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Optimal sizing of distributed energy resources for planning 100% renewable electric power systems

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A B S T R A C T

More utilities, energy providers, and governments are considering the transition to 100% renewable or carbon-free generation to satisfy electricity demand. This transition requires consideration of numerous factors including cost, resource adequacy, and geographical location, among others. Therefore, models that can explore the optimality of tradeoffs between multiple factors are crucial for planning this transition. An optimization problem formulation is proposed to analyze the amount of renewable generation and energy storage required to balance 100% of a utility's electricity demand on an hourly timescale over multiple years, while minimizing a desired cost. This formulation accounts for geographical location and accommodates regional energy trading, and it enables analysis of important metrics for planning, such as firm capacity, capacity factors, land area requirements, and amount of curtailed generation. This optimization-based approach is used to explore case studies in New Mexico, which is an area with significant potential for solar and wind generation in the United States. Considering multiple years of historical meteorological data and electricity demand data, results show that the amount of renewable generation required is an order of magnitude larger than the average demand, and that most of the generation is curtailed, which motivates a regional energy trading approach.

1. Introduction

There is a current trend of increasing renewable generation penetration in the operation of electric utilities, with solar and wind resources being the most prevalent. For integration of large amounts of variable renewable generation, several challenges need to be addressed. These challenges include operation under uncertain weather conditions and consumer demand variability, mismatch between demand and variable generation, as well as technical limitations, policy requirements, and economic considerations [1]. On the technical side, energy storage (ES) has the ability to facilitate operation of utilities using 100% renewable generation because it can mitigate the temporal mismatch between demand and solar and wind generation. ES is quickly becoming a viable flexible resource with many different technologies and applications [2]. Moreover, numerous energy management and optimization methods have been developed to take advantage of ES [3]. As it is currently cost-prohibitive in many places to obtain the amount of renewable resources and ES necessary to reach high levels of renewable penetration, finding the minimum amount of resources to satisfy requirements in terms of load balancing and reliability is an important problem. The goal of this work is to formulate an optimization problem that can be solved to begin understanding the renewable generation and ES requirements to plan for operation of a utility with 100% renewable energy.

Quantitative studies with details regarding the feasibility of systems with high penetrations of renewables have been performed for locations around the world. For example, using renewable resources to supply the energy required in all sectors of Ireland's energy system with a combination of biomass, hydrogen, and electricity is studied in Ref. [4]. Planning for 100% renewable energy electricity production in Portugal is considered in Ref. [5]. Two scenarios, a 50% renewable energy system and a 100% renewable energy system, for Macedonia are analyzed in Ref. [6]. The best ratio of wind and solar plants to help achieve future energy goals in the Croatian power system is explored in Ref. [7]. The technical and economic implications of increasing a variety of renewable energy sources in Finland are studied in Ref. [8]. The best mix of biomass, wind, and solar generation for achieving Mexico's

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Nomenclature

Model Parameters

k	Time index
τ	Time-step
s	ES SoE
η^{s}	ES self-discharge efficiency
η^{c}	ES roundtrip efficiency
η^{pv}	PV panel efficiency
η^{conv}	PV conversion efficiency
$\underline{v}$	Wind turbine cut-in speed
$v*$	Wind turbine rated speed
$\bar{v}$	Wind turbine cut-out speed
h	Wind turbine hub height
h_{meas}	Wind speed measurement height
a^{turb}	Wind turbine rotor area
$\bar{p}^{turb}$	Wind turbine power rating
ρ	Air density

Optimization Variables

p^{c}	ES charge power
p^{d}	ES discharge power
$\bar{s}$	ES energy capacity
$\bar{p}^{s}$	ES power rating
$\bar{p}^{w}$	Wind plant power rating
$\bar{p}^{pv}$	Solar plant power rating
p^{curt}	Curtailed power
p^{trade}	Traded power
β^{c}	Binary variable for charging
β^{d}	Binary variable for discharging

Optimization Parameters

i	Solar/wind plant index
n_{pv}	Number of solar plants
n_{w}	Number of wind plants
K	Optimization horizon
w^{s}	Weight on ES energy capacity
w^{p}	Weight on ES power rating
w^{w}	Weight on wind power rating
w^{pv}	Weight on PV power rating
w^{curt}	Weight on curtailed power
w^{trade}	Weight on traded power
δ	Fraction of unused SoE
γ	Fraction of initial/final SoE
$\bar{p}^{curt}$	Curtailed power allowed
$\underline{p}^{trade}$	Import power allowed
$\bar{p}^{trade}$	Export power allowed
p^{ℓ}	Electricity demand/load

Acronyms

PV	Photovoltaic
ES	Energy Storage
SoE	State of Energy
MILP	Mixed Integer Linear Program
GHI	Global Horizontal Irradiance
LCOE	Levelized Cost of Energy

goal of operating an electricity system with no more than 50% fossil fuels by 2050 is identified in Ref. [9]. The feasibility of a 100% renewable energy system has also been studied in Denmark [10]. In Denmark, wind power and biomass are expected to become the main sources of energy there as the country transitions to 100% renewable by the year 2050 [11]. Analysis of multiple ratios of solar and wind generation, along with pumped storage hydropower, for achieving Switzerland's 2050 renewable generation of electricity milestone is presented in Ref. [12].

The particular role of energy storage in the transition to more renewable energy has also been studied for countries around the world. The amount of energy storage required for a 100% renewable energy system in Japan, with mostly wind and solar, is found to be around 40 TW of storage in Ref. [13]. Studying the influence of size and efficiency of energy storage on a pathway towards a 100% renewable electricity system in Germany, the authors of [14] find that efficient energy storage devices are already highly beneficial for integrating renewable generation, and seasonal storage will be required when more than 80% of the electricity demand is met with wind and solar power. A review of model-based analyses of the role of storage in electricity systems with high penetrations of renewable generation, and a new dispatch and investment model, is presented in Ref. [15]. This model is used in Ref. [16] to study the German power system, and it shows that the need for storage grows sharply when renewable generation exceeds about 80%, and that requirements largely depend on costs and availability of other flexible generation options, such as biomass.

Many studies have been done on the European system as a whole and consider numerous topics. Reducing the amount of required storage and balancing resources with excess generation and varying the mix of solar and wind generation is considered in Ref. [17]. Reducing the amount of backup energy generation required using energy storage or grid extensions is studied in Ref. [18]. The impact of increasing transmission interconnections on system cost is explored in Ref. [19]. One possible scenario for the overall feasibility of a 100% renewable Europe by the year 2050 is presented in Ref. [20]. Furthermore, seven possible scenarios for a 100% renewable Europe are modeled in Ref. [21].

Several other studies on large-scale renewable energy systems have been done on the United States of America (USA). For example, optimizing the mix of solar and wind generation and transmission expansion to reduce costs and required storage or backup energy for the entire USA is discussed in Ref. [22]. In Ref. [23], a linear programming model is used to analyze the feasibility of multiple possible scenarios for high penetration of renewable generation in the USA. A study of the California system quantifies the energy storage required for high penetrations of renewable energy [24]. The advantages of wind-solar complementaries in California are also studied [25]. It has been shown that regional resource sharing can significantly damp the weather fluctuations dominating wind and solar production. For example, the authors of [26] show that if the entire USA is considered, with a national grid to match, weather fluctuations are sufficiently damped and that only 20% of the demand needs to be supplied by natural gas peakers, and electrical storage is not needed. Furthermore, the authors of [27] show that interconnecting wind farms over a multi-state region in the USA can enable a third or more of wind power generation to be used reliably to supply baseload power. The interplay of intermittency and temporal and spatial correlations for solar energy is reviewed in Ref. [28]. The covariability of solar and wind resources in the contiguous USA is studied in Ref. [29], and the authors find that, for greater than 80% of total annual electricity demand to be supplied by solar and wind, a strategic combination of energy storage, transmission expansion, excess capacity, and demand management is required.

Additional important factors for transitioning to a fossil-free electric grid have been considered in detail. For example, material resource requirements are studied in Ref. [30], and, using California as a representative example, the authors find that utilizing more local dispatchable renewables, such as biogas, hydropower, and geothermal or overbuilding variable renewable generation, such as wind and solar, is desirable to reduce the amount of material resources required. Cost is certainly an important factor to consider, and several studies have investigated models for determining the cost and value of these renewable energy systems. The design of markets for 100% renewable energy systems that ensures appropriate investment incentives, and a study of the particular case of Israel's power system, is considered in Ref. [31]. Cost-optimized scenarios for a 100% renewable energy-based electricity system in the Americas, including decentralized systems, fully interconnected systems, and varying mixes of renewable generation and energy storage, are analyzed in Ref. [32]. A capacity expansion model to determine value of ES in future scenarios with increasing wind and solar generation in multiple regions of the USA is presented in Ref. [33]. The authors of [34] evaluate the utility of ES assets considering the amount of renewable penetration, different market paradigms, and overall flexibility of the system by using a production cost model. In Ref. [35], pathways for least cost development of highly renewable systems are investigated including the optimal combination of wind and solar photovoltaics (PV) generation resources and the amount of ES for absorbing excess generation. Some studies include investigation into the heating, gas, and transport systems in addition to the electric grid. For example, the authors of [36] study smart energy systems for 100% renewable energy that include electricity, heating, and transport sectors in combination with varying timescale ES options, and the authors of [37] propose a large-scale energy planning model that is meant to aid public decision-makers and includes heating, electricity, and transportation. Furthermore, the policy actions needed for the incremental transition to high penetrations of renewables are discussed in Ref. [38]. In fact, the authors of [39] review relevant studies like those mentioned and argue that the principal barriers to fossil-free electricity systems are political, institutional, and cultural rather than related to technologies or the economy.

There are a number of related works that consider the problem of sizing multiple resources for stand-alone and so-called hybrid energy systems that include wind and solar PV (and perhaps diesel) generation and ES to balance desired demand or reliability requirements. An overview of issues related to stand-alone renewable energy systems including integration, sizing, and control is discussed in Ref. [40]. A review of research on optimal sizing and control of stand-alone hybrid solar and wind generation plants with battery storage for remote area power generation applications is given in Ref. [41]. A mixed-integer linear programming (MILP) optimization problem is formulated in Ref. [42] to size and schedule wind, solar PV, battery ES, and diesel backup in isolated systems to minimize the levelized cost of energy (LCOE) of a 20-year system lifetime assuming that the annual energy production and costs are constant over the lifetime. A MILP optimization problem for sizing components in hybrid renewable energy systems with battery ES in residential microgrids is proposed in Ref. [43] that also analyzes the impact of demand response of controllable appliances on component size requirements. A pattern search optimization and Monte Carlo simulation approach for sizing renewable resources and ES to minimize system cost while satisfying reliability requirements, and using autoregressive moving average (ARMA) models to account for uncertainties in generation and demand, is proposed in Ref. [44]. A chance-constrained optimization problem is formulated in Ref. [45] to determine trade-offs between wind turbine rating, rotor diameter, and battery size of stand-alone wind-battery systems for providing reliable power supply. Sizing locally available renewable energy resources to meet demand and required reliability of a cluster of villages in India to minimize cost of energy is considered in Ref. [46]. There is also work on sizing ES for specific applications, including for renewable ramp-rate support in California [47] and for meeting critical load with solar PV in islanded operation [48]. Most of the previous studies consider isolated systems rather than geographically distributed resources. Therefore, they do not optimize the size of each distributed renewable resource considering its geographical location. Furthermore, they do not consider energy trading between regions and its impact on resource sizing.

In this paper, an optimization problem formulation is proposed for determining the smallest resource sizes required to balance 100% of a utility's electricity demand with energy from renewable generation and ES, while minimizing a desired cost. The desired cost can incorporate weights to account for things like investment or capital costs, operating costs, Levelized Cost of Energy (LCOE), or some combination of these costs, over the lifetime of each system. This flexible formulation also allows energy trading with external energy providers and consumers and considers multiple types and locations of renewable resources to take advantage of, e.g., complementary wind and solar generation as well as complementary weather in geographically distributed locations. Given multiple desired locations for renewable generation and corresponding meteorological data, solving the optimization problem results in the minimum size of ES (both energy capacity and power rating), the minimum power rating for each renewable generation plant, and corresponding charge/discharge, curtailment, and trading schedules. In addition, case studies are presented using this optimization approach with multiple years of historical meteorological data and electricity demand data from a medium-sized utility in New Mexico, USA that accounts for the majority of the demand in the state. This analysis is important since New Mexico passed legislation, the “Energy Transition Act,” which mandates that 100% of the state's electricity is supplied with carbon-free resources by the year 2045 and that at least 80% of the state's electricity is supplied by renewable energy resources by the year 2040 [49]. The case studies demonstrate how the resulting renewable and ES resource requirements change from year to year and when energy can be imported and exported. The results are analyzed with metrics for reliability and total generation, as was done for assessing solar and wind complementarity in Texas in Ref. [50]. Specifically, firm capacity of generation, capacity factors of the renewable generation plants, required total area of land for the renewable resources, and amount of curtailed generation are analyzed.

Specifically, the contributions of this paper are as follows: 1) An optimization framework is proposed to optimize the size of distributed energy resources considering their geographical locations, capital costs, and regional energy trading to meet a desired electricity demand. 2) This optimization framework is used to analyze scenarios in which the majority of electricity demand in New Mexico, USA, is met with power from solar and wind generation and energy storage. The results provide a general outlook on resource requirements and adequacy, land requirements, and sensitivity to factors such as seasonal and annual weather trends, capital costs, and regional energy trading. Thus, the framework enables practical analysis for entities planning a transition to 100% renewable electric power systems.

The remainder of the paper is organized as follows. Models for the ES systems and renewable generation are discussed in Section 2. The proposed optimization problem formulation for sizing renewable and ES resources is formulated in Section 3. Case studies are presented in Section 4, and concluding remarks and future work are discussed in Section 5.

2. Energy storage and renewable power models

The following discrete-time, linear energy flow model is used for the State of Energy (SoE) dynamics of the ES system [3]:

$$s_{k+1} = \eta^{s} s_k + \eta^{c} p_k^{c} \tau - p_k^{d} \tau, \tag{1}$$

where s_k is the SoE of the ES system at time-step k, p_k^{c} is the charge power of the ES system at time-step k, p_k^{d} is the discharge power of the ES system at time-step k, η^{s} is the storage (or self-discharge) efficiency of the ES system, η^{c} is the ES round-trip efficiency, and τ is the length of the discrete time-step.

Standard models are used for solar PV and wind power generation that can be found in, e.g., Ref. [51]. Specifics for these models are given in the Appendix.

3. Optimization problem formulation

The problem considered is that of determining the size of renewable energy generation and ES resources required to meet 100% of a utility's demand with renewable generation, given locations for the renewable energy generating plants. Therefore, a mathematical optimization problem is formulated with the objective of minimizing energy resource sizes while ensuring that the utility's demand and generation are balanced at each time-step. This essentially results in a lower bound on the required sizes of renewable generation and ES resources at the system level without considering transmission or operational constraints. Specifically, solving the optimization problem gives the power rating of each renewable energy plant (solar PV or wind) at given locations, the power rating and energy capacity of ES, as well as the charge and discharge power at each time-step that minimize these power and energy requirements. It is necessary to also consider curtailment of generation to reduce the amount of excess energy that must be stored, and it may be reasonable to consider the ability to trade (import or export) power with other connected systems. Thus, the power to be curtailed and/or traded at each time-step is also found. These considerations motivate the following optimization problem formulation.

Given utility demand data and meteorological data (e.g., solar Global Horizontal Irradiance (GHI) and wind speed) for wind and solar PV generation locations, the following optimization problem is solved:

$$\underset{\substack{\bar{s},\bar{p}^{s},\bar{p}^{w},\bar{p}^{pv},p^{c},p^{d},\\ p^{curt},p^{trade},\beta^{c},\beta^{d}}}{\text{minimize}} J(\bar{s},\bar{p}^{s},\bar{p}^{w},\bar{p}^{pv},p^{curt},p^{trade}) \tag{2}$$

subject to the following constraints, for all $k \in \{0, 1, \ldots, K-1\}$:

$$0 \le p_{k,i}^{w} \le \bar{p}_i^{w} \, \forall i \in \{1,2,\ldots,n_w\} \tag{3a}$$

$$0 \le p_{k,i}^{pv} \le \bar{p}_i^{pv} \, \forall i \in \{1,2,\ldots,n_{pv}\} \tag{3b}$$

$$0 \le p_k^{c} \le \bar{p}^{s} \tag{3c}$$

$$0 \le p_k^{d} \le \bar{p}^{s} \tag{3d}$$

$$0 \le p_k^{c} \le M\beta_k^{c} \tag{3e}$$

$$0 \le p_k^{d} \le M\beta_k^{d} \tag{3f}$$

$$\beta_k^{c}, \beta_k^{d} \in \{0,1\} \tag{3g}$$

$$\beta_k^{c} + \beta_k^{d} \le 1 \tag{3h}$$

$$\underline{\delta}\bar{s} \le s_k \le (1-\bar{\delta})\bar{s} \tag{3i}$$

$$s_{k+1} = \eta^{s} s_k + \eta^{c} p_k^{c} \tau - p_k^{d} \tau \tag{3j}$$

$$s_0 = \gamma \bar{s} \tag{3k}$$

$$s_K = \gamma \bar{s} \tag{3l}$$

$$p_k^{\ell} = \sum\nolimits_{i=1}^{n_w} p_{k,i}^{w} + \sum\nolimits_{i=1}^{n_{pv}} p_{k,i}^{pv} + p_k^{d} - p_k^{c} - p_k^{curt} + p_k^{trade} \tag{3m}$$

$$0 \le p_k^{curt} \le \bar{p}_k^{curt} \tag{3n}$$

$$\underline{p}_k^{trade} \le p_k^{trade} \le \bar{p}_k^{trade} \tag{3o}$$

The variable K denotes the number of time-steps in the optimization horizon. The power ratings for the solar PV generation plants are defined as $\bar{p}^{pv} := \{p_1^{pv}, p_2^{pv}, \ldots, p_{n_{pv}}^{pv}\}$, where n_{pv} denotes the number of solar PV plants. The power ratings for the wind generation plants are similarly defined with n_w denoting the number of wind plants. The energy storage capacity and power rating are denoted as $\bar{s}$ and $\bar{p}^{s}$, respectively. The variables p_k^{ℓ}, p_k^{curt}, and p_k^{trade} denote the demand, curtailed, and traded power at time-step k, respectively. The wind generation or solar PV generation at site i at time-step k is denoted as $p_{k,i}^{w}$ or $p_{k,i}^{pv}$, respectively. The sequence of ES charge power is defined as $p^{c} := \{p_0^{c}, p_1^{c}, \ldots, p_{K-1}^{c}\}$, and the other sequences p^{d}, p^{curt}, and p^{trade} are similarly defined. The variables $\underline{\delta}$, $\bar{\delta}$, and γ are chosen fractions that are discussed in Section 3.2. Finally, the sequences of binary variables that determine whether the ES is charging or discharging are given by $\beta^{c} := \{\beta_0^{c}, \beta_1^{c}, \ldots, \beta_{K-1}^{c}\}$ and $\beta^{d} := \{\beta_0^{d}, \beta_1^{d}, \ldots, \beta_{K-1}^{d}\}$, respectively.

The optimization variables are the energy capacity and rated power (for both charging and discharging) of the ES, $\bar{s}$ and $\bar{p}^{s}$, respectively, the rated power of the wind and solar PV resources, $\bar{p}^{w}$ and $\bar{p}^{pv}$, respectively, the sequences of ES charge and discharge powers, p^{c} and p^{d}, respectively, the sequence of curtailed power p^{curt}, the sequence of traded power, p^{trade}, and the binary variables β^{c} and β^{d}. The sequence of traded power p^{trade} captures the possibility of importing (or exporting) more power into (or out of) the system. If p_k^{trade} is positive, it corresponds to imported power at time-step k, and if it is negative, it corresponds to exported power.

3.1. Objective

The objective function $J(\bar{s},\bar{p}^{s},\bar{p}^{w},\bar{p}^{pv},p^{curt},p^{trade})$ to be minimized is a function of the optimization variables and can be chosen to, e.g., appropriately capture the relative costs of energy from renewable generation, ES, and energy trading or curtailment.

Depending on the desired analysis, this could correspond to, e.g., investment or capital costs, operating costs, LCOE, or some combination of these costs, over the lifetime of each system.

One option for the objective function $J(\cdot)$ is a linear function written as:

$$J(\bar{s},\bar{p}^{\mathrm{s}},\bar{p}^{\mathrm{w}},\bar{p}^{\mathrm{pv}},p^{\mathrm{trade}}) := w^{\mathrm{c}}\bar{s} + w^{\mathrm{p}}\bar{p}^{\mathrm{s}} + w^{\mathrm{w}}\sum_{i=1}^{n_{\mathrm{w}}}\bar{p}_i^{\mathrm{w}} + w^{\mathrm{pv}}\sum_{i=1}^{n_{\mathrm{pv}}}\bar{p}_i^{\mathrm{pv}} + \sum_{k=0}^{K-1} w_k^{\mathrm{curt}}p_k^{\mathrm{curt}} + \sum_{k=0}^{K-1} w_k^{\mathrm{trade}}p_k^{\mathrm{trade}} \tag{4}$$

The weights w^{c}, w^{p}, w^{w}, w^{pv}, w_k^{curt}, and w_k^{trade} capture the desired tradeoffs between cost of ES capacity and power rating, wind power rating, solar PV power rating, curtailment, and traded power, respectively. This is formulated as a time invariant function but could just as easily be formulated as a time varying function that depends on relative costs over the optimization horizon. Additionally, unique values of w^{w} and w^{pv} could be defined for each renewable generation plant i.

3.2. Constraints

Constraints (3a) and (3b) ensure that the renewable power generation at every time-step at each renewable power plant is nonnegative and less than or equal to the corresponding power rating of the plant. Constraints (3c) and (3d) ensure that charge and discharge powers of the ES system at every time-step are nonnegative and less than or equal to the ES power rating. Constraints (3e)–(3h) ensure that charging and discharging the ES do not occur simultaneously. This is done with the binary optimization variables, β^{c} and β^{d}, and by choosing the value of the scalar M to be large, e.g., 10e9.

Constraint (3i) ensures that the SoE of the ES system at each time-step is within a desired range of the total energy capacity $\bar{s}$, with the limits on the upper and lower end of the capacity denoted by the fractions $\bar{\delta}$ and $\underline{\delta}$, respectively. In general, these fractions can be time-varying and are chosen to limit the depth of charge and discharge to improve system lifetime, operation, or safety. Constraint (3j) ensures that the energy flow dynamics of the ES system are satisfied at each time-step. Constraints (3k) and (3l) ensure that the states of energy of the ES system at the beginning and the end of the optimization horizon, respectively, are equal to a desired fraction γ of the energy capacity $\bar{s}$.

Constraint (3m) ensures that the demand is balanced by the power from the renewable generation, ES, curtailment, and traded power at each time-step k. Constraint (3n) limits the amount of curtailed power at each time-step k to be less than or equal to $\bar{p}_k^{\mathrm{curt}}$, and constraint (3o) limits the imported and exported power at each time-step k to be between $\underline{p}_k^{\mathrm{trade}}$ and $\bar{p}_k^{\mathrm{trade}}$. Values for these parameters may be considered as, e.g.,

$$\bar{p}_k^{\mathrm{curt}} := \alpha_k^{\mathrm{curt}}\left(\sum_{i=1}^{n_{\mathrm{pv}}} p_{k,i}^{\mathrm{pv}} + \sum_{i=1}^{n_{\mathrm{w}}} p_{k,i}^{\mathrm{w}}\right)\forall k \geq 0, \tag{5}$$

where α_k^{curt} is the fraction of renewable power allowed to be curtailed at each time-step k, and

$$\underline{p}_k^{\mathrm{trade}} := -\alpha_k^{\mathrm{trade}}\left(\sum_{i=1}^{n_{\mathrm{pv}}} p_{k,i}\mathrm{pv} + \sum_{i=1}^{n_{\mathrm{w}}} p_{k,i}^{\mathrm{w}}\right)\forall k \geq 0, \tag{6a}$$

$$\bar{p}_k^{\mathrm{trade}} := \alpha_k^{\mathrm{trade}} p_k^{\ell}\,\forall k \geq 0, \tag{6b}$$

where $\alpha_k^{\mathrm{trade}}$ is the fraction of renewable generation allowed to be exported each time-step (in (6a)) or the fraction of the demand that is allowed to be imported at each time-step k (in (6b)).

3.3. Computational complexity

Given a linear objective function, such as (4), the optimization problem formulated in (2)–(3) is a mixed-integer linear program (MILP). Depending on the optimization horizon K and the number of renewable generation plants considered, this problem may easily include hundreds of thousands of optimization variables and constraints. This is the case for the examples analyzed in the following section, where the optimization horizon includes four years of data at hourly time intervals and six renewable generation locations. All of the optimization problems in the next section were formulated as MILPs in Python using Pyomo [52] and solved using Gurobi [53] on an iMac with a 3.7 GHz Intel Core i5 processor. None of the optimization problems took longer than 1 min to solve, so it would be feasible to solve even larger optimization problems, with many more renewable generation locations or even longer time horizons.

4. Case studies

In this section, case studies are presented that consider renewable generation (specifically solar PV and wind), ES, and possible energy trading to balance 100% of the electricity demand for a medium-sized utility in New Mexico, USA, which accounts for the majority of the demand in the state. These case studies are meant to provide insights into the system level resource requirements for utilities transitioning to 100% renewable generation and are of practical importance for achieving New Mexico's legislative mandate of 100% carbon-free electricity by the year 2045 and at least 80% renewable electricity by the year 2040 [49]. Moreover, this framework can be similarly applied to other systems with comparable renewable energy goals, such as California [54] and several other states in the USA.

4.1. Data and renewable generation locations

Historical hourly electricity demand data for the Public Service Company of New Mexico (PNM) for years 2016–2020 are used and were retrieved from the Energy Information Administration (EIA) database [55]. The hourly demand from 2018 is shown in Fig. 1, and the profiles of each year's demand data are similar to that of 2018. Moreover, the average hourly demand for 2016–2019 is about 1595 MW. Hourly meteorological data, specifically Global Horizontal Irradiance (GHI) and wind speed data, were retrieved from NREL's National Solar Radiation Database (NSRDB) [56]. Both historical meteorological data for 2016–2019 were retrieved, as well as Typical Meteorological Year (TMY) data.

The locations for the solar PV and wind resources are given in Table 1 and shown on a map of New Mexico in Fig. 2. These locations correspond to existing renewable resources in New Mexico and were chosen to be representative of the geographically distributed renewable generation potential in the state.

4.2. Formulation

The optimization problem (2), subject to the constraints in (3) and with the objective function as defined in (4), is solved for multiple cases that consider different years and varying limits on the amount of trade power. These cases (and subcases, where ‘x’ denotes the case number) are described in Table 2. The model parameter values used in the ES model (1) and the renewable

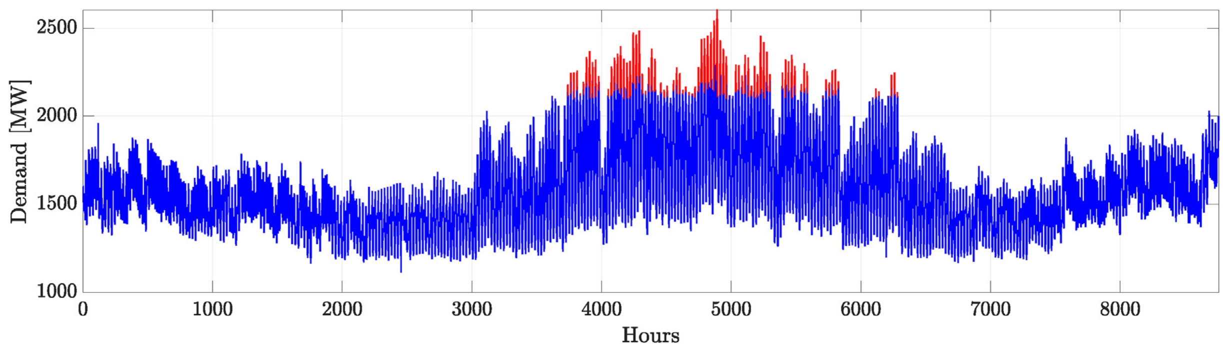


Fig. 1. 2018 electricity demand with example trading hours in red ($p_k^{\ell} > 2100$ MW). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

generation models in the Appendix are given in Table 3, and the optimization parameter values used are given in Table 4. The weights in the objective function (4) are chosen to be representative of the relative difference in capital cost for each resource. Namely, the cost of the ES system ($w^{c} + w^{p}$) is 1.5 times that of a wind or solar PV system (w^{w} or w^{pv}, respectively). Since the cost of curtailment or energy trading may be significantly less than these capital costs, the weights w_k^{curt} and w_k^{trade} are chosen to be equal to zero for all k in these analyses. Therefore, there is no cost, benefit, or penalty for curtailment or trading in these case studies. The resulting optimization problems are MILPs that were formulated in Python using Pyomo [52] and solved using Gurobi [53].

Table 1
Renewable resource locations.

Resource type and site number	(latitude, longitude)
Solar PV 1	(35.05,-106.54)
Solar PV 2	(32.53,-107.5)
Solar PV 3	(32.45,-103.38)
Wind 1	(36.3,-103.74)
Wind 2	(34.49,-105.62)
Wind 3	(34.69,-104.06)

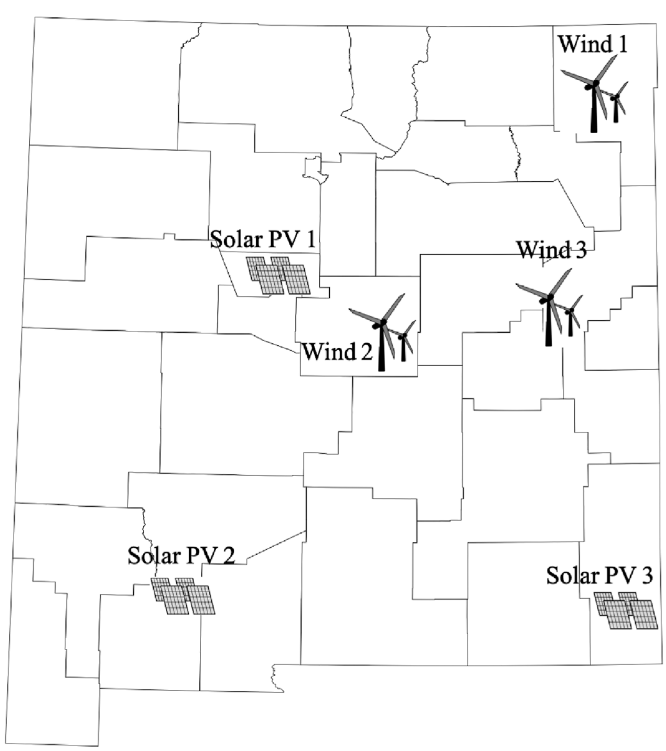


Fig. 2. County map of New Mexico, USA with renewable resource locations from Table 1 marked.

4.3. Results and discussion

The resulting resource sizes for all cases are given in Table 5. The renewable generation, curtailed power, traded power, and ES SoE and charge/discharge power results for the entire four years 2016–2019 for Case 2.9 are shown in Fig. 3. Those same results for one week in January 2016 and one week in June 2016 are shown in

Table 2
Cases.

Case	Description
1	2020 demand data and TMY weather data.
2	2016–2019 demand and weather data.
3	Case 2 with only solar PV resources.
4	Case 2 with only wind resources.
Subcase	Trade allowed when:
x.1	Never
x.2	Any hour
x.3	$p_k^{\ell} > 1600$ MW
x.4	$p_k^{\ell} > 1700$ MW
x.5	$p_k^{\ell} > 1800$ MW
x.6	$p_k^{\ell} > 1900$ MW
x.7	$p_k^{\ell} > 2000$ MW
x.8	$p_k^{\ell} > 2100$ MW
x.9	$p_k^{\ell} > 2200$ MW

Table 3
Model parameter values.

Parameter	Description	Value	Units
η^{s}	ES self-discharge efficiency	1.00	–
η^{c}	ES roundtrip efficiency	0.85	–
η^{pv}	PV panel efficiency	0.15	–
η^{conv}	PV conversion efficiency	0.90	–
$\underline{v}$	Wind turbine cut-in speed	4	m/s
v^{*}	Wind turbine rated speed	10	m/s
$\bar{v}$	Wind turbine cut-out speed	25	m/s
h	Wind turbine hub height	80	m
h_{meas}	Wind speed measurement height	50	m
a^{turb}	Wind turbine rotor area	5027	m^2
$\bar{p}^{turb}$	Wind turbine power rating	2	MW
ρ	Air density	1.2	kg/m^3

Table 4
Optimization parameter values.

Parameter	Description	Value	Units
τ	Time-step	1	hours
K	Optimization horizon (Case 1)	8760	hours
K	Optimization horizon (Cases 2–4)	35,040	hours
w^s	Weight on ES energy capacity	1	–
w^p	Weight on ES power rating	0.5	–
w^w	Weight on wind power rating	1	–
w^{pv}	Weight on PV power rating	1	–
w_k^{curt}	Weight on curtailed power	0 $\forall k$	–
w_k^{trade}	Weight on external/traded power	0 $\forall k$	–
δ	Fraction of unused SoE	0	–
γ	Fraction of initial/final SoE	0.5	–
$\bar{p}_k^{curt}$	Curtailed power allowed	$p_k^{pv} + p_k^w$	MW
$\underline{p}_k^{trade}$	Import power allowed	500 $\forall k$	MW
$\bar{p}_k^{trade}$	Export power allowed	−500 $\forall k$	MW

Table 5
Results (all results in GWh or GW).

Case	$\bar{s}$	$\bar{p}$	$\bar{p}_1^{pv}$	$\bar{p}_2^{pv}$	$\bar{p}_3^{pv}$	$\bar{p}_1^{w}$	$\bar{p}_2^{w}$	$\bar{p}_3^{w}$
1.1	26.22	5.32	9.19	2.86	7.48	0	0.89	0.44
1.2	18.64	3.69	6.45	1.82	5.30	0.01	0.63	0.24
1.3	21.25	4.50	7.10	3.65	5.21	0	0.48	0.57
1.4	22.70	4.58	8.02	2.73	6.62	0.46	0.83	0.47
1.5	25.28	4.86	8.63	3.38	6.24	0	0.81	0.61
1.6	25.51	5.33	8.76	3.19	7.64	0.10	0.83	0.46
1.7	26.22	5.32	9.19	2.86	7.48	0	0.89	0.44
1.8	26.22	5.32	9.19	2.86	7.48	0	0.89	0.44
1.9	26.22	5.32	9.19	2.86	7.48	0	0.89	0.44
2.1	29.48	5.23	14.78	1.90	7.10	0.65	3.87	0
2.2	21.50	3.48	9.36	1.96	4.28	0.75	2.89	0
2.3	21.26	4.51	14.86	0.77	6.54	2.08	1.23	0
2.4	23.35	4.57	15.82	0.53	7.32	2.86	1.63	0
2.5	25.02	4.80	17.33	0	7.15	3.16	2.54	0
2.6	26.84	5.72	16.37	01.45	7.63	1.08	3.07	0
2.7	28.42	5.41	15.37	01.71	7.37	0.81	3.79	0
2.8	29.48	5.23	14.78	01.90	7.10	0.65	3.87	0
2.9	29.48	5.23	14.78	01.90	7.10	0.65	3.87	0
3.1	27.47	4.93	28.27	02.57	16.40	0	0	0
3.2	19.90	3.65	20.27	01.46	11.69	0	0	0
3.3	21.06	4.59	12.87	09.96	12.01	0	0	0
3.4	23.37	4.66	19.97	10.23	9.89	0	0	0
3.5	24.96	4.55	23.84	05.30	16.47	0	0	0
3.6	25.56	4.63	23.03	04.02	18.64	0	0	0
3.7	26.37	4.62	28.57	03.60	15.89	0	0	0
3.8	27.47	4.93	28.27	02.57	16.40	0	0	0
3.9	27.47	4.93	28.27	02.57	16.40	0	0	0
4.1	148.56	13.47	0	0	0	25.04	39.80	34.25
4.2	108.02	11.32	0	0	0	16.88	26.86	20.13
4.3	125.25	11.70	0	0	0	20.65	35.33	30.23
4.4	128.81	12.09	0	0	0	21.11	36.54	33.44
4.5	133.75	12.83	0	0	0	23.77	36.54	34.25
4.6	142.05	13.41	0	0	0	24.95	37.75	34.25
4.7	146.56	13.38	0	0	0	25.07	39.80	34.25
4.8	148.56	13.38	0	0	0	25.07	39.80	34.25
4.9	148.56	13.47	0	0	0	25.04	39.80	34.25

Figs. 4 and 5, respectively. Fig. 3 shows that the generation is much larger, sometimes 8 times larger, than the demand in a given hour. Therefore, there is significant curtailment in the vast majority of hours to reduce the need to store all that excess energy. Fig. 3 also shows the seasonal trend in renewable generation: there is the most generation in the Spring and the most consistent (but less) generation in the Summer. This is due to the large but variable wind generation in the Spring and less wind but more consistent solar PV generation in the Summer. Finally, Fig. 3 shows that the ES is frequently used and charges and discharges through the entire range of SoE throughout all four years. Fig. 4 shows that the demand is relatively flat in the Winter and never exceeds the threshold of 2200 MW to allow energy trading. Moreover, curtailment is not needed every day of the week. On the other hand, Fig. 5 shows the demand varies more in the Summer. When the demand exceeds the 2200 MW threshold for energy trading, energy is imported for a few hours to reduce the peak demand, and energy is exported for a few hours when the demand is large enough but the generation is larger to reduce the curtailment.

The results for all cases are summarized in bar graphs in Figs. 6 and 7. For 100% of PNM's demand to be met by renewable generation produced within New Mexico at the six sites given in Table 1 and Fig. 2, the resources required are roughly 5 GW/25 GWh of ES, around 20 GW of solar PV, and almost 5 GW of wind. The average demand and peak demand from 2016 to 2019 (see data for 2018 in Fig. 1) are 1.6 GW and 2.6 GW, respectively, so these requirements are an order of magnitude larger than the demand. Fig. 6 shows that energy trading can significantly reduce the size of required ES, and the trend from subcase 2 to 9 shows that larger resources (both ES and renewable generation) are required when less energy trading takes place.

Remark 1. An important result is that, as the number of trading hours is reduced (i.e., subcases x.7, x.8, and x.9), the resource requirements plateau at the values required when no trading occurs (i.e., subcase x.1). This means that resources sized to ensure that a large fraction of the peak demand can be met solely with renewable generation (no trading) are also sufficient to meet the peak demand. In these case studies, the maximum allowable energy to be imported is 500 MW, which is just under *20%* of the peak demand of about 2600 MW each year. Therefore, the fact that the requirements plateau after trading is only allowed in hours when demand exceeds 2000 MW or 2100 MW means that resources sized to meet about *80%* of the peak demand are also large enough to meet *100%* of the demand. This means that there is no longer a need for peaker plants since the stored energy from excess generation resulting from meeting *80%* of the peak demand for an entire year is more than sufficient to balance generation and peak demand.

Remark 2. Fig. 7 shows that considering only solar PV generation (Case 3) does not significantly impact the required ES power rating or capacity, whereas considering only wind generation (Case 4) increases the required ES energy capacity by almost five times compared to Cases 1 and 2, and it requires the largest renewable power ratings by far. This may be due to the greater variability in wind generation as compared to solar PV. Therefore, to minimize both the total amount of renewable generation required and the ES power and energy requirements, it is advantageous to diversify the types of renewable generation.

4.4. Firm capacity

Firm capacity is often used as a measure of reliability of a generation fleet. Firm capacity is calculated as the number of hours over a given period of time that the amount of power generated exceeds the power demanded. In these case studies, the goal is to balance the demand 100% of the time, so the firm capacity of the renewable generation plus ES for all hours must necessarily be at least as large as the smallest demand during the year. Plots of the renewable generation and renewable plus ES firm capacities for Case 2.9 are shown in Fig. 8. For the considered scenario, solar PV alone has much greater firm capacity than wind generation alone. Firm capacity of renewable generation is improved when solar PV and wind are combined due to their complementarity. However, firm capacity of renewable generation alone is only greater than the demand for about one half of the hours over the four years

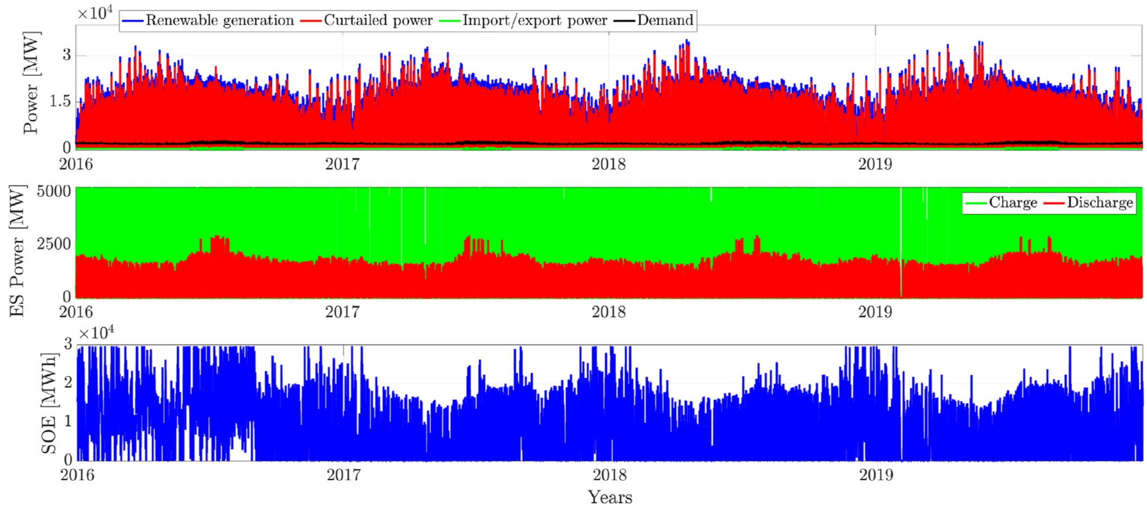


Fig. 3. Results for all four years for Case 2.9. Renewable generation, curtailment, import power, and demand are shown in the top subplot. ES charge and discharge are shown in the middle subplot, and ES SoE is shown in the bottom subplot.

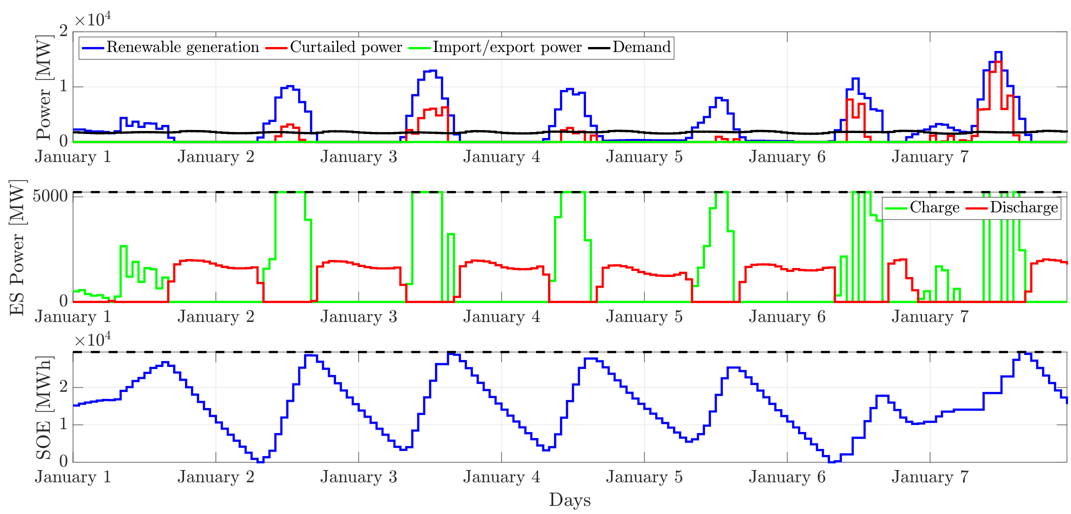


Fig. 4. Results for January 1–7, 2016 for Case 2.9. Renewable generation, curtailment, import power, and demand are show in the top subplot. ES charge and discharge are shown in the middle subplot, and ES SoE is shown in the bottom subplot.

2016–2019, which highlights the need for ES. The renewable plus ES firm capacity is computed as the renewable generation plus (minus) the discharge (charge) power in each hour, and then those hours are sorted by the largest to smallest capacity and are plotted in Fig. 8.

4.5. Capacity factor

Capacity factor is often used as a measure of a plant's total generation and is computed as the average power output from the site divided by the power rating. With solar PV and wind plants, the capacity factor of a given plant may change year to year as the weather is more or less conducive for generation. Therefore, it is an important metric to consider when choosing resource types and locations for renewable generation plants. The capacity factor for each renewable plant at the locations in Table 1 for multiple years of data and the power ratings shown in Table 5 are given in Fig. 9. The capacity factors for the solar PV plants for all cases are similar at values just above 20%. The wind plants generally have higher capacity factors than solar PV plants, but the capacity factors have greater variation from case to case. This shows that solar PV plants have lower capacity factors due to the lower availability of solar relative to wind (due to the sun only shining a fraction of the year), but they produce more predictable generation from year to year than wind plants.

4.6. Required land area for renewable generation

Assuming 1 MW of solar PV requires roughly 10 acres (0.04 km^2) of land [57], and 1 MW of wind requires roughly 50 acres (0.2 km^2) [58,59], the resulting areas of land required for the renewable power plants, with the power ratings in Table 5, are given in Table 6 and are shown in Fig. 10. For reference, the state of New Mexico has an area of roughly 315,200 square kilometers. The smallest total area required (corresponding to Case 1.2) is 728 km^2, or about 0.23% of the area of New Mexico. The result of 1366 km^2 from Case 2.2 may be more realistic and corresponds to about 0.43% of the area of New Mexico. The largest total area required, corresponding to Case 4.1 (only wind and no trade), is 20,050 km^2, or about 6.4% of the area of New Mexico. In scenarios with significant land use

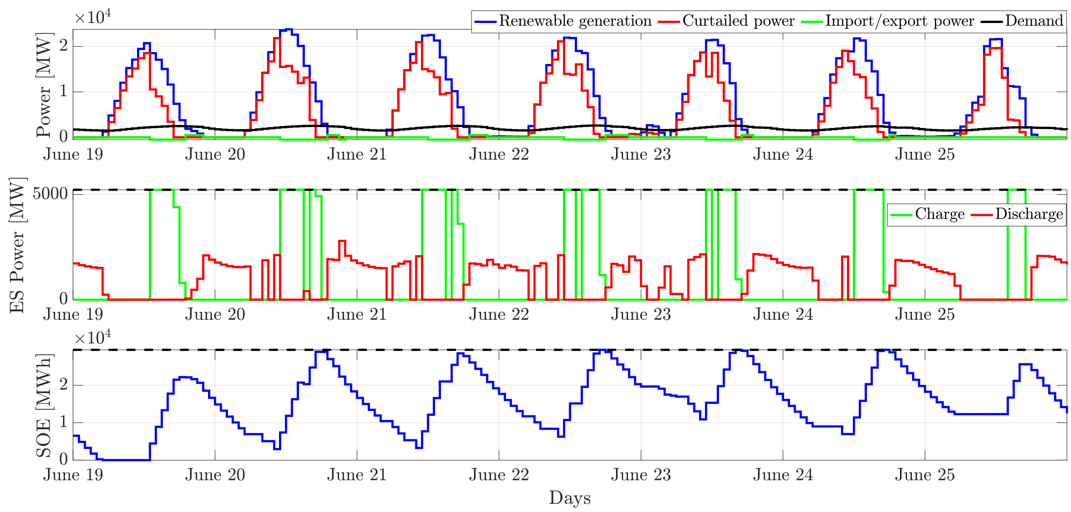
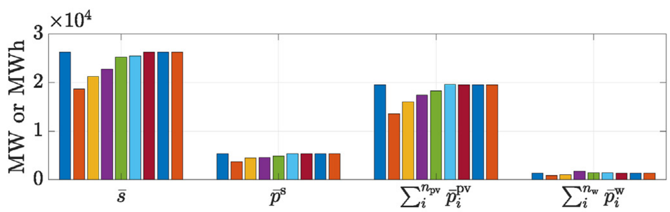
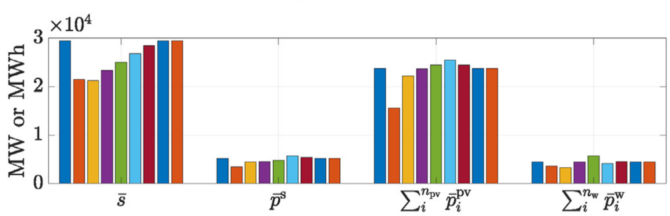


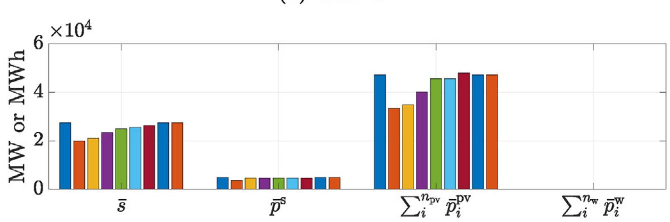
Fig. 5. Results for June 19–25, 2016 for Case 2.9. Renewable generation, curtailment, import power, and demand are show in the top subplot. ES charge and discharge are shown in the middle subplot, and ES SoE is shown in the bottom subplot.



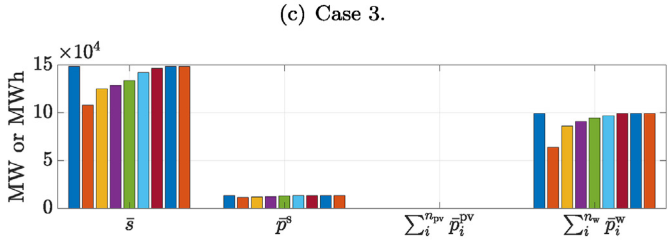
(a) Case 1.



(b) Case 2.



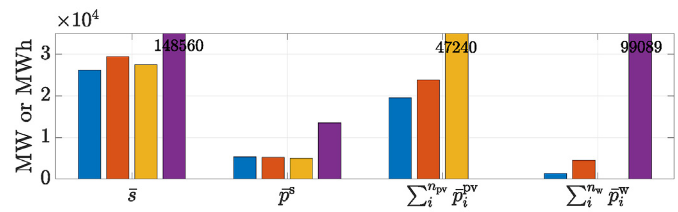
(c) Case 3.



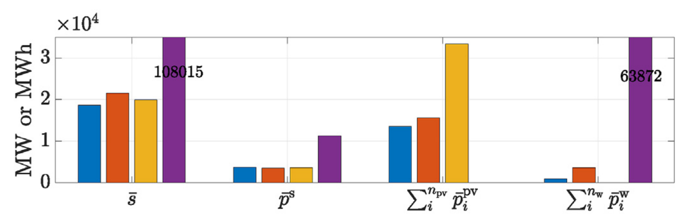
(d) Case 4.

Fig. 6. Summary of results for Cases 1–4. Each bar corresponds to a different subcase 1–9 going from left to right, respectively.

constraints, the relative costs of renewable generation in different locations can be penalized with the weights in (4), or hard constraints on the available area for a particular plant can also be included.



(a) No trade.



(b) Trade allowed all hours.

Fig. 7. Summary of results for Cases 1–4 corresponding to no trading allowed (subcase 1) or trading allowed any hour (subcase 2). The bars correspond to Case 1, 2, 3, or 4 (from left to right). Marked bar values are well beyond the vertical axis limit.

4.7. Curtailment

In these case studies, all excess energy can be curtailed, and the curtailed power is a large fraction of the total generation. This is because overbuilding the renewable generation significantly reduces the need for larger ES to store excess energy that is not used later and, therefore, significantly reduces the total cost of renewable plus ES resources. If the amount of curtailment is constrained, the required size of ES becomes enormous (particularly the power rating), and the optimization problem (2) may be infeasible due to constraints such as (3l).

In Table 7, the amount of curtailment is shown for the most extreme cases of no trading allowed and trading allowed every hour. When trading is not allowed, more than 62.72% of the total generation is curtailed in every scenario. Even when trading is allowed every hour, more than 46.67% of the total generation is

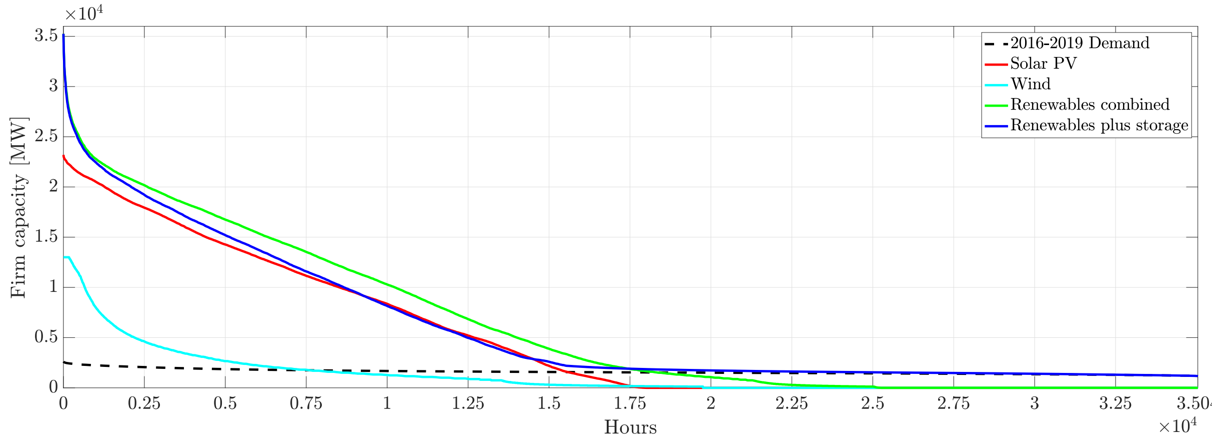


Fig. 8. Firm capacity of renewable generation and renewable generation with ES for Case 2.9. All data are sorted from largest value (hour 1) to smallest value (hour 35,040).

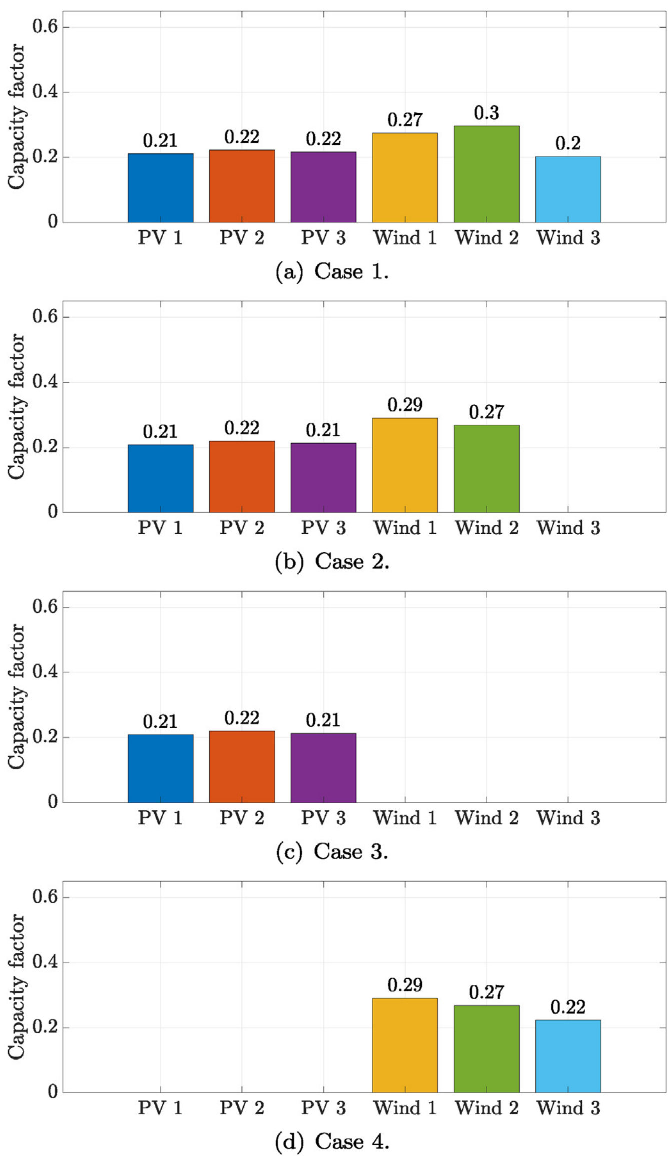


Fig. 9. Capacity factor of each renewable energy plant from Table 1 for Case 1 (a), Case 2 (b), Case 3 (c), and Case 4 (d). For Case 2, the capacity factor of Wind 3 is zero because the solution has no generation at that site (see Table 5).

Table 6
Required land area for renewable resources in km^2.

Case	Solar PV		Wind	
	No trade	Trade any hour	No trade	Trade any hour
1	790	549	269	179
2	963	631	914	735
3	1912	1352	0	0
4	0	0	20,050	12,920

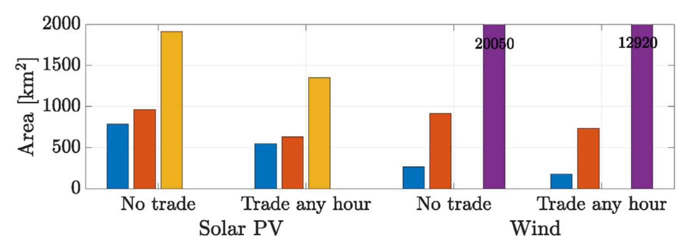


Fig. 10. Land area required for solar PV and wind renewable resources with and without trade. The bars correspond to (from left to right) Cases 1, 2, 3, and 4. The values for Case 4 are noted on the bars and are larger than the vertical axis limit.

Table 7
Renewable generation and curtailment.

Case	Total generation [MW]	% curtailed
1.1	39,832,977	62.72%
1.2	27,619,389	46.67%
2.1	218,533,355	72.67%
2.2	15,012,0372	56.59%
3.1	348,626,090	82.55%
3.2	246,492,820	73.11%
4.1	896,530,017	93.34%
4.2	581,573,957	90.00%

curtailed in every scenario. Using both solar PV and wind generation (Cases 1 and 2) reduces both the total generation and the percentage of that generation that is curtailed as compared to using only one renewable generation resource (Cases 3 and 4). The highest total generation and percentage of generation curtailed occurs when only wind generation is used (Case 4).

To provide 100% of the demand with renewable generation, a regional approach must be considered that can take advantage of significant generation in one region to provide energy to another region with deficit. Therefore, scenarios with significant energy trading between regions will be beneficial when looking to balance larger systems, such as that of the entire USA.

5. Conclusion and future work

An optimization-based approach was presented for determining the sizes of required renewable energy resources and energy storage to balance the electricity demand of a utility with 100% renewable generation. This optimization approach was used to analyze resource requirements for New Mexico, USA, to transition to a 100% renewable electric power system, considering historical hourly demand from a medium-sized electric utility and historical meteorological data. Key findings are as follows:

- For 100% of the Public Service Company of New Mexico (PNM) demand to be met by renewable generation produced within New Mexico at the six sites considered, the resources required are roughly 5 GW/25 GWh of energy storage, around 20 GW of solar PV, and almost 5 GW of wind. 25 GW of renewable generation is more than 15 times the average demand (1600 MW) over the years 2016–2019 and almost 10 times the peak demand (2600 MW) over those years. However, regional energy trading can significantly reduce the size of required resources.
- If renewable generation resources are sized to meet about 80% of the peak demand, they are also large enough to meet 100% of the demand. Thus, peaker plants are no longer required.
- Considering only wind generation increases the required energy storage capacity by about 5 times and requires the largest renewable power rating. Considering both solar PV and wind generation results in the smallest required resources, but the firm capacity of solar PV and wind combined is still only greater than the demand for about half of the investigated time period of 4 years. Therefore, there is a significant need for energy storage to increase the firm capacity of renewable generation.
- Wind plants generally have higher capacity factors, but the capacity factors vary from year to year. Solar PV plants have lower capacity factors but produce more predictable generation from year to year than wind plants.
- The area of land required for the renewable generation plants is on the order of 1000 square kilometers, which corresponds to roughly 1% of the area of New Mexico.
- A significant amount of the generation must be curtailed, from 46% to 73% or even more depending on the scenario considered. This is required to reduce the size of energy storage. A regional approach that allows significant energy trading between regions should be considered when analyzing larger systems to allow the export of excess energy and import of energy during deficit to potentially reduce the sizes of required local resources.

This work provides essentially a lower bound on the size of required resources to meet 100% of a utility's demand with renewable generation using a retrospective analysis. In future work, transmission system models will also be considered to ensure feasibility of the locations and sizes of the generation resources. In addition, a stochastic approach that takes into account future forecasts of demand and generation will be incorporated to address operational considerations that utilities will need to prepare for in the future.

Credit author statement

David A. Copp: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Formal analysis. **Tu A. Nguyen:** Conceptualization, Methodology, Writing – review & editing, Formal analysis. **Raymond H. Byrne:** Writing – review & editing, Supervision. **Babu R. Chalamala:** Writing – review & editing, Supervision, Funding acquisition.

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.

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Appendix

5.1. Solar photovoltaics generation model

Power generation from a PV system can be modeled as

$$p_k^{\mathrm{pv}} = \eta^{\mathrm{pv}} \eta^{\mathrm{conv}} a^{\mathrm{pv}} \varphi_k, \tag{7}$$

where p_k^{pv} is the power generated from the PV system at time-step k [kW], η^{pv} is the efficiency of each PV panel, η^{conv} is the conversion efficiency of the PV system, a^{pv} is the total coverage area of solar panels [m^2], φ_k is the Global Horizontal Irradiance (GHI) [kW/m^2] at time-step k, and the impact of temperature and tilt angle is neglected. This generation is uncertain due to the time-varying and stochastic nature of GHI.

5.2. Wind generation model

The power generation from a wind turbine can be modeled with Rayleigh wind speed distribution assumptions as [51].

$$p_k^{\mathrm{w}} = \frac{6}{\pi}\left(\frac{1}{2}\rho a^{\mathrm{w}} v_k^3\right), \tag{8}$$

where p_k^{w} is the power generated from a wind turbine at time-step k [W], ρ is the air density [kg/m^3], a^{w} is the swept area of the turbine rotors [m^2], and v_k is the wind speed at time-step k [m/s].

If wind turbine cut-in, rated, and cut-off wind speeds are included, denoted as $\underline{v}$, v^*, and $\overline{v}$, respectively, the power from the wind turbine at time-step k is given as

$$p_k^{\mathrm{w}} = \begin{cases} \dfrac{6}{\pi}\left(\dfrac{1}{2}\rho a^{\mathrm{w}} v_k^3\right), & \text{if } v_k \in [\underline{v}, v^*] \\ \dfrac{6}{\pi}\left(\dfrac{1}{2}\rho a^{\mathrm{w}} {v^*}^3\right), & \text{if } v_k \in [v^*, \overline{v}] \\ 0 & \text{otherwise}. \end{cases} \tag{9}$$

If the wind speed is measured at a height different from the height of the wind turbine, the wind speed can be adjusted using the following relation [51].

$$v_k = \tilde{v}_k \left(\frac{h}{h_{\mathrm{meas}}}\right)^{\beta}, \tag{10}$$

where $\tilde{v}_k$ is the measured wind speed at time-step k, h is the height of the wind turbine, h_{meas} is the height of the anemometer where the measurement is taken, and β is a friction coefficient, often chosen to be 1/7.

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