operating modes and compares it to a conventional HP system. The operating mode of the HP is displayed on the upper graph. The electrical energy to operate the HP is shown on the lower graph. The conventional system is only capable of switching between conventional operation and standby. The HP-TES system operates in discharging mode (utilizing the TES for indoor thermal heating) at the beginning of the day, and its associated electrical energy use is less during these hours. During midday, however, the HP-TES enters charging mode and switches between conventional heating mode to heat the indoor space and charging mode to heat the TES. Its average energy consumption is higher than the conventional system during these hours.

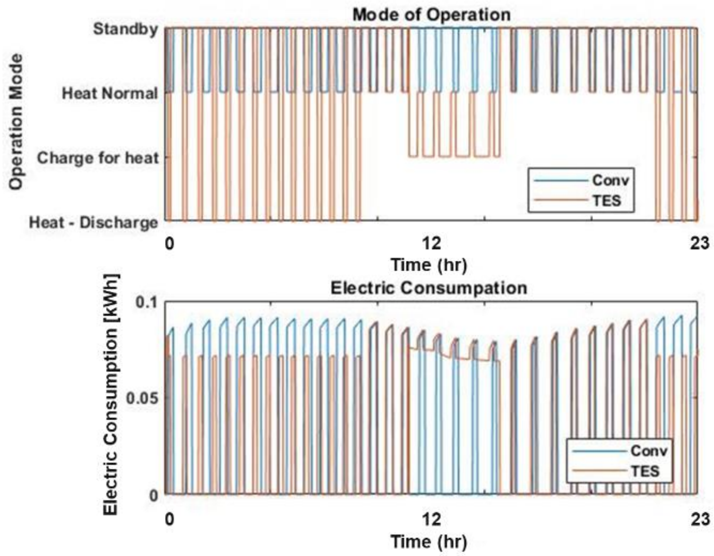

Figure 3. Operating mode and energy consumption of conventional HP system and a HP-TES

The VCHP uses a day-ahead weather forecasting to predict the hours of the next day's ambient temperature extremes (high and low) using the NOAA LCD data. This is highly idealized as the data contains perfect information. However, the level of detail necessary for this control algorithm could likely rely on real weather forecasting reports without issue.

This thermostat model records information on the thermal conditioning inertia of the building by tracking the total time the building is engaged in either heating or cooling for the past 72 hours. This inertia then dictates the preferred mode for TES-assisted on-peak conditioning and ensures the HP will not overcorrect itself. For example, in the winter months where heating is more likely to be required, the system will prime the TES for heating modes. If an unseasonably warm day occurs and building cooling is required, the HP will couple the building to the TES so that the building cooling recharges the TES for a future heating operation as the inertia would indicate as the more likely mode. Furthermore, if the HP overshoots the building setpoint temperature, this thermal conditioning inertia will prevent the system from switching to the opposite mode to overcorrect itself and will instead be put on standby. Implementation of this is elementary in conventional HP systems, but this dual mode HP-TES model adds some complexity that required this additional control algorithm. Future versions of the model may improve upon this.

Determined in part by the thermal conditioning inertia of the thermostat system, the thermostat bounds charging and discharging around the extreme temperature hours accordingly. For example, discharging the TES to cool the indoor space is done only during the five-hour window bounding the hour of the day's ambient high temperature, and charging to cool the TES is done only during the window bounding the hour of the day's ambient low temperature. No HP-TES decision making was influenced by emissions, utility rates, etc. Future iterations of this model may include such factors for advanced emissions mitigation or to maximize consumer monetary savings.

2.4 Building Model

The building type analyzed is estimated to be a 2000-3000 square foot, single-family detached home with central air conditioning as the primary source of cooling and central heat pump heating as the primary source of heating.

The building model was built based on the results found in Cui *et al.* (2018). The building model is a 4R4C thermal circuit. The RC constants were adjusted slightly from the source, but retain the same order of magnitude as presented there. The building model calculates the indoor space temperature from heat gains or losses from the ambient, and the heat from the VCHP. Dehumidification of the indoor space is not considered in the present report, but it is understood that dehumidification is an important use of HPs operating in this region. Future iterations of the model will include dehumidification of indoor spaces. The RC constants were validated by comparing the building's modeled energy consumption for heating and cooling to responses from the 2015 Energy Information Administration (EIA) Residential Energy Consumption Survey (RECS) for similarly featured buildings in the South and South East Central regions (*Residential Energy Consumption Survey (RECS)*, 2015).

Figure 4 shows the total hourly HP energy consumption for a residential building modeled in Macon, GA for January 2018. The energy consumption for the conventional system is highest in the early morning hours, which roughly corresponds to the lowest average hourly temperature. The HP-TES system has the lowest energy consumption during these hours due to the TES intervention. However, the HP-TES system uses more energy during midday when the TES is recharged. For this example, the HP-TES energy consumption to maintain a thermally conditioned space is nearly inverted compared to the conventional HP system.

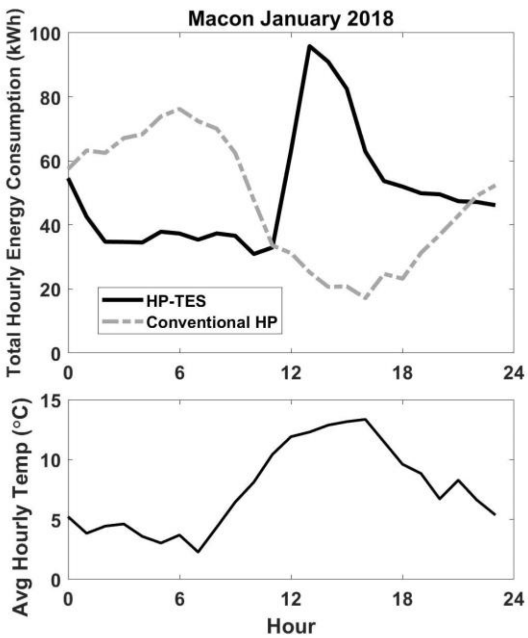

Figure 4. Total hourly HP-TES energy consumption modeled for Macon, GA in January 2018

2.5 Emissions and Grid Generation Model

Power plant emissions data were gathered from the EPA Continuous Emissions Monitoring (CEM) program, regulated by the US Code of Federal Regulations, Title 40, Chapter I, Subchapter C, Part 75, Continuous Emissions Monitoring. The data were accessed through the EPA Field Audit Checklist Tool (FACT). Data were collected for 2018 across all power plants operating in the Southern Company Balancing Authority territory, approximately 63 generating plants and 316 reporting generating units or monitoring locations. The CEM data collected contains only the fossil fuel power generation and do not include solar, wind, hydro, or nuclear energy sources. It is assumed that the non-fossil fuel and nuclear generation is unaffected by intervening technologies; these technologies are typically non-dispatchable or baseload. Thus, the analysis proceeds treating only fossil fuel generation as marginal technologies that respond to demand changes across the grid.

In the CEM data, the emissions from different generating technologies can be determined. The four main fossil fuel technologies in this region are natural gas combustion turbines (NGCT), natural gas combined cycle (NGCC), natural gas boilers (NGB), and coal. Oil or diesel combustion turbines comprise a minuscule portion of the energy generation in this region and are typically only called upon during transient periods to ramp up or complement the other four technologies. Figure 5 shows the relationship between change in generation of these technologies and the associated change in emissions. The slope of the line indicates the change of tons of CO_2 emitted by the change in MWhe of generation from that technology. The outlying data points in coal may be due to startup or shutdown procedures, or may be undercounting or over counting if the CEM monitoring location is temporarily moved or the reporting is out of sync. Future work is necessary to investigate this further and identify the source of outliers. However, these outlying data do not affect the linear trend observed. As expected, coal is the most CO_2 polluting technology (at about 0.98 t/MWh) followed by NGCT (0.62 t/MWh), NGB (0.53 t/MWh), and NGCC (0.42 t/MWh), and all agree with (Bruckner *et al.*, 2014). A similar regression was performed for SO_2, NO_x, and Hg emissions data collected through CEM, however, these did not yield a good linear fit (not shown here). Future work will investigate this further.

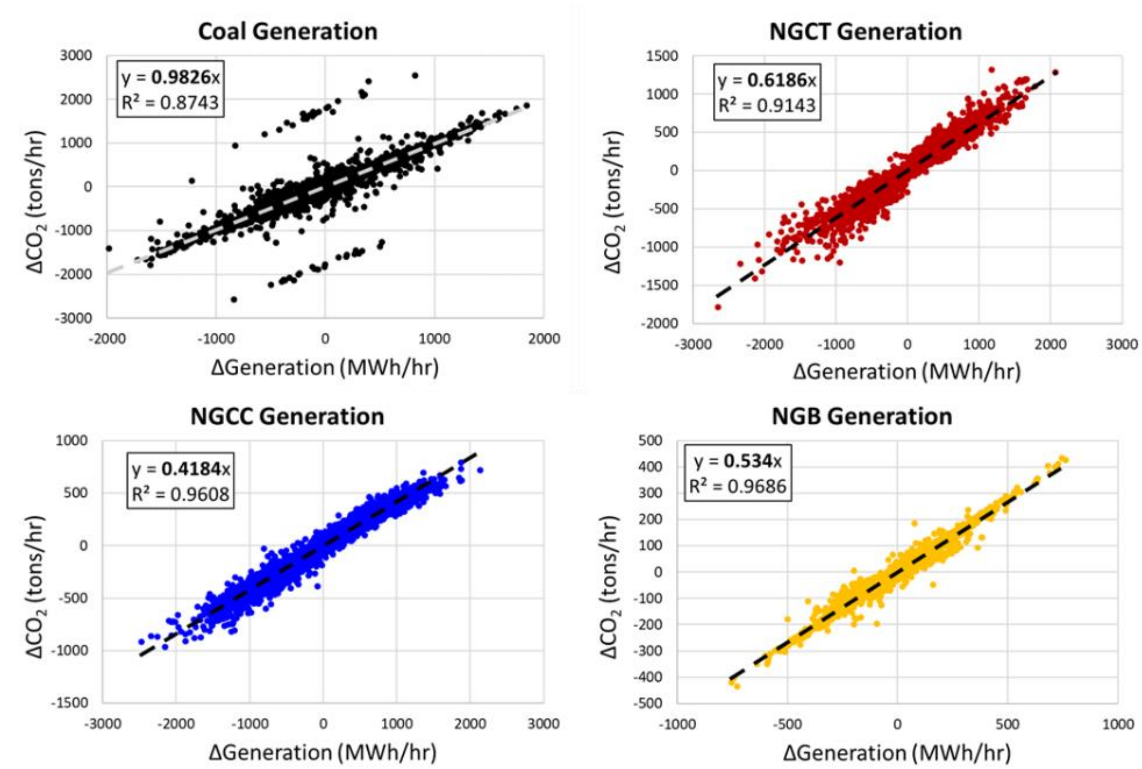

Figure 5. Emission factors (EF) for main fossil fuel technologies from 2018 CEM data

As the demand on the grid changes, grid operators respond by dispatching different power plants and different generation technologies. Deciding which plants and technologies are dispatched is dependent on the current total generation, the capacity factor of online units, operating costs, demand forecasts, and more. Those generating units and technologies that are dispatched to meet demand are on the margin. The model developed to determine the marginal technology, and thus associated emissions, is loosely based on the methodology outlined in Siler-Evans et al. (2012).

For every day of each month, the hourly generation and emissions of each technology are summed. This creates a profile containing all energy generation and emissions for a month in a 24-hour format. For example, all data corresponding to 2pm are summed across each day of the month. To determine a typical hourly marginal technology dispatch for that month, the change in hour-to-hour generation of each technology is compared to the hour-to-hour change of all fossil fuel generation. This results in a normalized marginal factor (MF) which weights the magnitude of each technology to respond to changes in generation across the whole system.

To illustrate the MF, Figure 6 shows the results for July 2018. In this figure when the graph is negative, the total system generation is decreasing and when the graph is greater than zero, the total system generation is increasing. As an example, in hour 13, the MF for NGCT is ~0.33. This indicates that as the system generation increases, NGCT account for ~33% of this new generation; NGCT are turning on to meet demand for this hour. In hour 22, the MF for is ~-0.44. This indicates that as the system generation decreases, 44% of this decrease are NCGT shutting down or reducing generation. In hour 1, the MF for NGCT is ~0.05; any change in system demand is not significantly the result of NGCT. This illustrates NGCT used as a marginal technology during this month and for specific hours. Furthermore, the MF from Figure 6 allow speculation as to how the system generation portfolio might respond if demand changes for a specific hour as the result of an intervening technology. These MF are used to determine the effect of intervention as if it happened proportionately across all technologies.

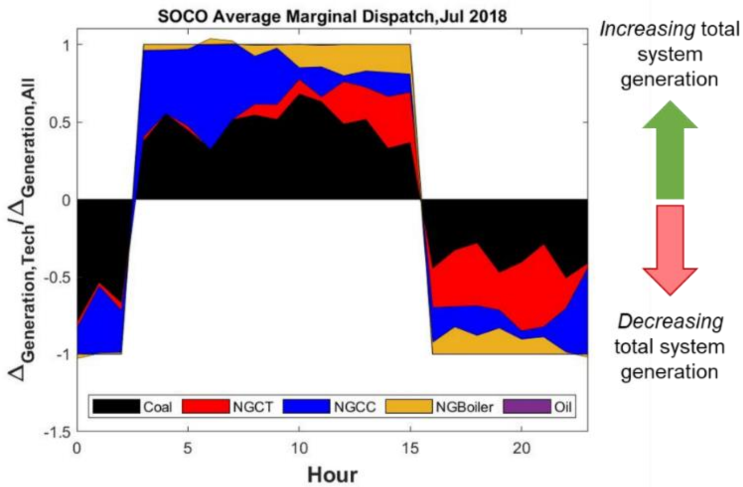

Figure 6. Marginal factors (MF) of different generation technologies for July 2018

It may appear that coal is a dominant technology on the margin. However, coal does not respond to changes in demand in the same way NGCT is dispatched; operators generally run coal plants on a predetermined schedule spanning several days for forecasted baseload. This schedule is based on historical data and demand predictions made by the system operator hours or days in advance. Coal is not load-following and is not well equipped to respond to short-term hourly demand fluctuations. By evaluating these MF data over a month, this fact is obscured by day-to-day variations.

2.6 Model Scalability

To estimate the number of affected households, data from EIA RECS was used. Filtering for the South and South East Central regions, the approximate number of households matching the building model analyzed was found. However, the EIA regions do not coincide with the SOCO region under analysis. Therefore, county-level population data from the US Census Bureau was used to determine the approximate number of persons in the SOCO territory relative to the EIA regions. This provided a weight that was applied to the number of households from the EIA RECS microdata. This estimation resulted in approximately 330,000 households within in the SOCO region that match the housing profile modeled here.

The county-level US Census Bureau population data is also used to weight the building model results around each of the 13 NOAA weather stations. It is assumed that all 330,000 households utilize an identical HP-TES system and use the same decision-making operating logic. All households surrounding one of the weather stations are responding to its weather data only. Differences arise across the territory due to slightly different ambient conditions recorded at different weather stations, and because this region spans two time zones. All aggregated data is converted to EST, but households will operate in accordance with their local time and weather conditions.

3. RESULTS & DISCUSSION

3.1 Aggregated Building Energy Consumption

The building model integrated with and without HP-TES model were run for the 13 NOAA weather stations. The models without TES are assumed to be the baseline energy consumption portfolio of the building. The models with HP-TES systems show the energy consumption portfolio if this intervention technology were implemented. The difference in energy consumption between the two models quantifies the effect of the HP-TES system. These results are then scaled and aggregated according to the procedure outlined in Section 2.6.

Figure 7 shows these aggregated results for the total change in energy consumption of all modeled buildings across the region. It is evident that there is a large increase in energy consumption in the early morning hours of the summertime months. This corresponds to the recharging of the TES system for the next day's indoor cooling service.

However, there is not an equivalent reduction in energy consumption during the midday hours of the summertime months. This indicates that the energy consumption to charge the TES for cooling, even when the ambient temperature is lowest, is greater than the energy savings achieved by employing the TES for indoor cooling. The only instance in which there is a strong inversion of energy usage is during January. It is noted that January and February 2018 were colder than normal for this region.

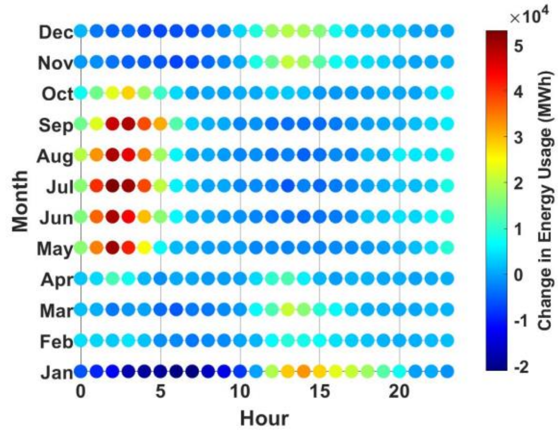

Figure 7. Aggregated results for total change in energy consumption if all eligible buildings operated HP-TES systems

3.2 Effect of Total Grid Generation

If the results of Figure 7 are assumed to be intervening on the grid-level fossil fuel generation, there may be potential to smooth the energy demand curve. Figure 8 shows the effect that this HP-TES system may have across the entire region for the month of January. The differences are small, but there is an increase in generation in the midday hours, and a small reduction of generation in the early morning hours.

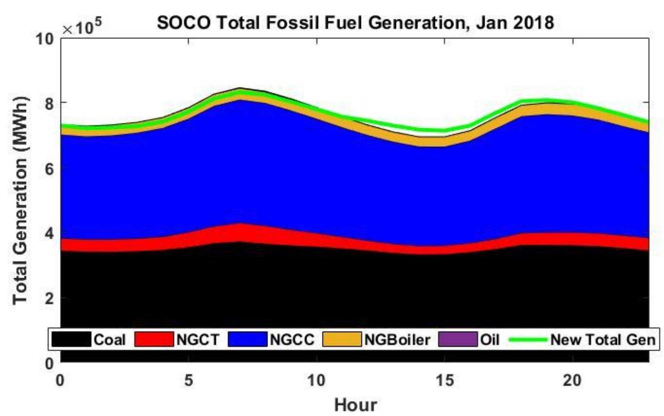

Figure 8. Estimated change in total fossil fuel generation for January 2018 if all eligible buildings operated HP-TES systems

3.3 Effect of Total Grid Emissions

It is difficult to know what a system grid operator may do if an intervening technology at scale significantly changes the system demand. This decision ultimately affects the emissions produced by grid-level energy generation. How the grid operator would change the generation portfolio is assumed here in two ways: 1) weighted favorably to reduce CO_2 emissions, and 2) weighted according to the MF for each technology (Figure 6). Then using the emission rates shown in Figure 5 for each technology, the total effect that this HP-TES system may have on grid-level emissions can be determined

By weighting favorably to reduce CO_2 emissions, it is assumed that any decrease in total generation due to the intervening HP-TES system reduces the use of NGCT. And any increase in total generation increases NGCC. The rationale for this is that NGCT is a predominant marginal technology and NGCC is considered more baseload.

Effectively, this means that each incremental MWh has a net emissions reduction of 0.20 tCO_2 (i.e., equivalent to the difference between the respective emissions rates for NGCT-NGCC, or 0.62-0.42). It would be more favorable to reduce coal, but this is considered baseload in this region and time, and thus unlikely to be affected by intervening technologies.

By weighting according to the MF (Figure 6), any increase or decrease in total system generation increases or decreases all technologies proportionately to their MF for that hour and month. The rationale for this weighting method is that if all households did install this technology and operated it in this manner, the system grid operator would be able to predict and plan for this in their baseload schedules, and thereby mimic historical dispatch protocols and observed trends.

The results for CO_2 emissions are shown in Figure 9. Here, only in the month of January under the favorable CO_2 weighting does the system decrease its total CO_2 emissions. All other months and using the MF weighting, CO_2 emissions increase overall. This is attributed to the net increase in energy of operating the HP-TES system as outlined in Section 3.1. For the favorable CO_2 weighting, the net increase in NGCC generation offsets any reduction of NGCT, despite NGCC having a lower CO_2 emission rate than NGCT. And for the MF weighting, the increase in baseload generation, particularly coal, increases the CO_2 emissions across the whole year.

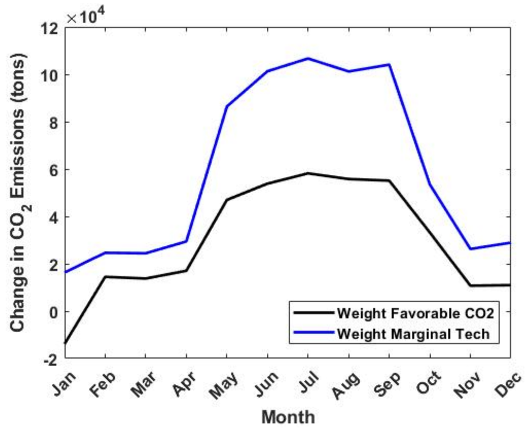

Figure 9. Effect of grid-produced CO_2 emissions if all eligible buildings operated HP-TES systems

Effects on SO_2 and NO_x emissions can be determined using the data from CEM, and an identical process to the CO_2 methodology. The only instance in this case study where emissions decrease is NO_x under the favorable CO_2 scenario.

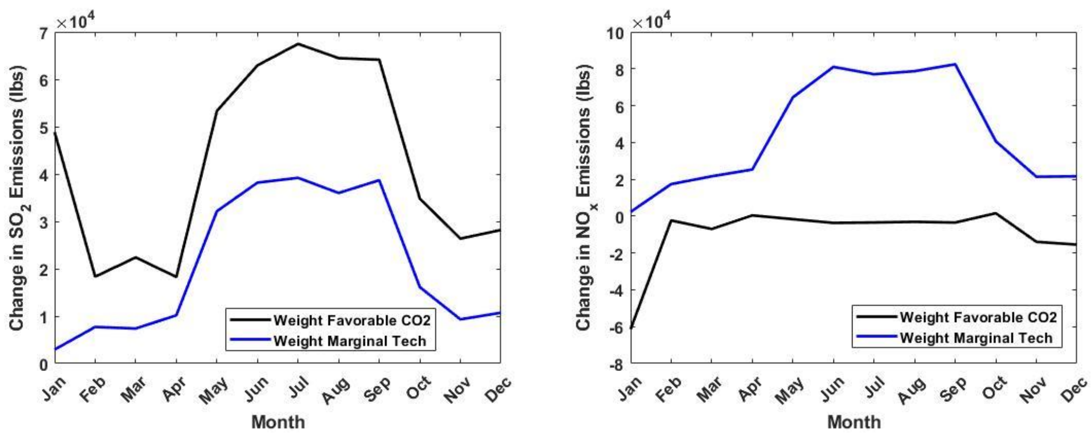

Figure 10. Effect of grid-produced SO_2 and NO_x emissions if all eligible buildings operated HP-TES systems

4. CONCLUSION

This study sought to build a framework around which the grid-level emissions impact of intervening technologies can be estimated. As a case study, the framework is used to estimate the effect of wide-spread adoption of residential HP-

TES systems in the 2018 Southern Company Balancing Authority region. 2000-3000 square foot single-family, detached homes with central air conditioning cooling and primary heat pump heating are included in this case study. The TES stores heat at 20°C without losses. Buildings in 13 select locations were modeled using NOAA LCD weather data, a 4R4C building thermal model, and a VCHP as a heating and cooling source, and the results scaled across the region according to US Census Bureau county-level population estimates and EIA RECS household numbers. Emissions data were collected from EPA CEM data for all fossil fuel generation plants within the SOCO region.

This case study indicates that installing this HP-TES system and operating under the strict assumptions made in this model, a total increase in energy generation might be expected. Some leveling of the demand curve is observed, however. Constrained by the 2018 SOCO generating portfolio, a net increase in power plant emitted CO_2, NO_x, and SO_2 is shown. This region was not equipped with low-carbon marginal technologies in 2018 and thus the HP-TES systems could not exploit diurnal load-shifting.

The results from this case study are not definitive, or widely applicable to HP-TES systems or other intervening technologies. Many assumptions and simplifications are necessary for a single unified model of this scope, and there is much room for improvement around this framework. Future steps include refining the building model, exploring more building types and sizes, using real HP-TES performance data, modeling other TES temperatures, including higher resolution weather data, interpolating between weather stations, using advanced regression of grid emissions, exploring other energy grids and regions, and investigating low-carbon generation portfolios including curtailed renewables or predicted future grid mixtures.

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ACKNOWLEDGEMENT

This work was sponsored by the U. S. Department of Energy's Building Technologies Office under Contract No. DE-AC05-00OR22725 with UT-Battelle, LLC. The authors would like to acknowledge Mr. Sven Mumme, Technology Manager – Building Envelope, U.S. Department of Energy Building Technologies Office.