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Power availability of PV plus thermal batteries in real-world electric power grids

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HIGHLIGHTS

- The power availability from photovoltaics and thermal battery was investigated.
- Novel thermal battery technologies can improve renewable energy dispatchability.
- The power availability vastly improves if CO_2 emissions are reduced.

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ABSTRACT

As variable renewable energy sources comprise a growing share of total electricity generation, energy storage technologies are becoming increasingly critical for balancing energy generation and demand.

In this study, a real-world electricity system was modeled rather than modeling hypothetical future electric power systems where the existing electricity infrastructure are neglected. In addition, instead of modeling the general requirements of storage in terms of cost and performance, an existing thermal energy storage concept with estimated capital cost that are sufficiently low to enable large-scale deployment in the electric power system were modeled. The storage unit is coupled with a photovoltaic (PV) system and were modeled with different storage capacities, whereas each storage unit had various discharge capacities.

The modeling was performed under a baseline case with no emission constraints and under hypothetical scenarios in which CO_2 emissions were reduced. The results show that power availability increases with increasing storage size and vastly increases in the hypothetical CO_2 reduction scenarios, as the storage unit is utilized differently. When CO_2 emissions are reduced, the power system must be less dependent on fossil fuel technologies that currently serve the grid, and thus rely more on the power that is served from the PV + storage unit.

The proposed approach can provide increased knowledge to power system planners regarding how adding PV + storage systems to existing grids can contribute to the efficient stepwise decarbonization of electric power systems.

1. Introduction

The use of variable renewable energy (VRE) resources, such as wind power and solar photovoltaics (PV), is expanding rapidly as a share of total power generation and is critical to the decarbonization of electrical power systems [1–3]. The weather-dependent intermittency of VRE sources complicates the planning and management of power systems as the electric power generation can no longer be directly modulated to match the electricity demand. Energy storage will therefore be an increasingly critical component of future energy systems with high

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penetrations of VRE sources. Energy storage can charge excess electricity in periods with high generation and low demand, and then discharge the electricity in periods with low generation from the VRE sources to match the load in periods with high electricity demand [4,5]. In addition, energy storage stabilizes the grid by providing additional electricity supply when there is a surge in electricity demand or a sudden drop in supply from the VRE sources. Energy storage also enables cost reduction of the grid by allowing for an increased share of cheap VRE technologies in the electricity supply portfolio [6], and reduces potential curtailment of the electricity generation from VRE sources during periods when the generation exceeds the demand [7].

The need for inexpensive storage over periods with different lengths, from seconds to days and even seasonal storage, has accelerated in accordance with the increasing share of VRE technologies in electric power systems [6,8]. Pumped hydropower storage (PHS) and compressed air energy storage (CAES) are well-established technologies for large-scale energy storage, although they are only applicable in a few geographic areas. Hydrogen storage is thought to be a promising long-term storage solution. However, due to the high capital cost of charging and discharging, it has the greatest potential in the seasonal storage regime for getting sufficient low energy storage capital cost [9].

Lithium-ion batteries have been the state-of-the-art technology for short-term storage. However, capital costs between US$80 and US$100 kWh^{-1} make them unaffordable for the multi-day storage objectives required to completely decarbonize the grid [4,5,10]. Concentrated solar power with thermal energy storage (CSP-TES) has been seen as a promising option, but major projects around the world have been plagued by delays, cost overruns and mechanical issues, and interest has waned in recent years [11,12]**.** Studies suggest that achieving cost-efficient multi-day storage requires a capital cost reduction to US $3–30 kWh^{-1} [5,13]. Resolving this issue could enable more rapid decarbonization of the power system, resulting in a 25% reduction in global GHG emissions [14,15]. Therefore, one of the most significant issues that needs to be resolved to achieve the GHG emission reduction targets is to enable cost-effective pathways for increasingly implementing energy storage technologies into the electricity system.

A storage concept based on Thermal Energy Storage (TES) has shown promising potential to achieve sufficiently low capital cost in the multi-day storage regime. TES stores the electricity as heat rather than electrochemically, and then converts it back to electricity when needed [16]. The Thermal Energy Grid Storage (TEGS) concept, detailed in [17], stores electricity as sensible heat in graphite storage blocks and uses thermophotovoltaics (TPV) to convert heat back to electricity on demand [17,18]. While the conversion of heat to electricity results in significant efficiency penalties, storing energy as heat instead of electrochemically can be vastly cheaper, and thus the round-trip efficiency (RTE) penalty compared to electrochemical batteries (~ 90%) can potentially be a worthwhile tradeoff [17]. To maximize the conversion efficiency from heat to electricity, the heat is stored at extremely high temperatures (~2400 °C). In a recent work by [19], the authors demonstrated a world-record high conversion efficiency of 41% using TPV, and reported a projected conversion efficiency of 50% in the future. As such this technology can achieve a projected cost below US$ 20 kWh^{-1} at gigawatt scales.

In addition to the projected low cost, a unique property of TEGS compared to Li-ion battery technology is the fact that, since energy is stored as heat in graphite blocks and thereafter converted to electricity using TPV, it enables the possibility of fully decoupling the charge and discharge capacities of the storage unit. This allows the TEGS to charge (i.e., store heat) at a much higher capacity than that required for discharging. The benefit of such a mechanism is that a large amount of energy can be charged in a short amount of time when generation surpluses exist and discharged over a longer period to cover the electricity load in periods where demand exceeds supply. The TEGS system also has advantages in terms of durability, safety, and replaceability which make this technology a promising option to adopt into decarbonized electricity systems. In comparison to the state-of-the art Li-ion batteries, the TEGS system is more durable due to the construction materials. While the lifetime of electrochemical Li-ion batteries is affected by the depth of discharge and the number of cycles, the construction materials (graphite and tin) have no clear degradation mechanism and enables TEGS system to have an expected lifetime of 30 years or more (while li-ion are replaced after approximately 10 years). All construction materials of the TEGS system are at thermodynamic equilibrium giving no risk for chemical reactions. Additionally, it is housed in an inert environment with no immediate access to oxygen, preventing fire hazard. In terms of replaceability, the TEGS unit consists of separate components (Graphite storage blocks for storing heat, and a power block with thermal photovoltaics for generating electricity) which can be replaced separately if needed.

The body of existing literature counts several studies that have employed different approaches to evaluate the value of using storage to increase the dispatchability of VRE sources, and the different studies have highlighted the storage requirements (capital cost and storage duration) to enable the full decarbonization of the power system. Table 1 shows an overview of some relevant studies, where the key findings in each work are highlighted.

The vast number of previous studies on modeling the value of energy storage in emerging power systems, mainly focus on modeling hypothetical future electric power systems starting from scratch (i.e., "greenfield" models) [6,20–25]. However, such studies can, in many

Table 1
Overview of relevant work addressing the value of energy storage.

Ref.	Year	Key findings
[21]	2016	Large-scale deployment of available battery technologies requires cost reductions
[24]	2016	Pathways to fully renewable systems are feasible with high cost and overgeneration.
[4]	2016	Cost reduction for storage technologies is required to reach widespread profitability.
[22]	2017	The availability of how low-carbon technologies impact the optimal capacity mix and generation patterns were demonstrated.
[8]	2018	To reliably meet 100% of total annual electricity demand, weeks of energy storage are required to support with electricity.
[20]	2018	The role of energy storage units in power systems with high shares of VRE was analyzed. The importance of storage increases with the increasing share of renewable-based power technologies.
[23]	2018	Firm low-carbon resources consistently lower decarbonized electricity system costs, and the availability of firm low-carbon resources reduces costs 10%–62% in zero-CO_2 cases
[25]	2019	The benefits of hydro power and storage units were analyzed. Three decarbonized power systems with distinct grid expansion strategies were compared. Cutting transmission volume does not increase the total costs.
[7]	2019	Curtailment of renewable energy generation can be avoided using energy storage.
[5]	2019	Energy storage cost below $20 kWh^{-1} can enable cost-competitive baseload power.
[30]	2020	Hydrogen storage with up to 2 weeks of discharge duration is expected to be cost-effective in future power systems.
[31]	2020	Hydrogen storage enable for sector coupling in real-world power systems.
[32]	2020	Electricity triangle assures a consistent framework for the energy transition.
[10]	2020	Current Li-ion capital cost exceed storage value in many instances.
[26]	2020	Decarbonization is less expensive with Energy Storage Systems, given sufficient low-cost assumptions
[6]	2021	Energy capacity costs must be $\leq$US$20/kWh to reduce the electricity price by $\geq$10%.
[33]	2021	Power systems with 100% RE is possible using existing technologies.
[34]	2021	There is a need for analytic tool development to model how to achieve a power system that are 100% decarbonized.
[35]	2021	Clean firm resources are cost-effective in decarbonizing the grid
[9]	2022	Green hydrogen cost between $0.79/kg and $1.94/kg in 2030 can be achieved
[27]	2022	The demand for power capacity will drive future adoption of higher battery power capacity

cases, lead to vague results as this requires a complete change of the current electricity mix. This is in many cases challenging to implement due to policy considerations. In addition, by modeling greenfield cases, infrastructure that already exists is neglected.

Another approach to modeling the electric power system is by studying scenarios using the current electricity infrastructure (i.e., “brownfield studies). The benefit of such studies compared to greenfield studies is that this enables insight into how the existing electricity system can transform towards decarbonization from the current electricity infrastructure and hence give insight into which measures that must be taken to decarbonize the current electricity system.

Some former literature has applied a brownfield modeling approach when studying decarbonization pathways but lacks in modeling the potential value of using specific storage technologies [5,10,26–28]. These studies model the storage requirements in general, whereas all studies show that the capital cost must be below US \$20 kWh^{-1}. No previous work has modeled the potential of using an emerging storage concept based on TES that already exists on a lab scale [17,18].

In this study, a framework for addressing the value of using TEGS that has sufficiently low capital cost to be economically used in an electric grid is proposed. Using a Capacity Expansion Model (CEM) [29], a hypothetical PV + TEGS system that is interconnected to an existing real-world grid in the Northeastern US is considered. The TEGS unit charges excess electricity from PV during periods of surplus generation. When the grid demands electricity and the PV plant cannot deliver sufficient power due to a lack of solar availability, the stored energy is discharged. Different storage sizes with varying discharge capacities connected to the PV plant are modeled to optimize power availability. To investigate how emission constraints affect the energy availability of PV + storage systems, a hypothetical future scenario is modeled for the existing power system where CO_2 emissions are reduced.

The main contributions of this study are: Rather than modeling the power system as a greenfield case study, an abstract representation of an existing grid, i.e., a “brownfield” model is analyzed to address how adding a PV + storage system can contribute to decarbonizing the grid. Instead of modeling general requirements of storage to enable the full decarbonization of the power system, a TES unit that currently exists at lab-scale and has promising cost projections that are well-documented in the literature is modeled [17]. This study can provide increased knowledge to power system planners on how coupling emerging storage technologies and PV systems to existing grids can contribute to stepwise decarbonizing of the grid in a more short-term horizon.

2. Methods

2.1. Modeled electric power system

In this study, an idealized single node representing the electric grid region in the New England power system in North America is modeled. This system considers one grid zone that represents a simplified power system topology of the states of Massachusetts, New Hampshire, and Rhode Island. The electricity demand, capital cost and performance data for the different generation technologies in these regions were collected from the NREL annual technology baseline (ATB) and the U.S. Energy Information Administration (EIA). The Github library PowerGenome[1] was used to collect the input data and shape them to the required format for the CEM. The weather data used to construct the hourly generation profiles for solar and wind resources are collected from Vibrant Clean Energy (without any usage restrictions) using PowerGenome. The data from Vibrant Clean Energy is obtained from the National Oceanic and Atmospheric Administration (NOAA) High-Resolution Rapid Refresh (HRRR) weather forecast model. The weather forecast model is run every hour over a 3-km horizontal resolution that covers the United States. The weather year for modeling VRE availability in this study was the year of 2020.

The average annualized electricity demand for the modeled grid is 9.4 GWh, with a peak load of 16.7 GWh. Fig. 1 illustrates the hourly electricity demand in the modeled power system.

The blue graph shows the electricity demand with an hourly resolution, while the black graph shows the running average electricity demand with a weekly resolution. Clearly, the electricity demand is highest during summer due to increased usage of air conditions in high-temperature periods, and the lowest electricity usage is during the spring and autumn period when there is little need for heating and cooling.

At the supply side, the total installed generation capacity for the modeled grid zone is 15 gigawatts (GW). Fig. 2 shows the share of installed capacity for the different technologies. Natural Gas (NG) is the dominant power supply technology, accounting for 59% of the installed capacity. In the existing power grid, VRE sources such as wind and solar PV represent a smaller share (14%) of the overall electricity generation mix.

The hypothetical PV + storage power system is connected to the existing power system through a transmission grid network. The transmission grid network has a maximum capacity of 200 MW. Fig. 2 shows how the hypothetical system is connected to the existing grid, where the combined system can fully participate in the power system by exchanging electricity on demand. In this study, the storage unit were chosen to be modeled in conjunction with a PV plant, which is believed to be the most dominant source of electricity generation in the future power market [1,2,36]. In addition, the normal profile of the daily generation from PV plants is believed to be a good match with storage technologies, as it can store electricity when the PV plant power generates a large amount of electricity during mid-day (and the demand is often low during mid-day) and discharge the stored electricity when the sun is set (during early morning and afternoon/evening).

In this study, PV plants with installed peak power capacities of 100 MW and 1 GW were analyzed (see the Supplementary material for the GW scale modeling), which is represents the range of typical sizes of utility-scale solar energy farms in the U.S. [37].The storage unit was modeled with different energy storage capacities and are specified in the storage modeling Section 2.2.2. The modeled system does not influence the overall electricity price in the grid and is therefore considered a price taker.

2.1.1. Thermal energy grid storage (TEGS)

To charge the TEGS unit, excess electricity is used to fuel resistive heating materials (graphite), transforming the electricity into heat at a temperature exceeding 2500 degrees Celsius. Then, the energy is transferred to graphite conduits via thermal radiation. Inside the conduits, liquid tin is used as the heat transfer fluid. The tin is heated from 1900 °C to 2400 °C, transforming the energy input into sensible heat and increasing its enthalpy. The liquid tin is continuously pumped through the conduits and then conveyed to the graphite blocks in the storage unit. When the 2400 °C tin is pumped through the graphite blocks via conduits, it heats the graphite blocks from 1900 °C to 2400 °C via thermal radiation. Consequently, this cools the tin back to 1900 °C. The tin is then reheated by being pumped back through the resistance heaters. This process constitutes the charging process until the graphite blocks are heated back to peak temperature. The storage unit should have a sufficiently large thermal mass to enable storage unit to be charged for long periods with low heat loss.

The operating temperature and heat loss of the TEGS system is crucial design parameters, as lower temperatures result in lower capital cost per energy (CPE) due to reduced insulation requirements, while higher temperatures lead to higher capital costs per power (CPP) due to

[1] The PowerGenome Github library collects source data from EIA, NREL, and EPA and formats the input files for the CEM model. The GitHub library could with associated documentation could be found here: https://github.com/PowerGenome/PowerGenome

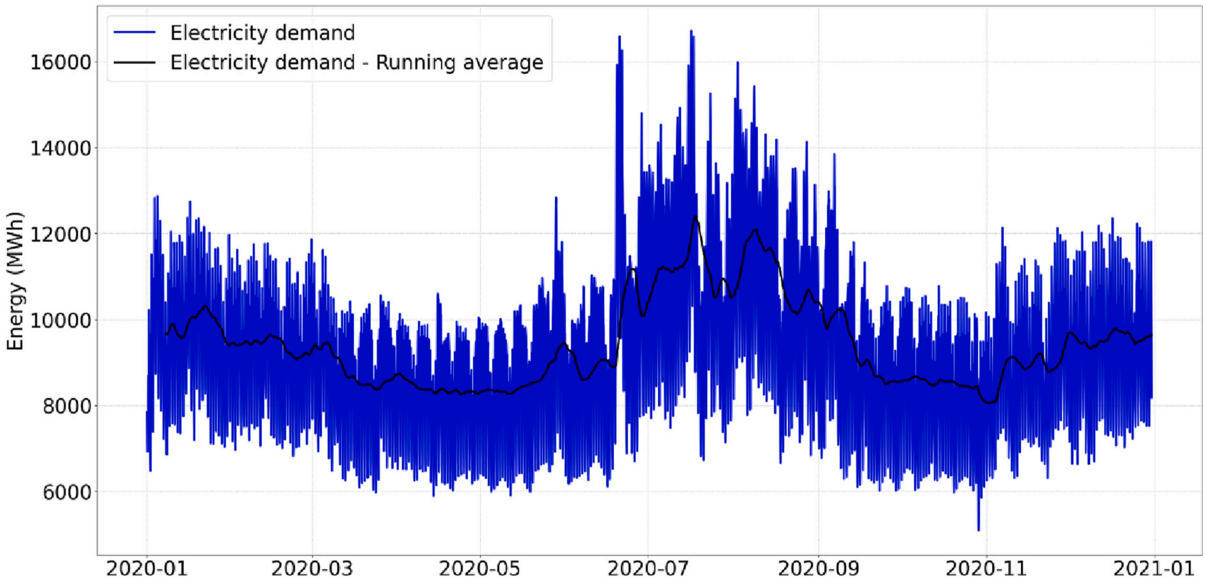

Fig. 1. Hourly electricity demand for the modeled power system.

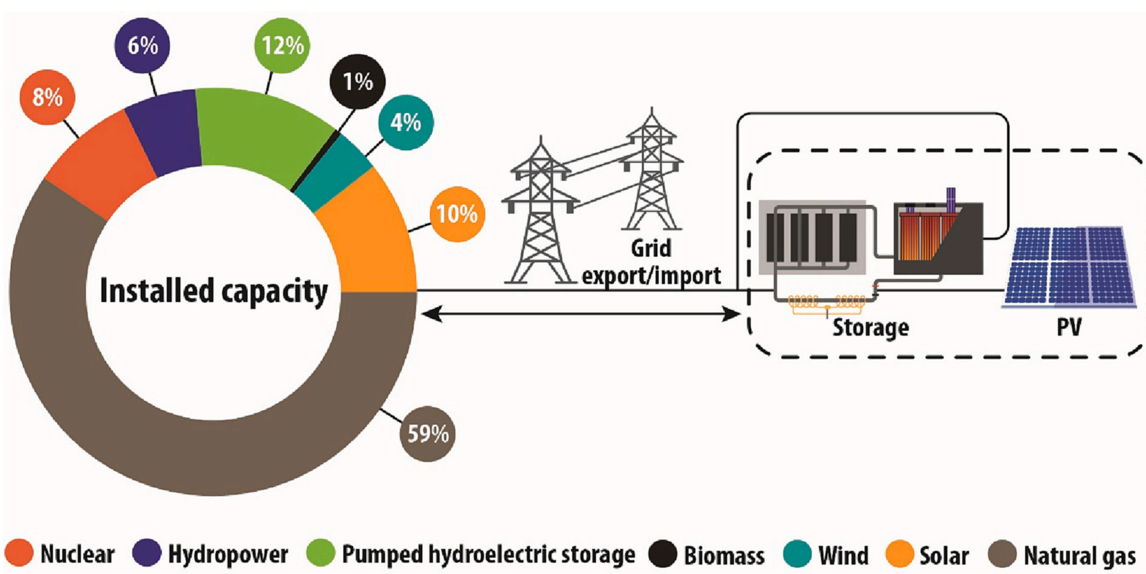

Fig. 2. The modeled New England grid zone is interconnected with a hypothetical PV + storage system. The existing power system is dominated by electricity generation from the NG. Solar and wind power represent a smaller share of electric power systems.

the need for more Thermophotovoltaic equipment. The Supplementary material section 1.3 presents an optimization procedure of the TEGS unit to identify the most cost-effective design when operating in the electric power system representing New England. It was found that optimizing the TEGS design with a daily heat loss of 1–3% and an operating temperature of 2400 °C proves to be the most cost-effective engineering design. Therefore, in this study, the modeled TEGS system has a daily heat loss of 1% and a temperature of 2400 °C.

During discharging, liquid tin is pumped through the graphite storage to a power block. The power block consists of graphite conduits with unit cells. Each unit cell of piping creates a rectangular cavity lined with tungsten foil. This is a diffusion barrier to prevent graphite deposition onto the TPV cells. Inside each cavity, the TPV cells can be lowered into the unit cell cavity. Here the TPV cells will be illuminated with the light emitted by the tungsten foil, which is heated by the light emitted by the graphite conduit carrying the tin. This net transfer of energy converts a large fraction (> 50%) of the energy to electricity, which causes the tin's temperature to decrease to 1900 °C before being pumped back to the graphite storage unit, where the tin is reheated again during the charging phase.

In this way, the TEGS is a rechargeable grid-scale thermal battery that can store energy as heat and supply electricity to the grid on demand, with an estimated RTE of 50%. The TPV conversion efficiency (i.e., the discharge efficiency from heat to electricity) entirely determines the RTE [17,18] . The charging efficiency (from heat to electricity) is assumed to be 100%.

2.2. Capacity expansion model (CEM) configuration and storage modeling

2.2.1. Capacity expansion model (CEM)

The analysis utilizes GenX [26], an electric power system CEM that evaluates a cost-optimal portfolio of electricity generation technologies, storage, and transmission to serve a given electricity demand. A detailed description of all features the GenX model is described in Jenkins et al. [26]. The GenX CEM modeling procedure is subject to operational (electricity demand and generation) and policy (CO2 emission) constraints.

In this study, the operational constraints that are activated in the CEM are (1) the thermal generators' commitment on start-up/shut-down decisions, minimum and maximum up/down times (6 h), as well as hourly ramping limits for thermal generators (0.64, indicating the maximum increase and decrease in power output as a faction of the nameplate capacity), (2) transmission capacity limits between the existing electric grid and the hypothetical PV + TEGS system, (3) TEGS storage constraints on maximum hourly charge/discharge capacities and efficiency, stored energy, and daily heat loss, (4) Maximum capacity of the hypothetical PV plant that are coupled with the TEGS storage unit. The policy constraint activated in GenX in this study was the maximum limit on the allowed CO2 emissions in the grid. Here, the power system was modeled with a baseline scenario without any CO2 constraints (i.e., the model finds the cost-optimized electricity mix regardless of CO2 emissions) and with a scenario where the CO2 emissions are reduced by 50%. When the emissions are constrained by 50%, the electricity system must be less dependent on fossil-fuel-based technologies such as NG. That is, this requires to retire more of the current NG capacity in the grid and install more of the current VRE sources as well as utilize the hypothetical PV + TEGS system to a higher degree that has zero emissions associated with it.

To fully capture high-resolution temporal dependencies in the grid, the grid operation were modeled for each hour of the year. The resulting CEM configuration was solved as a mixed integer linear program (MILP). The Gurobi solver was used for the optimization problem in GenX as it provides the capability of solving MILP problems computationally efficiently [36]. The Gurobi optimization solver was applied using 16 cores with 128 GB RAM. All model scenarios were terminated with a 1% or lower optimality gap.

The objective function of the GenX model in this study is computed as the power system cost (PSC) grouped into the costs associated with the operation cost of the existing generators and cost associated with adding the hypothetical PV + TEGS system. The objective function in GenX is computed as

$$\begin{aligned} PSC = (Fix.Cost_{VRE} + Fix.Cost_{THERM} + Var.Cost + Start.Cost_{THERM}) \\ + Inv.Cost_{TRANS} + Inv.Cost_{PV} + Inv.Cost_{TEGS} \end{aligned} \tag{1}$$

here the $\mathrm{Fix.Cost_{VRE}}$ and $\mathrm{Fix.Cost_{THERM}}$ is the investment and Fixed O&M cost of the existing VRE and thermal capacity. The Var.Cost is the variable cost of generator dispatch, cost of non-served energy (periods where the electricity demand is not met), and cost of violating operating reserve requirements. The $\mathrm{Start.Cost_{THERM}}$ is the cost for startup and shutdowns for thermal power plants (NG). The $\mathrm{Inv.Cost_{TRANS}}$, $\mathrm{Inv.Cost_{PV}}$, and $\mathrm{Inv.Cost_{TEGS}}$ is the investment cost of adding the hypothetical system to the existing power grid.

2.2.2. Storage modeling

Three different TEGS sizes coupled with the 100 MW PV plant were modeled. The modeled energy storage capacities were as follows: 1) 400 MWh, 2) 600 MWh, and 3) 800 MWh. The sizes reflect the minimum TEGS storage capacity required to obtain the sufficient low capital cost of < U.S. $ 20/kWh for long-duration energy storage [17,18]. For each storage size, the charging capacity (i.e., the amount of energy that can be charged within one hour) is 100 MW, and the discharging capacity is in the range of [5, 100] MW. The storage unit is modeled to have a daily heat loss of 1%. As for other CEM studies evaluating storage [10], the storage capacity degradation or dynamic operation range (efficiency and capacity) is not modeled as it will significantly decrease the computational efficiency.

The storage configurations were modeled under the baseline case (with no CO2 reduction constraint) and 50% CO2 reduction scenarios. In total, 66 scenarios were modeled to address PV + TEGS energy availability with different storage sizes, discharge capacities, and CO2 constraints.

Since it is of interest to model the potential of utilizing TEGS to decarbonize future electric power systems, which are increasingly dependent on VRE technologies, the TEGS system is assumed to have a 50% RTE.

3. Experimental evaluations

In this study, it is of interest to assess the amount of time the hypothetical PV + TEGS system is available to the grid on demand. The Power availability factor (PAF) was computed to describe power availability. The PAF is computed as the percentage of time during the year the modeled PV + storage system can deliver at least a minimum quantity of power requested by the grid. Moreover, PAF allows the examination of the power availability of the combined power plant, as it measures how often it can supply a minimum amount of power to the grid. A power plant with a 100% PAF can always provide a given minimum amount of power to the grid.

In the case of solar PV, the electricity generation suddenly drops when the sun no longer shines (owing to cloud cover or when the sun sets). This sudden drop in electricity generation reduces the PAF because the PV plant no longer generates at the rated power. Here, storage units can be used to charge whenever there is a low net demand for power in the grid and to discharge when there is a higher demand for power. Fig. 3 illustrates an example of how the storage unit can be used to shape the output to provide constant baseload power. Once the PV plant starts generating electricity over derated power (e.g., 20 MW), excess electricity is used to charge the storage unit. When the solar plant generates less electricity than the derated power, the storage unit starts discharging to satisfy the demand for electricity.

Fig. 3 illustrates how the combined PV and storage system can provide constant baseload power, disregarding the electricity demand in the grid. However, when the system is connected to an electricity grid, it becomes significantly more complex. The system should not provide constant baseload power to the grid but should be able to supply the requested power to the grid system operator.

In this study, the periods where the hypothetical PV + storage system cannot provide the requested electricity to the grid on demand are detected.

The grid is requesting electricity from the hypothetical PV + storage system in all periods when there is no excess electricity in the grid that can be used to charge the TEGS unit (i.e., no export from the grid to charge the TEGS unit). The unwanted periods when the electricity grid request (i.e., no excess electricity that can be exported from the grid to the PV + storage system) power arise for the following reasons: 1) The PV system does not deliver the required power, and 2) The TEGS system cannot discharge the requested power as the State of Charge (SOC) is already zero. Such critical periods can be calculated as:

$$\text{Percentage Not Available} = \frac{\text{When}\big(\big(\mathrm{PV_{gen}} + \mathrm{TEGS_{discharge}} < \text{Derated power}\,\big) + (\mathrm{SOC} = 0)\big)}{8760\ \text{hours}} \times 100 \tag{1}$$

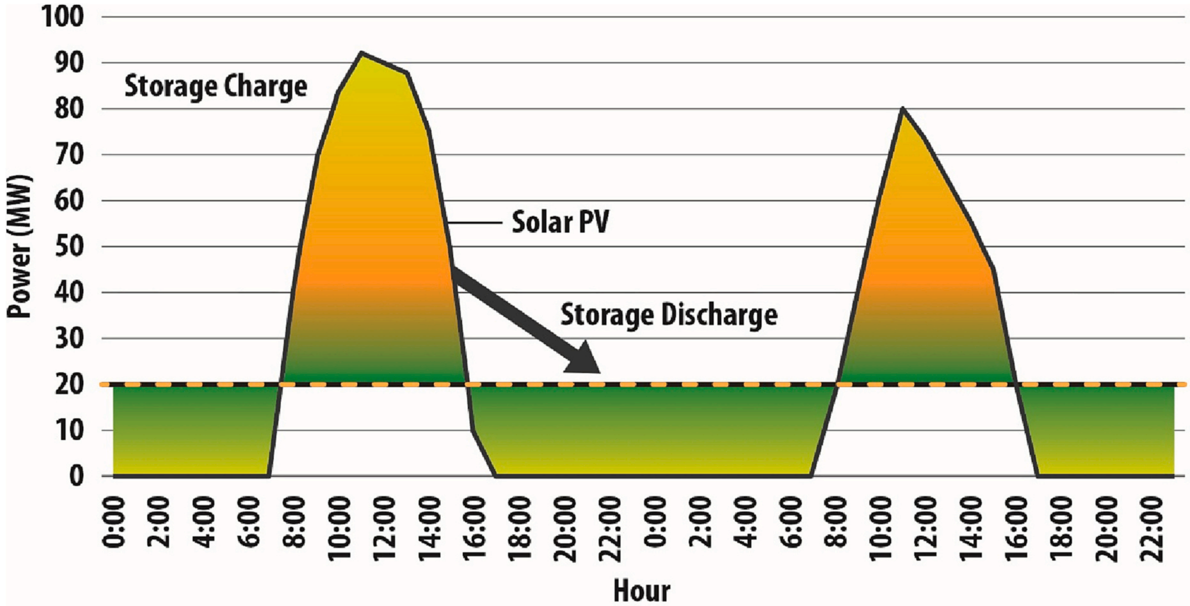

Fig. 3. Example illustration where storage is used to provide a constant baseload power to the grid by charging when there is excess electricity and discharging when the PV plant does not generate electricity.

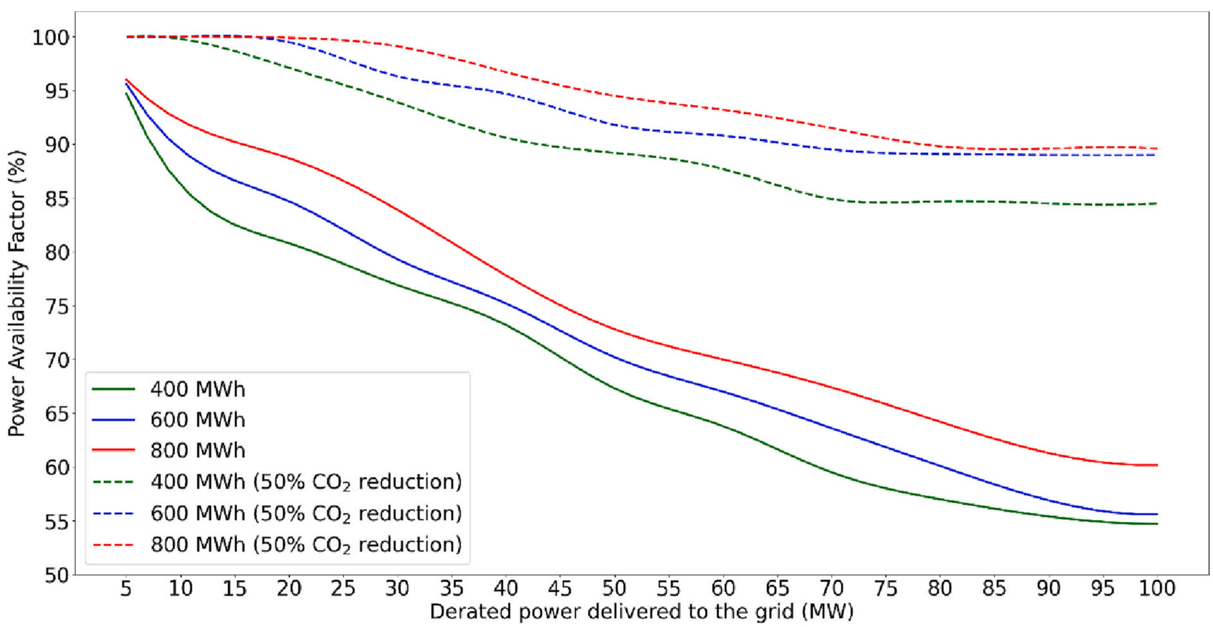

Fig. 4. Percentage of time during the year when the hypothetical system can deliver the requested power to the grid.

The system Percentage Not Available (PNA) gives information about the percentage of time during a full year the system cannot provide the requested electricity to the grid. On contrary, the PAF will be calculated as:

$$PAF = 1 - PNA \tag{2}$$

4. Results and discussions

The resulting yearly PAF of the hypothetical PV + TEGS system as a function of different discharge powers is provided in Fig. 4. Here, the yearly PAF is computed from Eq. (1) and Eq. (2) using the resulting data from the GenX optimization schedule of the New England electric grid region. The more the system is derated, the more often it can deliver the required power. This is reasonable because the more the system is derated, the more the storage system can discharge at a lower-rated output for a longer period. The PV + TEGS system can contribute 5 MW to the grid for about 95% of the hours throughout the year if the storage system has a discharge capacity of 5 MW.

For the 600 MWh storage unit, the PV + TEGS system can contribute 5 MW to the grid for about 95% of the hours throughout the year if the storage system has a discharge capacity of 5 MW. The results for the other storage sizes are similar, with a PAF of 94% and 96% for the 400 MWh and 800 MWh units, respectively. If the discharge capacity is 100 MW, the PV + TEGS system can deliver 100 MW to the grid approximately 55–60% of the hours during the year for all storage sizes (400 MWh, 600 MWh, and 800 MWh).

Interestingly, there is a large difference between the scenarios with and without CO_2 reduction constraints. The electric power system dynamics change completely once CO_2 emissions were reduced by 50%. In this case, the increased retirement of the NG makes the grid more dependent on the hypothetical PV + TEGS system, which results in the system supplying the necessary power 100% of the time for a derated power between 5 MW and 20 MW for the TEGS unit with a storage capacity of 600 MWh and 800 MWh. This is remarkably higher than the baseline case, where the system cannot deliver the required power 5–15% of the time for such derated powers. When modeling the PAF for the PV + TEGS system at the GW scale (see the Supplementary material), similar results are obtained. The PAF increases when lowering the derated power in both the baseline and the CO_2 reduction scenarios. In addition, the PAF is significantly higher when modeling the CO_2 reduction scenario compared to the baseline scenario.

The large (30% higher PAF on average in the 50% CO2 reduction scenario) difference between the CO2 reduction scenarios indicates that the electric power system dynamic changes significantly if the grid must be less dependent on NG.

Now the hypothetical PV + storage system plays a more important role in the grid because it does not emit any CO2, and as such, the cost-minimization schedule of the CEM optimizes the grid to ensure that the PV + storage system can deliver the requested power to the grid more often during the year.

Fig. 5 selects one derate level from Fig. 4 to investigate how the PAF changes with different CO2 reduction scenarios. More specifically, Fig. 5 illustrates how the PAF changes with decreased CO2 emissions for a storage unit of 600 MWh that discharges 20 MW to the grid. Clearly, reducing CO2 emissions results in a higher PAF. The maximum PAF was achieved at 50% CO2 reduction. Reducing CO2 emissions requires the power system to be less dependent on fossil fuel technologies, such as NG, and thus must rely more on the power served by the PV + storage system.

Modeling scenarios with >50% CO2 reduction results in an infeasible solution with the CEM optimization. That is, the objective function of the GenX model to cost-optimize the portfolio of electric power generation to serve the demand for electricity is not fullfilled. Therefore, to enable the possibility of further reducing the CO2 emissions in the modeled grid, the existing portfolio of electric generation technologies must be expanded and include more emission-free technologies that can serve the demand for electricity.

Fig. 6 shows how the hypothetical system operates in the different emissions scenarios (baseline and 50% CO2 reduction). Here, an example of the 600 MWh storage unit with a 20 MW discharge capacity that has a yearly PAF of 79% (baseline) and 100 (50% CO2 reduction) from Fig. 4 is illustrated. The weekly examples show the hourly operation of the hypothetical system during a typical winter week in January. The uppermost and lowermost Figure show how the system operates in scenarios with and without constraining CO2 emissions. From both graphs, TEGS is used frequently to discharge power to the grid whenever there is low electricity generation from the solar PV, which reduces the intermittency problem of PVs by increasing the number of hours the hypothetical system can deliver the required power to the grid. In addition, TEGS also charges power from the grid whenever there is a drop in the demand to increase the SOC, which illustrates the benefit of using storage units that are coupled with VRE resources.

The yellow area highlights a critical period in the uppermost graph. The critical period is defined as the incidents where the grid has an increasing net load (blue line), but the system cannot deliver the requested power because there is no generation from the PV system, and the storage unit cannot discharge the required power to the grid because the SOC is already zero. The net load is given as the total electricity demand subtracted by the electricity generation from solar and wind power.

However, considering the 50% CO_2 reduction scenario, the system interacts differently with the grid, and it is clear that the CEM optimizes the hypothetical system to have more energy available at more times because the grid now is more dependent on the hypothetical system (because the grid can use less NG). For the particular example week, the PV + storage system can deliver the requested power to the grid at all times for the 50% CO_2 reduction scenario.

Like the winter week example shown in Figs. 6, 7 shows how the hypothetical system operates with the grid during a typical summer week. Here, thanks to the higher solar availability, the system can deliver most of the required power to the grid using only the PV plant, and the storage system is used less frequently. However, for the baseline case, there are several periods in which the grid requests energy and the storage unit cannot provide sufficient power to the grid because the SOC is already zero. This is because the grid is mainly dependent on NG, which can supply power whenever there is low solar availability, and the TEGS system is only used to provide additional peak power when the demand suddenly increases.

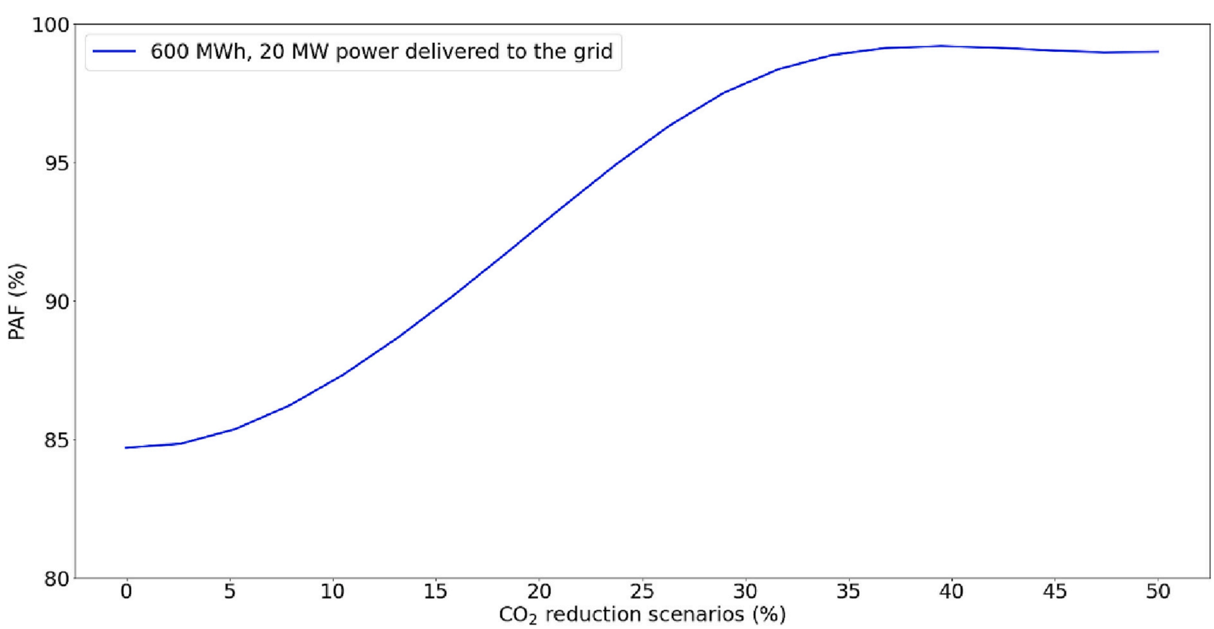

Fig. 5. Percentage of time the hypothetical system can deliver the requested 20 MW power to the grid as a function of CO_2 reduction scenarios.

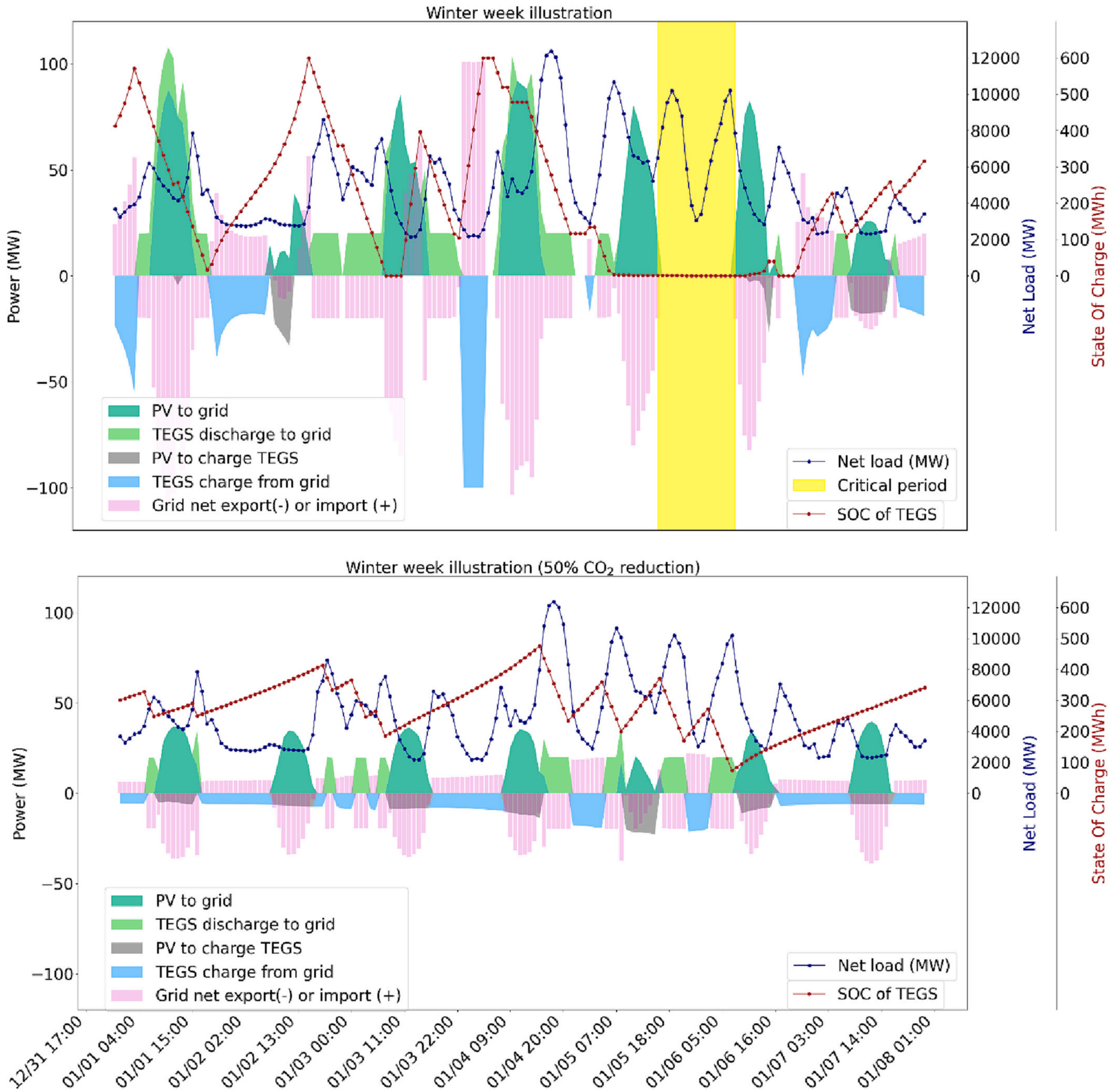

Fig. 6. Winter week illustrations for a 100 MW PV plus a 600 MWh TEGS system that can discharge 20 MW. Baseline case without constraining CO_2 emissions (uppermost graph) and future scenario with reduced emissions lowermost.

Under the 50% CO_2 reduction scenario, the grid is much more dependent on the power from the storage unit whenever there is no PV generation. It is clear that instead of providing peak power to the grid, the PV system is used to charge the TEGS unit to a higher degree to ensure that the SOC is never zero and thus can discharge the derated power to the grid at all times when the PV system does not generate electricity.

5. Conclusion

In this study, the potential of using energy storage to tackle the intermittency problem of VRE sources by increasing the dispatchability of a hypothetical PV plant were analyzed. An existing electricity grid region in North America were modeled using a CEM and investigated how different storage configurations can reduce the number of periods in which a hypothetical PV + storage system cannot provide the required power to the grid.

Because of the high capital cost of electrochemical batteries, a TES technology with a projected capital cost that fulfills the requirements (< US$ 20 kWh^{-1}) to enable full decarbonization of the grid was considered. The energy availability of the hypothetical system was modeled under different storage sizes and discharge capacities. Additionally, the optimization schedule was repeated under a hypothetical future scenario in which CO_2 emissions were constrained to be reduced by 50%. In total, 66 different scenarios were modeled. To capture the high-resolution dependencies in the electricity generation balance, a full year with hourly resolution was optimized using the CEM.

The results support the added value of using storage to increase the

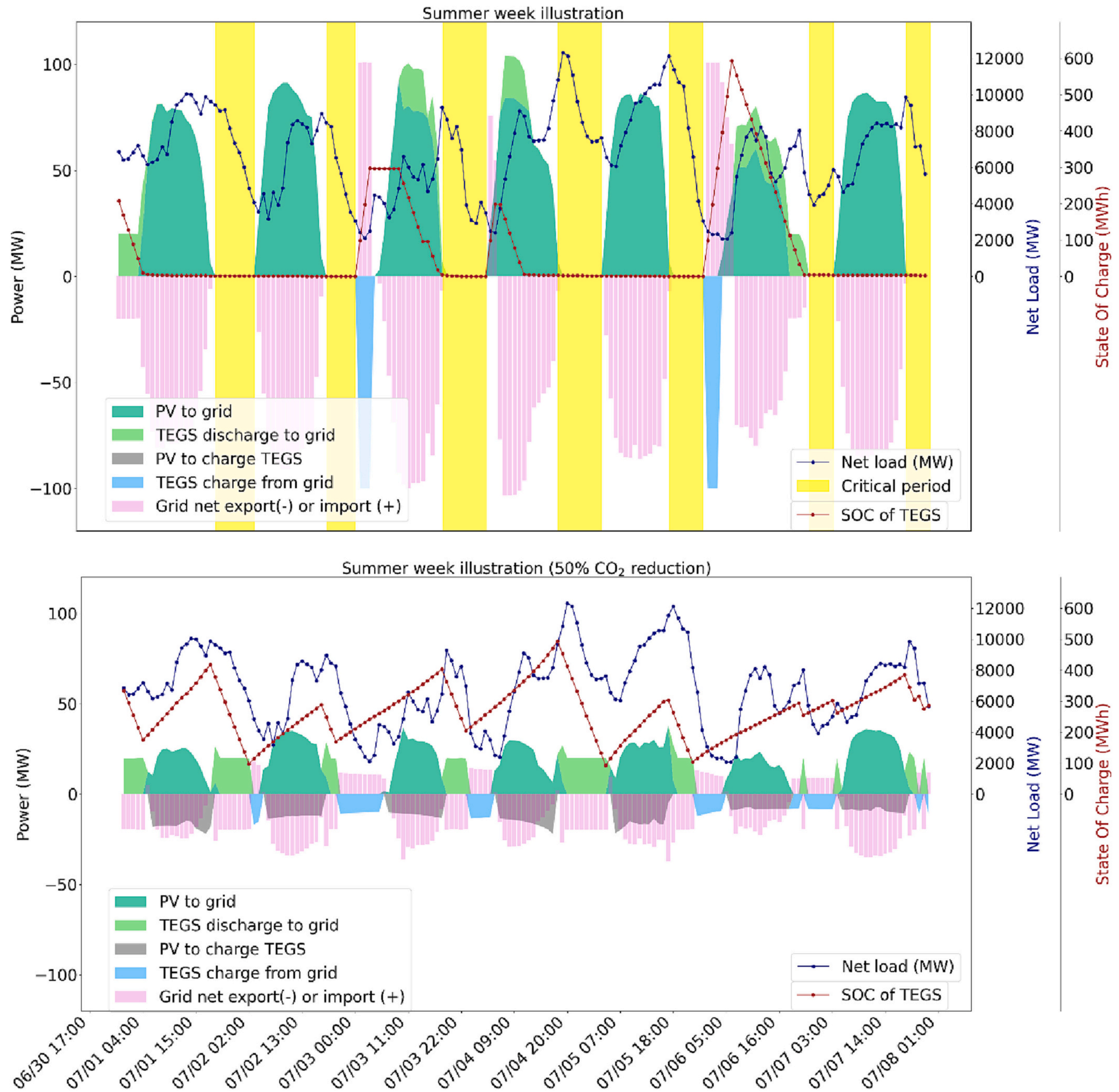

Fig. 7. Illustrations of a typical summer week for a 100 MV PV plus 600 MWh TEGS system that can discharge 20 MW. Baseline case without constraining the CO2 emissions (uppermost graph), and future scenario with reduced emissions lowermost.

dispatchability of PV, as it significantly increases the PAF compared to PV systems alone. The percentage of time during the year the system could deliver the required power to the grid increased when the discharge capacity of the system decreased. In addition, increasing the storage size increases the energy availability, as more energy can be stored and thereafter discharged over a longer period when there is a demand for electricity in the grid. The findings were consistent when the PV plus TEGS system were evaluated at both the megawatt and gigawatt scale.

Interestingly, there was a significant change in the electricity grid generation dynamics when the CO_2 emissions were reduced by 50%. Here, because the grid can no longer rely on the same share of NG technology, the most cost-efficient grid is achieved when the PV + TEGS system is utilized to a higher degree, as these technologies do not emit any CO_2.

This shows that decreasing the maximum allowed GHG emissions in the grid significantly increases the value of using storage to increase the dispatchability of PV systems.

The study findings could provide increased knowledge to power system planners regarding how adding PV + storage systems to existing grids can contribute to the efficient stepwise decarbonization of power systems.

5.1. Limitations and suggested future research

This study presented an idealized representation of an existing grid (i.e., "brownfield" CEM approach) in the New England grid region. However, the authors are fully aware that the grid representation might not fully capture all details of the existing grid, and there can be differences (sizes of the power plants, electricity demand on the grid, share of the existing generation technologies) between our abstract grid representation and the current real-world grid that ISO New England operates. In addition to the transmission line between the existing grid and hypothetical PV + storage system, the current grid were modeled as a single-zone grid region without considering transmission losses or congestion between generators and demand.

This study's major objectives are to evaluate a hypothetical PV + storage system's power availability and discuss the significance of integrating such technologies to assure a successful step-by-step decarbonization of the electric grid. Therefore, modeling the transmission lines between the existing generators is not considered, as it is outside the scope of this study and will significantly increase the computational intensity of the CEM.

The CEM is fully deterministic, assumes perfect foresight in planning and operational decisions, and does not account for uncertainty in VRE generation [39–42]. Therefore, this study does not aim to be used as a power planning tool for ISOs to assess the PAF of PV + storage systems in the day-ahead electricity market, but shows how storage, in general, will be a valuable technology to address the intermittency issue of VRE. A suggested future study is to frame the CEM to account for the uncertainty regarding the expected electricity generation from VRE sources. This will allow the use of the CEM as a decision-making tool for optimizing the management of the electricity grid in the day-ahead market.

Credit author statement

Odin Foldvik Eikeland performed all analyzes and had the main responsibility for writing the manuscript. Colin C. Kelsall and Kyle Buznitsky contributed to the inception of the study and discussions during the analysis. Shomik Verma provided feedback on the draft of the paper, contributed to the discussions of the results, and provided supervision on how to do the modeling on the computing cluster. Filippo Maria Bianchi contributed by providing feedback on the draft and supervising how to structure the manuscript. Matteo Chiesa assisted in the analysis and interpretation of the results and contributed to the inception of the manuscript. Asegun Henry supervised the inception of the study and provided feedback and guidance in the analysis and interpretation of the results.

Odin Foldvik Eikeland wrote the manuscript with input from all authors.

CRediT authorship contribution statement

Odin Foldvik Eikeland: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Colin C. Kelsall:** Methodology, Investigation, Conceptualization. **Kyle Buznitsky:** Data curation, Formal analysis, Investigation. **Shomik Verma:** Investigation, Formal analysis, Conceptualization. **Filippo Maria Bianchi:** Writing – original draft, Supervision, Investigation. **Matteo Chiesa:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Asegun Henry:** Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Project administration, Methodology, Investigation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2023.121572.

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