Can storage reduce electricity consumption? A general equation for the grid-wide efficiency impact of using cooling thermal energy storage for load shifting

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Abstract
This study estimates changes in grid-wide, energy consumption caused by load shifting via cooling thermal energy storage (CTES) in the building sector. It develops a general equation for relating generator fleet fuel consumption to building cooling demand as a function of ambient temperature, relative humidity, transmission and distribution current, and baseline power plant efficiency. The results present a graphical sensitivity analysis that can be used to estimate how shifting load from cooling demand to cooling storage could affect overall, grid-wide, energy consumption. In particular, because power plants, air conditioners and transmission systems all have higher efficiencies at cooler ambient temperatures, it is possible to identify operating conditions such that CTES increases system efficiency rather than decreasing it as is typical for conventional storage approaches. A case study of the Dallas–Fort Worth metro area in Texas, USA shows that using CTES to shift daytime cooling load to nighttime cooling storage can reduce annual, system-wide, primary fuel consumption by 17.6 MWh for each MWh of installed CTES capacity. The study concludes that, under the right circumstances, cooling thermal energy storage can reduce grid-wide energy consumption, challenging the perception of energy storage as a net energy consumer.

1. Introduction
The electric grid’s stability depends on the continual balance of the system’s supply and demand, generally requiring that electricity output should match consumption. Energy storage can ease this requirement by absorbing or discharging energy whenever generation and consumption are mismatched. This decoupling effect can provide useful services to the grid including peak demand reduction, load shifting, and buffering the intermittent output of variable renewable energy resources [1].

A noteworthy drawback of energy storage is its inefficiency. Pumped hydro, compressed air, chemical batteries, and all other storage mediums are less than 100% efficient, wasting some energy during their charge-discharge processes [1, 2]. Consequently, numerous studies show how energy storage can increase the electric grid’s overall energy consumption and emissions due to storage inefficiencies and to shifting electrical demand in time from lower- to higher-emitting power plants [3–5], an inconvenient reality for policies that include storage in their carbon reduction strategies.

Yet, though an individual storage technology increases energy consumption at its connection point to the grid, its load shifting effects can improve the efficiency of the grid as a whole. For example, the efficiency of the generator fleet and the transmission and distribution (T&D) network increases as ambient temperature, relative humidity, and line current decrease [6–9]. Generally, in cooling-dominated climates, peak demand and high ambient temperature occur during the daytime (when power plants, air conditioners, and the T&D network are less efficient), while low demand and low ambient temperatures occur at night. Thus, storage could shift demand to cooler, drier, and less-congested times of day thereby...
Energy storage is regularly included in strategies aimed at reducing electric grid CO$_2$ emissions and pollution [33, 34], though many studies indicate that energy storage can increase energy consumption and emissions in the power sector [3–5]. Fares and Webber, for example, show how residential battery systems coupled with rooftop solar arrays can reduce peak demand and peak power injections via load shifting, but increase energy consumption and emissions compared to solar arrays without storage. Increased energy consumption is caused by the inefficiencies of the battery. Increased emissions are due to the increased energy consumption and to shifting electrical demand in time from lower- to higher-emitting power plants in the generator fleet [5].

These studies portray energy storage as a net energy consumer, but expanding the system analysis boundary could reveal net efficiency gains in other parts of the electric grid. For example, there are numerous technologies whose energy efficiency can change throughout the day depending on a variety of factors. Power plant efficiency improves as ambient temperature and relative humidity decrease [6, 7]. T&D network efficiency improves with decreasing ambient temperature and line current, among other factors [8, 9]. Air conditioning equipment efficiency improves significantly with lower ambient temperatures [35, 36].

While the energy efficiency of these components have been studied individually, the literature rarely considers their combined effect on the efficiency of the electric grid as a whole. This letter fills that gap by developing a general equation for calculating the electric grid’s efficiency at converting fuel energy downstream of the power plant into cooling energy delivered to the building. This equation shows that, under the right circumstances, CTES can shift electric demand in ways that reduce grid-wide energy consumption, thereby implying a net efficiency greater than 100% compared with a baseline of conventional afternoon operation.

3. Methods

This study generalizes the generator fleet, T&D network, chiller, and CTES system by modeling it as a series of energy conversions for translating generator fuel into cooling as shown in figure 1, where each conversion process has its own energy efficiency or coefficient of performance (COP). The methods section describes the development of an efficiency model for each part of the system (sections 3.1–3.4) and the system as a whole (section 3.5). Table 1 summarizes the nomenclature.

3.1. Generator fleet average efficiency

The average efficiency of the generator fleet is approximated by modeling a natural gas combined-cycle (NGCC) and a Rankine cycle power plant and averaging their efficiencies depending on the
The system is generalized as a series of energy conversions required to translate generator fuel into building cooling.

Table 1. Nomenclature.

| Variable | Definition | Units | Base value |
|----------|------------|-------|------------|
| \( \Lambda_{cc} \) | heat rate of combined cycle generator | Btu fuel/kWh elec. | – |
| \( \Lambda_{rankine} \) | heat rate of Rankine cycle generator | Btu fuel/kWh elec. | – |
| \( T \) | ambient temperature | °C | – |
| \( H \) | relative humidity | % | 60 |
| \( \eta_{cc} \) | efficiency of combined cycle generator | %/100 | – |
| \( \eta_{rankine} \) | efficiency of Rankine cycle generator | %/100 | – |
| \( \beta_{cc} \) | base combined cycle fleet efficiency | %/100 | 0.47 |
| \( \beta_{rankine} \) | base Rankine fleet efficiency | %/100 | 0.32 |
| \( \gamma \) | fraction of Rankine power plants in the generator fleet | %/100 | 0.42 |

Transmission and Distribution Network [8]

| Variable | Definition | Units | Base value |
|----------|------------|-------|------------|
| \( q_s \) | conductor solar heat gain | kWh | – |
| \( q_c \) | conductor convection heat loss | kWh | – |
| \( q_r \) | conductor radiated heat loss | kWh | – |
| \( I \) | conductor current fraction of maximum rated current | %/100 | 0.55 |
| \( T_c \) | conductor temperature | °C | – |
| \( T_{ref} \) | reference temperature | °C | 20 |
| \( R_{tc} \) | resistance at conductor temperature | Ω/ft | – |
| \( R_{tref} \) | resistance at reference temperature | Ω/ft | 4.45 E–5 |
| \( \alpha \) | solar absorptivity | – | 0.7 |
| \( Q_s \) | solar and sky radiated heat flux | W/ft² | 91.93 |
| \( A' \) | projected area of conductor | ft² per lineal ft | 0.0672 |
| \( \sin(\theta) \) | solar heat term based on solar and conductor azimuth | – | 0.996 |
| \( D \) | diameter of conductor | in | 0.806 |
| \( \epsilon \) | emissivity | – | 0.5 |
| \( \phi \) | angle between conductor axis and wind air stream | deg | 45 |
| \( K_b \) | convection heat term that accounts for angle \( \phi \) | – | 0.8549 |
| \( k_f \) | air thermal conductivity coefficient | W/ft | – |
| \( \rho_f \) | air density | lb/ft³ | – |
| \( V_w \) | velocity of wind air stream | ft/sec | 2 |
| \( \mu_f \) | absolute viscosity of air | lb/(ft · h) | – |
| \( L \) | transmission losses | kWh | – |
| \( \zeta \) | transmission disposition | – | – |
| \( \beta_{TD} \) | base transmission and distribution network efficiency | %/100 | 0.95 |
| \( \eta_{TD} \) | efficiency of transmission and distribution network | %/100 | – |

Chiller and Ice Storage

| Variable | Definition | Units | Base value |
|----------|------------|-------|------------|
| COP | coefficient of performance | kWh cooling/kWh elec. | – |
| \( \phi \) | COP de-rating factor for ice production mode | %/100 | 0.80 |
| \( \eta_{CTES} \) | efficiency of cooling thermal energy storage | %/100 | 0.97 |

System Level

| Variable | Definition | Units | Base value |
|----------|------------|-------|------------|
| \( E_{cooling} \) | cooling energy demand | MWh | – |
| \( E_{fuel} \) | primary generator fuel required to meet cooling demand | MWh | – |

Rankine-to-combined-cycle ratio of generation fleet capacity. While Rankine cycle power plants generally include nuclear, coal, and natural gas boiler generators, this study focuses on coal power plants due their larger share in the power sector.

The power plant models are developed in Thermoflex [37], a third-party thermodynamic modeling software used to estimate thermal power plant performance given default or user-defined inputs for individual components such as boilers, steam turbines,
and condensers and meteorological conditions such as temperature and humidity. The combined cycle and Rankine cycle models used for this study are based on samples provided with the Thermoflex software. The combined cycle model has one GE 7HA gas turbine and one steam turbine. The output of the gas turbine can be adjusted as a percentage of its rated power output. The Rankine cycle model includes a boiler and steam turbine. The steam turbine’s output scales according to the user-defined heat input, which was arbitrarily defined as 1000 MW<sub>th</sub> for the sake of simplicity. The Rankine cycle model does not explicitly model combustion and can be used to estimate the performance of any steam turbine power plant regardless of fuel type. For both the combined cycle and Rankine cycle models, the pressure set point for the condenser changes with meteorological conditions. Higher temperatures result in higher condenser pressure and lower power output and efficiency from the steam turbine.

Running the Thermoflex models at different ambient temperatures and humidities yields the heat rate Λ regressions in equations (1)–(2) in units of Btu<sub>fuel</sub>/kWh<sub>elec</sub>. The second calculation in equations (1–2) translates the heat rate into energy efficiency η, where β<sub>cc</sub> and β<sub>rankine</sub> are the average rated efficiencies of the combined cycle and Rankine portions of the generator fleet used as the γ-intercept of efficiency equations. This study uses base values of β<sub>cc</sub> = 0.47 and β<sub>rankine</sub> = 0.32, the average rated efficiencies of ERCOT’s coal and NGCC generator fleets [38].

\[
\Lambda_{cc}(T, H) = 6448.7 - 7.451T - 0.744H + 0.0722TH + 0.164T^2 + 0.00012H^2
\]
\[
\eta_{cc}(T, H) = \frac{3412}{\Lambda_{cc}(T, H)} \times \frac{1}{\Lambda_{cc}(T, H)} \times \frac{1}{\text{Btu}_{fuel}} \times \frac{1}{\text{kWh}_{elec}} - 0.534 + (\beta_{cc} = 0.47)
\]

\[
\Lambda_{rankine}(T, H) = 8397.8 - 18.550T - 2.287H + 0.224TH + 0.434T^2 + 0.00120H^2
\]
\[
\eta_{rankine}(T, H) = \frac{3412}{\Lambda_{rankine}(T, H)} \times \frac{1}{\Lambda_{rankine}(T, H)} \times \frac{1}{\text{Btu}_{fuel}} \times \frac{1}{\text{kWh}_{elec}} - 0.413 + (\beta_{rankine} = 0.32)
\]

Many generator fleets contain both combined-cycle and Rankine cycle power plants. The model represents these mixed fleets using equation (3), where γ is the fraction of Rankine cycle generators in a particular generator fleet. This study uses a base value of γ = 0.42 (i.e. a fleet with 42% Rankine cycle and 58% combined-cycle generation capacity), representative of the ERCOT generator fleet. Figure 2 charts the influence of γ, ambient temperature, and relative humidity on average generator fleet efficiency.

\[
\eta_{gen}(T, H) = (1 - \gamma)\eta_{cc} + \gamma\eta_{rankine}
\]

Though every generator’s efficiency curve is different, this study assumes the generator efficiency model in equation (3) reasonably approximates the average efficiency of a heterogeneous generator fleet, with the Rankine fraction γ and base generator efficiency terms β<sub>cc</sub> and β<sub>rankine</sub> adding flexibility to the model. Adjusting these terms helps capture changes in the generator dispatch. For example, many generators will turn off during low demand, which alters the average efficiency of the generator fleet. In that case, the γ, β<sub>cc</sub>, and β<sub>rankine</sub> terms can adjust to reflect the changing status of the on-line fleet.

This study models small additions of CTES and focuses on average generator fleet efficiency, though a more detailed representation of the generator fleet might be needed if CTES load shifting reaches a significant scale. The net effect on the system efficiency will depend on which power plants are dispatched during the day and which ones are dispatched during the night, both of which vary by season, location, meteorological and astronomical conditions (which affect wind and solar availability, which, in turn, affects the thermal generator dispatch), and price spreads between natural gas and coal. Additionally, if a generator is normally operating at full capacity during the afternoon, turning it down because of significant load shaving might reduce its base efficiency. Alternatively, if a power plant is operating at partial capacity at night, turning it up to charge CTES might increase its base efficiency. Those many finer aspects are not modeled here, but are anticipated with the model’s general equations and could be explored in future work.

### 3.2. Transmission and distribution efficiency

T&D losses increase with electrical current and line resistance, where electrical current increases with system electricity demand and line resistance increases with the temperature of the line’s electrical conductor material. Conductor temperature depends on electrical current, ambient temperature, wind speed, solar radiation, and other factors contributing to the heat balance equations shown in equation (4) [8, 9].

Solving this system of equations yields the conductor temperature T<sub>c</sub>, resistance R<sub>c</sub>, and losses I if the ambient temperature T and current I are known. This study uses a model developed by Bockarjova [8], who illustrates the model with using a single 397.500 ACSR 30/7 high-voltage transmission line with 600 A capacity, 0.235 ohm mile<sup>-1</sup> resistance, 0.5 emissivity, and 0.7 solar absorptivity. While this simple scenario does not model the intricacies of current flow in a multi-bus transmission grid, it generally quantifies how transmission line efficiency changes with ambient conditions and current flow. While a multi-bus transmission grid model might better represent the ERCOT network, this study applies Bockarjova’s scenario by assuming that all transmission lines have equal current flow and equating the normalized current flow with the normalized ERCOT load. Thus, ambient temperature and normalized current (i.e. rather than using Amps, current is expressed as, e.g. 0.55 meaning that the lines are at 55% of their rated capacity because the system is at
Figure 2. Average generator fleet efficiency varies with Rankine fraction $\gamma$, temperature, and humidity for a fleet with Rankine and combined-cycle generators. Generally speaking, ambient conditions affect Rankine cycle generators more than combined cycle generators, and thermal power plant efficiency improves at night when the weather is cooler. Table 1 lists the generator parameters' base values.

Table 2. Any heat balance equation parameters not defined by Bockarjova [8] are assumed to have these values. Air properties ($\rho_f$, $\mu_f$, and $k_f$) are calculated using equations or data provided by [39–42].

| Parameter | Assumed value | Justifying assumptions |
|-----------|---------------|------------------------|
| $A'$      | $(12D)/144$ [ft²/lineal–foot] | Power line is perpendicular to sun’s path (i.e. the conductor’s whole cross section is projected towards the sun) |
| $\phi$    | 45 [degrees] (0.25$\pi$ [radians]) | Wind angle to conductor varies between 0 and 90 degrees at a uniform distribution, averaging to 45 degrees |
| $\rho_f$  | $39.69 (1.8T + 491.67)$ [lb/ft³] | Standard atmospheric pressure. Air molecular weight is 28.97 [39] |
| $\mu_f$   | $4.227 \times 10^{-2} + 9.068 \times 10^{-5} T$ [lb/(ft·h)] | Standard atmospheric pressure. [41] |
| $k_f$     | $2.169 + 0.0214 T$ [W/ft] | Standard atmospheric pressure. [42] |

55% of peak demand) can be fed into Bockarjova’s scenario to approximate how CTES load shifting impacts T&D efficiency. The T&D model is solved using the parameter values defined by Bockarjova [8], with any undefined parameters being given the values shown in table 2.

$$\eta_{TD}(T, I) = 1 - \frac{L_{TD}(T, I)}{I^2 R_T}$$

The efficiency is calculated by dividing the loss $L$ by the disposition $\zeta$ and subtracting the quotient from 1. In this study, the disposition is approximated by solving for a reference normalized current $I$ of 0.55 (the annual, average, normalized demand in ERCOT), ambient temperature $T$ of 20 °C (the annual, average temperature in the Dallas–Fort Worth case study region), and T&D efficiency $\beta_{TD}$ of 0.95 [43]. That disposition is used to calculate the T&D efficiency at other currents and ambient temperatures per equation (5). The $I$, $T$, and $\beta_{TD}$ parameters can be changed to more accurately represent a specific T&D network. Figure 3 visualizes how temperature and line current influence T&D efficiency.

3.3. Chiller efficiency

In a typical commercial air conditioning system, a chiller uses a working fluid to transfer heat from a building’s interior to the outdoors. Lower ambient temperatures provide a colder heat sink for the chiller, improving its energy efficiency [36, 44]. The coefficient of performance (COP) measures a chiller’s efficiency, where COP = Rejected Heat/Electric Work Input [45], and a higher COP is more efficient.

This study models chiller COP by fitting a power function to the performance data of the RTAC140h—a high-efficiency, air-cooled chiller manufactured by the Trane Corporation [46]. In addition to ambient unloading curves, the RTAC140h performance data also indicates an efficiency derating factor $\phi$ of 0.80 when the chiller is operating in ice-making mode [46],
Figure 3. T&D efficiency varies with temperature and line current flow according to equation (5). Generally speaking, T&D efficiency improves at night, in the summer, when temperature and line current are lower. Table 1 lists the T&D parameters’ base values.

Figure 4. Chiller COP varies with ambient temperature and whether the chiller is in cooling mode or ice-making mode according to equation (6). Chiller efficiency improves at lower temperatures. Table 1 lists the chiller parameters’ base values.

meaning that the chiller’s COP in ice-making mode is 80% of its COP in cooling mode. Equation (6) shows the chiller model. Figure 4 shows how chiller COP varies with ambient temperature and humidity. The convex shape means that COP improves exponentially with lower ambient temperatures.

\[
\begin{align*}
\text{COP}_{\text{cooling}}(T) & = 48.4187T^{-0.744} \\
\text{COP}_{\text{ice}}(T) & = \text{COP}_{\text{cooling}} \times (\varphi = 0.80)
\end{align*}
\] (6)

3.4. Cooling thermal energy storage efficiency
CTES storage efficiency depends on ambient temperature and the operational strategy used for charging and discharging the ice-storage tank. A model presented by MacPhee [47] shows how the round-trip energy efficiency of a CTES system using a ‘partial storage’ strategy varies from 97.5%–99% depending on ambient temperature, storage duration, and other factors. This study assumes a partial storage CTES strategy with a five-hour, nighttime charge cycle and a five-hour, daytime discharge cycle. This operation coincides roughly with a case study presented by MacPhee [47], with the efficiency modeled in equation (7), where \( T \) is the average temperature over the five hour time window in °C.

\[
\eta_{\text{CTES}} = 0.997 - 0.0005T
\] (7)

3.5. System efficiency
As shown in figure 1, the grid-wide system is modeled as a series of energy conversion processes between the fuel energy input of the generator fleet to the cooling delivered by the CTES system to the building. Equation (8) describes this model, where sections 3.1–3.4
Figure 5. System energy consumption increases with ambient temperature and relative humidity.

The system efficiency calculation in equation (8) can be used to approximate the impact of CTES on an electric grid’s overall efficiency. By assuming that CTES will be used for shifting cooling load from time $t_1$ to ice-making load at time $t_2$, and that the system parameters vary from $t_1$ to $t_2$, the system efficiency at each time can be calculated. The difference in energy consumption between $t_1$ and $t_2$ reveals the net change in energy consumption caused by CTES load shifting.

4. Results and discussion

The model results depend greatly on the system’s climate and operational characteristics. In an attempt to generalize the application of the model, section 4.1 presents a graphical analysis of the system efficiency’s sensitivity to ambient temperature, relative humidity, base generator fleet efficiency, and T&D electric current. A case study in section 4.2 shows how to apply the model to a specific scenario.

4.1. Sensitivity analysis

Figures 5–7 present a sensitivity analysis for the general, grid-wide, efficiency model assuming the base values in table 1 unless indicated otherwise. The results show the impact of different system parameters on system efficiency and approximate the effects of CTES utilization on system energy consumption. For example, figure 5 approximates how shifting load from one set of weather conditions to another will impact energy consumption. If the system uses CTES to shift cooling demand at 40°C and 20% humidity to ice-making demand at 28°C and 60% humidity, system energy consumption will change from 0.850 to 0.825 MWh fuel per MWh cooling, reducing system-wide energy consumption.

Similarly, figure 6 shows how system energy consumption changes at different Rankine fractions. Altering the Rankine fraction can capture the effects of changes to the generator fleet dispatch on the system-wide energy demand as discussed in section 3.1. Figure 7 shows how system energy consumption changes at different line currents in the T&D network. Lower line current might occur when demand is lower and less energy is traveling over the T&D network.

Figure 8 compiles some of the sensitivity parameters into a single chart, showing the change in primary fuel consumption caused by CTES load shifting depending on daytime temperature, nighttime temperature reduction, and change in Rankine fraction $\gamma$ under the constant humidity, T&D current, and base generator efficiency values shown in table 1. For example, suppose that daytime temperature is 35°C, daytime Rankine fraction is 42%, nighttime temperature is 22°C, and nighttime Rankine fraction is 22%. In the center panel (35°C daytime temperature), the ‘−20%’ series (change in $\gamma$) has a value of −0.145 [MWh Fuel per MWh Cooling] when the nighttime temperature...
reduction (x-axis) is 13 Δ°C (daytime temperature—nighttime temperature). Thus, energy consumption is reduced by 0.145 MWh under that scenario.

A few conclusions can be drawn from figure 8. First, lower daytime temperatures require less nighttime temperature reduction to break even (cross the y = 0 axis) on changes in energy consumption. The chiller efficiency’s non-linear improvements at lower ambient temperatures drives this result (see figure 4), suggesting that lower nighttime temperatures contribute to greater energy consumption savings. Second, changes in Rankine fraction γ are less influential at lower daytime temperatures as the non-linear chiller efficiency improvements overshadow changes in generator fleet efficiency. Third, energy consumption decreases with larger nighttime temperature reduction. Together, these conclusions suggest the CTES load shifting will provide the greatest system-wide efficiency gains in climates with lower nighttime temperatures and greater nighttime temperature reduction.

4.2. Dallas-fort worth, Texas case study

Changes in temperature, humidity, line current, and generator fleet efficiency contribute to the changes in system-wide energy consumption caused by shifting load from daytime cooling to nighttime ice-making via
CTES. Analyzing the daily changes of these parameters during the ‘cooling season’ at a specific location can provide important information about how CTES will perform in that area.

The cooling season includes all days where some building air conditioning is necessary. The need for air conditioning can be approximated using the ‘cooling degree day’ (CDD) calculation in equation (9) [48]. This equation compares the daily, average ambient temperature to a 65 °F (18.33 °C) reference temperature. It assumes that, if the daily, average, outdoor air temperature is 65 °F or more, then an average building will require air conditioning to maintain an indoor temperature of 70 °F [48]. If a particular day has a CDD greater than 0, some cooling will likely be needed, and that day should be included in the cooling season.

\[
CDD = \frac{T_{\text{max}} + T_{\text{min}}}{2} - 18.333 \tag{9}
\]

The following example uses 2015 load and generator fleet data for ERCOT and 2015 weather data for the Dallas–Fort Worth International Airport (DFW) [49] in Texas, USA to simulate how annual demand and weather patterns might influence system-wide energy consumption changes due to CTES load shifting during the DFW cooling season. The simulation assumes that CTES will be charged (i.e. the chiller will operate in ice-making mode) during each day’s five lowest ambient temperatures and discharged (i.e. ice will be melted allowing the chiller to turn off) during each day’s five highest temperature. Figure 9 shows DFW’s averaged five-lowest and averaged five-highest temperature for each day in the cooling season. Figure 10 shows the averaged relative humidities concurrent with those temperatures. On average, from nighttime to daytime, ambient temperature increases by 10.1 °C and relative humidity decreases by 33% RH.

This simulation example also captures changes in T&D line current and average generator fleet efficiency. This study assumes that line current equals the normalized ERCOT load, i.e. line current is 1.00 (i.e. at 100% capacity) at peak demand and 0.00 when there is no demand. On average, from nighttime to daytime, line current decreases by 0.21 per figure11. Note that the shoulder seasons have the lowest nighttime load/current and the summer has the largest differences between daytime and nighttime load/current.

The average generator fleet efficiency is estimated by quantifying how the ERCOT generator fleet’s Rankine fraction, average on-line coal generator efficiency, and average on-line NGCC efficiency vary with system demand. These calculations ERCOT generator fleet data [38] and fuel prices of 3.50 and 2.50 $/MMBtu for natural gas and coal (based on five-year ERCOT averages) and assume that generators will be dispatched in order of their marginal cost until the amount of on-line generation equals the load. Under those assumptions, the Rankine fraction \( \gamma \) is calculated by dividing the on-line coal capacity by the sum of on-line coal and NGCC capacity. The average combined-cycle \( \beta_{cc} \) and Rankine \( \beta_{\text{rankine}} \) efficiencies are calculated by averaging the rated efficiencies of the on-line combined cycle and coal generators. Figure 12 shows the results of these calculations in terms of ERCOT load. Applying these calculations to the average five-hour load concurrent

![Figure 8](image-url)
Figure 9. During the 2015 cooling season in DFW, the average peak daytime temperature exceeds the average lowest nighttime temperature by a mean of 10.1 °C, a minimum of 2.5 °C, and a maximum of 16.8 °C.

Figure 10. During the 2015 cooling season in DFW, the average nighttime humidity exceeds the average daytime humidity by a mean of 33% RH, a minimum of ~22% RH, and a maximum of 62% RH.

Figure 11. During the 2015 cooling season in DFW, the average daytime line current exceeds the average nighttime line current by a mean of 0.21, a minimum of 0.01, and a maximum of 0.47. Note that line current is assumed to equal the normalized ERCOT load.
with the daytime and nighttime CTES time periods yields Rankine fraction and base generator efficiency values for equations (1)–(3) producing the average fleet efficiencies shown in figure 13. On average, from nighttime to daytime, absolute base generator fleet efficiency increases by 2.89%.

Solving equation (8) for the temperature, humidity, and load of a daytime or nighttime datum yields the system-wide energy consumption caused by that daytime cooling or nighttime ice-making. Figure 14(a) shows the system energy consumption rate for each day in the cooling season. In this figure, CTES load shifting would move some energy demand from daytime cooling to nighttime ice-making. If a day’s nighttime ice-making uses less energy than its daytime cooling, then its energy consumption has been reduced by CTES load shifting, and it will be shown as a negative value in figure 14(b). Thus, in the DFW simulation, it is often (but not always) more efficient for the whole-grid system to produce ice at night than to operate chillers during the day. Of the 214 d in the 2015 DFW cooling season, 185 d experience reduced energy consumption (annual total of −18.2 [MWh Fuel per MWh Cooling]) and 29 d experience increased energy consumption (annual total of +0.6 [MWh Fuel per MWh Cooling]) due to CTES load shifting.

In the DFW example, providing 1 MWh of daytime cooling during the hottest hours of each day requires the annual consumption of 144.5 MWh of primary fuel. Generating 1 MWh of ice storage during each night of the cooling season consumes 126.9 MWh of primary fuel, annually. Thus, each MWh of CTES capacity
Figure 14. Daytime energy needs for cooling are greater than nighttime energy needs for ice-making in 185 d out of the 214 day cooling season for DFW in 2015. Nighttime consumption rate minus daytime consumption rate is $-0.082$ on average with a minimum of $-0.235$ and a maximum of $0.068$.

Figure 15. CTES load shifting impacts the efficiency of different system components as ambient conditions (influencing the chiller ($\Delta$), generator fleet (‘x’), and T&D network (‘+’)) and ERCOT electricity demand (influencing the generator fleet (‘o’) and T&D network (‘*’)) change throughout the year.
installed in the DFW area could lower annual generator fuel consumption by 17.6 MWh, a reduction of 12.2%.

Figure 15 shows the relative efficiency change for the different components of the system throughout the cooling season. Chiller efficiency (Δ) can increase up to 30% from daytime to nighttime during the shoulder seasons when nighttime temperatures are lowest, but can also decrease by 10% or more when the inefficiency of ice-making outweighs the benefits of lower ambient temperatures. Generator efficiency associated with ambient conditions (‘x’) improves most during the summer months when the temperature difference between night and day is larger, nighttime humidity is lower, and Rankine fraction is higher due to greater electricity demand as compared to the shoulder seasons. Improvements to the base generator efficiency due to fleet dispatch (‘o’) also change most in the summer when the load difference and Rankine fraction difference between night and day is larger compared to the shoulder seasons. These differences have a similar effect on the T&D network efficiency due to line current (‘*’), though ambient conditions (‘+’) have only a small influence on the T&D network efficiency.

The chiller and generator fleet impact overall energy consumption much more than the T&D network, whose high efficiency is relatively stable. Chiller efficiency improves most during the shoulder seasons, while generator fleet efficiency improves most during the summer, allowing the two system components to balance each other and create year-round energy savings without significant seasonality (see figure 14).

The generator fleet properties and system load profile significantly impact changes in the generator fleet efficiency. For example, ambient conditions would influence a fully-Rankine fleet more than a fully-combined-cycle fleet. Wind generation output, often greater at nighttime, might reduce nighttime load and force less-efficient power plants to turn off, increasing the average efficiency of the nighttime generator fleet and the energy savings from CTES load shifting. On the other hand, solar generation output, often greater at daytime, might reduce daytime load, increasing daytime generator fleet efficiency and reducing the energy savings from CTES load shifting.

### 5. Conclusions

By conducting a systems-level analysis rather than individual component-level analysis and by approximating the electric grid as a series of technologies for converting generator fuel into building cooling, this study presents a model for calculating the grid’s system-wide efficiency as a function of ambient temperature, relative humidity, base generator efficiency, and T&D network current. The generalized results shown in figures 5–7 visualize how shifting chiller load from cooling to ice-making earlier in the day can influence system-wide energy consumption. These results support the conclusion that, under the right circumstances, cooling thermal energy storage (CTES) can enable load shifting strategies that reduce energy consumption across the whole electric grid.

In the specific example of the Dallas–Fort Worth, Texas metro area, the results show that using CTES to shift demand from cooling during the hottest hours of the day to ice-making during the coolest hours of the day can reduce annual primary fuel consumption by 15.9 MWh for each MWh of installed CTES capacity. Results from this case study suggest that a system with low nighttime temperatures, large daily swings in temperature and electric demand, and a generator fleet whose efficiency decreases steadily with increasing load will experience the greatest efficiency improvements from CTES load shifting.

These conclusions expand the portrayal of storage as a net consumer of energy in the electric grid. While all energy storage technologies experience energy losses during their charge/discharge cycles, their ability to shift the timing of electric demand has a broader influence on the operation of the grid. Shifting the load toward times of lower ambient temperature, lower relative humidity, greater base generator efficiency, and/or lower T&D network current can increase the efficiency of the whole electric grid. Under the right circumstances and using the right technologies and operational strategies, these grid-wide efficiency gains can overcome the efficiency losses inherent in storage technologies resulting in lower energy consumption overall.

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### References

[1] Lund P D, Lindgren J, Mikkola J and Salpakari J 2015 Review of energy system flexibility measures to enable high levels of variable renewable electricity Renew. Sust. Energy Rev. 45 785–807

[2] Ferreira H L, Garde R, Fulli G, Kling W and Lopes J P 2013 Characterisation of electrical energy storage technologies Energy 53 288–98

[3] Fares R L and Webber M E 2017 The impacts of storing solar energy in the home to reduce reliance on the utility Nat. Energy 2 17001

[4] von Appen J, Braslavsky J H, Ward J K and Braun M 2015 Sizing and grid impact of PV battery systems—a comparative analysis for Australia and Germany IEEE Int. Symp. on Smart Electric Distribution Systems and Technologies (EDST) (Vienna, Austria) pp 612–19
[5] Nyadamsh B, Denny E and O'Malley M 2010 The viability of balancing wind generation with large scale energy storage Energy Policy 38 7200–7208
[6] Barigozzi G, Perdichizzi A and Ravelli S 2011 Wet and dry cooling systems optimization applied to a modern waste-to-energy cogeneration heat and power plant Appl. Energy 88 1366–76
[7] Zhang H and Rubin E S 2010 Performance and cost of wet and dry cooling systems for pulverized coal power plants with and without carbon capture and storage Energy Policy 38 5653–60
[8] Bockarjova M and Andersson G 2007 Transmission line conductor temperature impact on state estimation accuracy IEEE Conf. on Power Tech (Lusanne, Switzerland) pp 701–6
[9] Luo L, Cheng X, Zong X, Wei W and Wang C 2015 Research on transmission line loss and carrying current based on temperature power flow model 3rd Int. Conf. on Mechanical Engineering and Intelligent Systems (Yinchuan, China) pp 120–7
[10] Evapco Inc. 2007 Thermal ice storage application and design guide
[11] Sanaye S and Hemmatian M 2016 Ice thermal energy storage (ites) for air-conditioning application in full and partial load operating modes Int. J. Refrig. 66 181–97
[12] Silvetti B 2002 Application fundamentals of ice-based thermal storage ASHRAE J. 44 30–5
[13] Henze G P, Felsmann C and Knabe G 2004 Evaluation of optimal control for active and passive building thermal storage Int. J. Therm. Sci. 43 173–83
[14] Ruan Y, Liu Q, Li Z and Wu J 2016 Optimization and analysis of building combined cooling, heating and power (BCHP) plants with chilled ice thermal storage system Appl. Energy 179 738–54
[15] Zhang Z, Turner W D, Chen Q, Xu C and Deng S 2011 Tank size and operating strategy optimization of a stratified chilled water storage system Appl. Therm. Eng. 31 2656–64
[16] Lee W-S, Chen Y-T and Wu T-H 2009 Optimization for ice-storage air-conditioning system using particle swarm algorithm Appl. Energy 86 1589–95
[17] Henze G P, Bifar B, Kohn D and Becker M P 2008 Optimal design and operation of a thermal storage system for a chilled water plant serving pharmaceutical buildings Energy Buildings 40 1004–19
[18] Chen H-J, Wang D W and Chen S-L 2005 Optimization of an ice-storage air conditioning system using dynamic programming method Appl. Therm. Eng. 25 461–72
[19] Dunn B, Kamath H and Tarascon J-M 2011 Electrical energy storage for the grid: a battery of choices Science 334 928–35
[20] Hadipaschalis I, Poullikkas A and Effthimiou V 2009 Overview of current and future energy storage technologies for electric power applications Renew. Sust. Energy Rev. 13 1513–22
[21] Braun J E 1990 Reducing energy costs and peak electrical demand through optimal control of building thermal storage ASHRAE Trans. 96 876–88
[22] Lawrova O, Cheng F, Abdullah S, Barsun H, Mammoli A, Dreissmayer D, Willard S, Arellano B and Van Zeyl C 2012 Analysis of battery storage utilization for load shifting and peak smoothing on a distribution feeder New Mexico IEEE 2012 Conf. on PES Innovative Smart Grid Technologies (ISG'T) (Washington, DC, USA) pp 1–6
[23] Barzin R, Chen J J, Young B R and Farid M M 2015 Peak load shifting with energy storage and price-based control system Energy 92 305–14
[24] Leadbetter J and Swan L 2012 Battery storage system for residential electricity peak demand shaving Energy Buildings 55 685–92
[25] Sortomme E and El-Sharkawki M A 2012 Optimal scheduling of vehicle-to-grid energy and ancillary services IEEE Trans. Smart Grid 3 351–9
[26] Divya K and Ostergaard J 2009 Battery energy storage technology for power systems—an overview Electr. Power Syst. Res. 79 511–20
[27] Osubalov A, Chartouni D and Ohler C 2007 Optimizing a battery energy storage system for primary frequency control IEEE Trans. Power Syst. 22 1259–66
[28] Lund H 2007 Renewable energy strategies for sustainable development Energy 32 912–9
[29] Denholm P and Hand M 2011 Grid flexibility and storage required to achieve very high penetration of variable renewable electricity Energy Policy 39 1817–30
[30] Harris C, Meyers J P and Webber M E 2012 A unit commitment study of the application of energy storage toward the integration of renewable generation J. Renew. Sust. Energy 4 013120
[31] Clayton M E, Stillwell A S and Webber M E 2014 Implementation of brackish groundwater desalination using wind-generated electricity: a case study of the energy-water nexus in Texas Sustainability 6 758–78
[32] Heide D, Greiner M, Von Brennen I and Hoffmann C 2011 Reduced storage and balancing needs in a fully renewable European power system with excess wind and solar power generation Renew. Energy 36 2515–23
[33] Wei M, Nelson J H, Greenblatt J B, Mileva A, Johnston J, Ting M, Yang C, Jones C, McMalton E J and Kammern D M 2013 Deep carbon reductions in California require electrification and integration across economic sectors Environ. Res. Lett. 8 014038
[34] Bartos M, Chester M, Johnson N, Gorman B, Eisenberg D, Linkov I and Bates M 2016 Impacts of rising air temperatures on electric transmission ampacity and peak electricity load in the united states Environ. Res. Lett. 11 114008
[35] Cetin K S 2015 Smart technology enabled residential building energy use and peak load reduction and their effects on occupant thermal comfort: paper 5 Ph.D. Thesis University of Texas at Austin
[36] Powell K M, Cole W J, Elakria U F and Edgar T F 2013 Optimal chilling loading in a district cooling system with thermal energy storage Energy 50 445–53
[37] Thermoflow, Inc. 2017 Thermoflux thermal power system modeling software (www.thermoflow.com/)
[38] Electric Reliability Council of Texas 2016 ERCOT generation by resource type in 2016. Available via ERCOT dataport: (https://mis.ercot.com) (Accessed: April 2017)
[39] The Engineering Toolbox 2017 Air Temperature Pressure and Density (www.engineeringtoolbox.com/air-temperature-pressure-density-d_771.html)
[40] The Engineering Toolbox 2017 Absolute or Dynamic Viscosity Online Converter (www.engineeringtoolbox.com/dynamic-viscosity-d_571.html)
[41] The Engineering Toolbox 2017 Air Absolute and Kinematic Viscosity (www.engineeringtoolbox.com/air-absolute-kinematic-viscosity-d_601.html)
[42] The Engineering Toolbox 2017 Air Properties (www. engineeringtoolbox.com/air-properties-d_156.html)
[43] US Energy Information Administration 2017 How much electricity is lost in transmission and distribution in the United States, Frequently Asked Questions: (www.eia.gov/tools/faqs/)
[44] Motta S Y and Domanski P A 2001 Impact of elevated ambient temperatures on capacity and energy input to a vapor compression system—literature review Natl Inst. Technol. 21 1–10
[45] Cengel Y A and Boles M A 2006 Thermodynamics: An Engineering Approach (Refrigeration Cycles Chapter) (New York: McGraw-Hill)
[46] Trane Corporation 2017 Trane TRACE 700 software with chiller performance curves: (www.trane.com/commercial- north-america/us/en/products-systems/design-and-analysis-tools/tools/analysis-tools/trace-700.html) (Accessed: April 2017)
[47] MacPhee D and Dincer I 2009 Performance assessment of some ice TES systems Int. J. Therm. Sci. 48 2288–99
[48] Weather Underground 2017 What are heating degree days and cooling degree days (www.wunderground.com/about/faqs/degreedays.asp) (Accessed: July 2017)
[49] National Renewable Energy Laboratory 2017 National Solar Radiation Database (https://nrdc.nrel.gov/) (Accessed: June 2017)