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Pathways to specialized renewable energy generation: insights from integer portfolio optimization in a globalized electricity market

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Abstract

Background Research on portfolio optimization for energy generation often does so from a financial perspective. This study addressed a unique challenge: determining which companies, amidst a globalized electricity market, should be retained for climate risk preservation during specialization. Utilizing weather and generation data from 106 power plants across Argentina, we adapted integer-portfolio-optimization tools. Originally designed for financial index funds, these tools helped us construct a portfolio of power plants for a resilient energy mix.

Results Our findings revealed optimal companies for retention by analyzing different portfolio configurations, where the number of plants was adjusted iteratively. In each iteration of the model, we selected a set of representative plants that minimize climate risk, which sometimes resulted in a plant being included in one portfolio but not another. This approach identified the specific companies and technologies essential for a diversified and climate-resilient energy portfolio while ensuring a strategic transition toward specialization and stabilizing generation risk in the face of variable weather conditions.

Conclusions This paper presents a groundbreaking solution for specialization in a globalized energy market. Through portfolio optimization, we identified pivotal companies for each stage of the transition in Argentina. Firms like Parque Eólico La Genoveva and Complejo Hidroeléctrico Centrales Cacheuta Alvarez Condarco, showcased the balance needed for wind and hydroelectric sources. These insights should be used to guide policymakers to ensure a controlled and effective transition while maintaining stable generation risk.

Keywords Energy transition, Index fund, Integer portfolio optimization, Renewable energy

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Background

Three fundamental characteristics of future energy markets are: (i) almost all electricity will be generated by variable renewable energy technologies (VRE) such as wind turbines and solar cells, and by hydropower sources, all of which are directly dependent on weather; (ii) further transnational integration of energy markets will be required with the aim of diversifying the climate and weather risk to which generation through these technologies is exposed; (iii) energy storage, especially green hydrogen technologies, is one of the emerging technologies being discussed as a way to transfer electricity consumption over time and across dispersed geographic areas. While hydrogen can play a role in the future energy landscape, its efficiency in the context of electricity storage and re-generation needs to be carefully evaluated. It may be more rational to use hydrogen directly in transportation or to replace natural gas in industrial processes, where it can be more efficient. Therefore, while hydrogen is mentioned as a potential technological solution, it is not the focus of this paper, which instead concentrates on the optimization of the energy generation portfolio. Further research is needed to thoroughly evaluate the role and efficiency of hydrogen in sustainable energy systems. These three points are closely interrelated and emphasize the urgency of establishing clear policy guidelines, legal frameworks, and the infrastructure necessary for an adequate development of future energy markets throughout the world and, in particular, of future energy networks. Such energy networks will consist of extended power "super" grids [1–3], but they will be more general than that, as they will also include economic transactions between energy providers and consumers located in very distant areas, using green hydrogen and other innovations in terms of storage. In short, fully integrated transnational energy markets operating over large geographic areas and covering neighboring or distant countries in regions as diverse as Western Europe or South America are likely to be the norm in future energy markets.

Amidst the global shift toward renewable energy sources and the increasing complexity of transnational energy networks, policymakers and energy stakeholders face a critical challenge: how to navigate a rapidly evolving landscape while ensuring a resilient and sustainable energy future. This challenge extends beyond the mere transition to renewable technologies; it involves making strategic decisions that not only optimize energy generation but also manage the inherent variability associated with weather-dependent renewables. The decisions made today will shape the future energy markets, affecting the reliability, affordability, and sustainability of electricity supply. In this context, our study delves into the intricate web of energy generation, climate risk, and economic considerations, offering a systematic approach to aid governments in preserving a stable yet competitive energy landscape in an era defined by globalization, specialization, and renewable energy dominance.

An example of the type of policy challenges that governments around the world will face in the coming decades, as the energy transition progresses and this new reality arrives, is the following: which hubs or clusters of energy generation firms, within national territories, should the government ideally encourage, in order to consolidate a competitive advantage for electricity generation within a given (potentially very large) transnational economic energy network? In the case of VRE companies, comparative advantages are naturally linked to the geographical location of the generation plants they use for energy conversion. This location determines, to a great extent, the weather configuration faced by the generation technologies of these firms and, therefore, the electricity generation that they can (physically) contribute to the network.

Here, we propose an optimal way for governments to make decisions in this particular aspect. Our approach is aimed at governments that need to preserve a certain level of climate risk associated with electricity generation in the country and want to decide which companies need to be supported optimally (e.g., facilitating access to credit, providing capital injections, allowing temporary tax exemptions, offering subsidies, etc.). However, we recognize that in some jurisdictions, such as the European Union, direct support to individual companies may be restricted by legal regulations. In such cases, our approach may be adapted to comply with local regulations and function as supporting mechanisms that do not contravene antitrust and competition laws. The aforementioned government objective refers to the possibility of consolidating generation in a smaller number of plants that are highly competitive and strategically selected to maintain climatic and operational stability. This approach is not intended to favor large generation monopolies, but rather to explore how specialization in certain technologies and locations could contribute to a more stable and efficient energy transition.

Encouraging the dissemination of multiple small- and medium-sized generation sources is crucial for market diversification and competition. However, it is also important to consider scenarios where plant consolidation may offer specific advantages in terms of stability and climate resilience, especially in regions with variable climate conditions. These firms will be more likely to become generation leaders when local markets become even more specialized as required by the globalization of energy markets and, at the same time, they will be strategically chosen to preserve a certain risk configuration. Note that our requirement that this subset of companies emulate as closely as possible the generation risk due to actually observed weather conditions is critical from a national energy security perspective. Indeed, another way to posit our research problem is: which companies should the government be willing to support, in order to preserve the current configuration in terms of weather generation risk within the national borders of the country, if it needs to rely only on a subset of companies among those that are already operating?

These firms are likely to exhibit greater possibilities of becoming regional leaders within the large (and transnational) economic energy network of the future. Note that we are not addressing the more general optimization problem of deciding, from a central planner's perspective, which are the optimal locations and what the optimal proportions of VRE plants across the country, based on historical weather settings [2, 4–9]. Rather, we are providing a methodology for deciding which subset of companies, within those already in operation, are capable of generating electricity by closely mimicking a given weather risk configuration in the dynamics of national electricity generation. We recognize that this approach could discourage the birth of new generation companies, which could be detrimental in the long term. Support for a subset of existing companies aims to ensure stability and climate resilience during the energy transition. However, we understand that encouraging competition and the entry of new companies is crucial for innovation, market efficiency, and the diversification of energy sources. A dynamic and competitive energy market is essential for sustainable development and adaptation to future energy and climate needs. To address this concern, it is important to consider complementary policies that balance support for existing companies with incentives for the creation of new generation companies. These policies can include subsidies, lines of credit and regulatory support for new companies, thus ensuring a diversified and competitive energy market.

It is crucial that decision-makers and policymakers reflect on the need to balance strategic consolidation with fostering a diversified and competitive energy market. Although specialization can offer benefits in terms of climate stability and resilience, it should not come at the expense of competition and innovation. By considering policies that support both existing and new companies, sustainable and adaptive development of the energy sector can be ensured, aligned with global trends of diversification and competition. This balanced approach is essential to creating a robust and dynamic energy market that can meet future challenges effectively.

In our empirical application, we used historical weather records and actual locations of Argentinian power plants. Our goal was to preserve as much as possible the configuration of weather risk shaped by the $n = 106$ energy plants in our sample, which consisted of solar (34), wind (38) and hydropower plants (34). We showed how to select a subset of q plants, with $q \ll n$, which better replicated the observed weather risk configuration in the country. In our example, weather risk was fully described by the correlation matrix (ρ) of the original n series of weather variables that measured the main input used in each case to generate power, according to the respective generation technology in each of the n energy original plants. That is, the correlation matrix between the meteorological series of solar irradiation recorded on the earth's surface, wind speed and precipitation were examined for different geographical points in Argentina. The reason for working directly with the weather series, rather than with the transformed electricity series, was that in our problem, the stochasticity was entirely due to the weather. The generation was simply a deterministic function of the fundamental weather factors. Other potential sources of uncertainty, such as technology malfunctions, were omitted from our analysis because they fell outside the scope of our goals.

Our choice of Argentina as a case study was based on several strategic factors. First, Argentina has unique geographic and climatic diversity, ranging from the plains of the Pampa to the elevations of the Andes and the coasts of the Atlantic Ocean. This variability provided a complex and representative scenario to examine how portfolio optimization strategies can adapt to diverse meteorological and geographic conditions. Next, Argentina has experienced significant growth in installed renewable energy capacity in recent years, making it a pertinent case to explore transition strategies toward more sustainable electricity systems. Furthermore, the availability of georeferenced data for power plants in Argentina improved the accuracy and applicability of our analysis. It is important to note that, although we mentioned the situation in Europe as a reference, our approach and results were not limited to this context. Rather, we sought to contribute to the global understanding of energy transitions and optimization, with practical applications that could be extrapolated to diverse environments, including those in Latin America and other regions with similar geographic and climatic characteristics.

We solved our optimization problem for a sequentially decreasing number of plants, q, starting from $q = n - 1$ and ending at $q = 1$, and also estimated the expected generation risk associated to each step. This information was crucial to assess the risk of an energy transition that requires specialization, according to weather conditions, from countries and companies. The proposed methodology allowed starting from any correlation matrix and participation vector in the generation mix of the n energy plants. Therefore, although our application corresponded to the scenario mentioned above in which the government wishes to keep the weather risk environment as stable as possible during the transition to specialization, our proposal could also be easily adapted to reflect any possible environment of interest to a policy maker, that is, with participation quotas potentially being very different from the actual ones in the different plants, and according to the different generation technologies. We found that in Argentina, around 71 power plants diversified across the three generation technologies sufficed to preserve the weather risk of the original 106 plants without loss of information. Our results also emphasized that given the sequential nature of the optimization problem at each step, the model diversified across technologies and also across locations, guaranteeing a natural diversification of weather risk across the country.

Our study stands out for introducing an innovative methodology based on financial portfolio techniques to identify an optimal set of power plants while preserving the climate risk configuration. We applied advanced risk metrics, such as value at risk (VaR) and Expected Shortfall (ES), to variations in climate factors, to improve the accurate assessment of risks associated with renewable energy generation. Argentina served as a practical case, highlighting the usefulness of our methodology in a context of transition toward a more specialized electricity market. In the critical discussion, we explored the pros and cons of relying on a small number of companies for power generation while addressing crucial factors such as technical risk management, security of supply, and the adaptability of the power system to changing climate conditions. Our study offers innovative and practical results, thereby contributing to transition strategies toward renewable energies in different national and regional contexts.

The global transition toward more sustainable energy highlights the central importance of renewable energy. In our research, we recognized the need to address this change gradually and strategically based on the challenges linked to changes in a country's energy matrix. Preserving the share of renewable energy emerged as an essential strategy as it ensures a smooth transition and mitigates technical and economic risks. Our motivation lies in the premise that the energy transition must be gradual to preserve the experience and contribution of existing renewable energy sources, thus guaranteeing stability and paving the way toward cleaner technologies. The proposed model acts as a strategic guide by optimizing plant portfolios to maintain a significant share of renewables while minimizing climate risks. This perspective addresses the complexity of energy transitions, and it offers valuable guidance to decision-makers for long-term sustainable energy policies.

The rest of this document is organized as follows. Section two provides a brief literature review of recent studies which explore the possibility of relying on a 100% generation mix based on renewables. This section also examines literature in which portfolio optimization techniques are used to solve problems regarding optimal ways to carry out planning in power markets. Next, section three contains the details of our methodological proposal that closely follows contributions from the literature of integer programming for constructing index funds. Thereafter, section four presents our main results, and section five provides our conclusion.

Integration of diversification and renewable energy studies

This study contributes to two branches of academic literature. First, it expands the set of studies that analyzes diversification opportunities and addresses the problem of deciding on the optimal generation mix using portfolio theory from finance. Second, it relates to a new branch of the energy literature that analyzes, from a policy perspective, the possibility of transitioning to an electricity-generation mix fully consisting of renewable sources.

In the former set of studies, some authors have explored the risk-minimization problem subject to a certain level of reward that a firm wants to achieve, using Markowitz's portfolio theory, and assimilated the problem of deciding on the optimal shares of generation technologies a firm can invest in an asset allocation problem [10–14]. In the same group, some studies approached the problem by changing the perspective from the firm to that of the government or the policy maker. In these cases, the policy maker wished to optimize the generation mix of the country using VRE technologies and considered the intermittency of this sort of generation due to weather uncertainty [7–9]. To this end, a variety of approaches based on classic optimization techniques and fuzzy multi-objective optimization have been proposed. A last set of authors in this first group went beyond the national boundaries and directly explored transnational optimization of renewable energy sources [2, 4, 6]. Most of the time, these authors focused on the case of a European super grid. Santos-Alamillos et al. [2] and [15] have notably explored the diversification possibility of resorting to different geographical locations to generate electricity, which is at the core of our study. The initial authors examined various ways to distribute new renewable energy capacity across Europe, aiming to maximize the performance of a unified European power super-grid in terms of power yield while minimizing fluctuations. The latter authors proposed a portfolio optimization model for constructing a wind-energy portfolio, which considered a large harvesting region in the US. The authors' goal was to reduce the prediction of wind generation and the conditional value at risk of the portfolio. Unlike the abovementioned studies, we explored a distinct optimization problem separate from that considered by policymakers or firm managers. That is, we addressed the related (but totally different) issue of deciding which power plants and technologies, within those already operating, are optimal to support in order to achieve a similar risk configuration based on the correlation between the intermittent generation sources.

The second set of studies includes one by [16], which used a global weather model to calculate thermal loads consistent with renewable supplies, and studies by [17–21] all of which explored ambitious policies of 100% renewable energy by different countries and on different planning horizons. Jacobson et al. [22] explored achieving 100% clean energy from wind, water, and sunlight (WWS) worldwide. This study offers solutions for matching energy demand with WWS supply, storage, and transmission. WWS could cut energy costs, reduce environmental impacts, and address global warming. In addition, Jacobson et al. [23] outlines roadmaps for 145 countries to transition from fossil fuels to 100% wind–water–solar (WWS) energy, aiming for completion by 2050. In Europe, the importance of considering meteorological variability and its effects on wind and solar energy generation is crucial. Several studies, such as that of [24] have analyzed the optimal composition of renewable energy resource portfolios, taking into account transmission constraints and conventional generation capacity in European countries. Furthermore, Maimó-Far et al. [25] highlighted how spatial granularity in the description of climate resources influences renewable energy planning and improves the exploitation of complementarities and reducing variability. Wohland et al. [26] showed that multidecadal variability in wind and solar generation in Europe has a significant impact, and they emphasized the need for dynamic energy planning. These studies stress the importance of considering climate and weather variability in the expansion of renewable energy in Europe and underscore the need for flexible and adaptive management strategies to ensure an effective and sustainable energy transition. Unlike them, our focus was not on exploring the possibility of a 100% renewable energy grid. Instead, we started from the desirability of this policy objective and explored optimal ways to arrive there while promoting specialization in regions with certain weather conditions within a given country.

Methods

Our methodology consisted of two steps. First, we performed an optimization using the correlation matrix of observed weather configurations and progressively reduced the number of power plants that better preserve the actual weather/climate risk configuration observed in Argentina during the sample period. Second, we estimated risk measurements for each of the optimal portfolios found in the first step through the use of value at risk statistics.

Optimization model

The core of our research rested in constructing an optimal portfolio that reflected the original risk structure attributable to climate uncertainty while considering the installed capacity of renewable energy sources in Argentina. We constructed each of these optimal portfolios throughout our methodology which can be conceptualized as an "index fund" [27] that faithfully represents the actual energy generation mix in the country.

The optimization process unfolded in multiple steps, with its primary objective being the selection of a reduced set of power plants from a larger set, such that this subset was highly representative of the total population of plants in terms of installed capacity and, critically, the underlying climate risk structure. These steps were pivotal for the transition toward climate specialization in energy generation, a central aim of our study. Given a target population of n plants, q plants were selected to represent the target population as faithfully as possible, given the observed shares of installed generation capacity for each technology at each plant.

We proposed a large-scale optimization model that enabled the consolidation of the diverse mix of renewable energy generation in Argentina into a smaller set of specialized plants. This resulting set, comprising a portfolio of q plants, was specifically designed for energy generation from wind, solar, or hydro sources. Unlike conventional approaches that seek efficiency in terms of mean and variance, our approach centered on preserving the underlying risk structure related to climate uncertainty. This is particularly relevant for intermittent generation technologies dependent on climatic factors such as wind speed, solar radiation, and precipitation [28].

The optimization model was based on grouping climate-related information associated with each plant into categories with similar statistical characteristics. Subsequently, the model selected one representative plant from each category to be part of the optimal portfolio of specialized plants. In summary, the primary goal of this model was to maximize the similarity between the original n plants and their q representatives in terms of the climate-risk structure. Formally, this maximization of similarity was expressed through a set of equations and constraints that ensured the resulting portfolio was highly representative of the total population of plants and preserved the original risk structure due to climate uncertainty. These equations and constraints were essential to achieving our objective of transitioning toward climate specialization in energy generation and ensuring stability in energy production under variable climate conditions throughout this transition. We had that:

Variables

$$\rho_{ij} : \text{Correlation between plant i and plant j}$$

$$x_{ij} = \begin{cases} 1 \; if \; j \; was \; the \; most \; similar \; plant \; to \; plant \; i \; in \; the \; optimal \; portfolio \\ 0 otherwise \end{cases}$$

$$y_j = \begin{cases} 1 \; if \; the \; plant \; j \; was \; selected \; in \; the \; optimal \; portfolio \\ 0 otherwise. \end{cases}$$

Objective function

$$Z = \text{Max} \sum_{i=1}^{n} \sum_{j=1}^{n} \rho_{ij} x_{ij} \tag{1}$$

Subject to

The choice of plants in the optimal portfolio was equal to q.

$$\sum_{j=1}^{n} y_j = q.$$

Each plant i has a plant j that represented it in the optimal portfolio.

$$\sum_{j=1}^{n} x_{ij} = 1 \text{for } i = 1, \ldots, n.$$

Each plant i could be represented by plant j, only if j was in the optimal portfolio.

$$x_{ij} \leq y_j \text{ for } i,j = 1, \ldots, n.$$

Variable ρ_{ij} represented the correlation between plant i and plant j. In other words, it quantified how similar the weather and climate risk profiles were between two power plants. Higher values of ρ_{ij} indicated a stronger similarity in risk. x_{ij}, This binary variable took a value of 1 if plant j was selected as one of the most similar plants in the optimal portfolio for plant i. Otherwise, it took a value of 0. It helped determine which plants were included in the specialized portfolio for each plant i. y_j. Similarly, this binary variable took a value of 1 if plant j was selected to be part of the optimal portfolio. It helped determine which individual plants made up the overall specialized portfolio.

The objective function Z aimed to maximize the overall similarity between the original set of n power plants and their representatives in the optimal portfolio. It did so by summing the products of the correlation coefficients ρ_{ij} and the binary variables x_{ij} while considering all pairs of plants i and j. In simpler terms, the objective was to find the combination of plants in the optimal portfolio that best preserved the weather and climate risk structure of the original set of plants.

Regarding constraints, the first constraint ensured that the number of plants chosen for the optimal portfolio was equal to q. This constraint controlled the size of the portfolio and ensured it included the desired number of plants. The second constraint ensured that each plant i was represented by exactly one plant j in the optimal portfolio. It guaranteed that each original plant was included in the specialized portfolio and avoided duplication. The third constraint determined that a plant i could be represented by plant j ($x_{ij} = 1$) only if plant j was actually selected in the optimal portfolio ($y_j = 1$). In other words, if plant j was not part of the portfolio, it could not represent any other plant.

Once the optimization model was solved, and a specific set of q plants had been selected for the optimal portfolio, the weight w_j was calculated for each plant j in the portfolio. This weight represented the proportion of the total installed generation capacity of all plants (C_i) that each selected plant contributed to the specialized portfolio. It provided insights into the relative importance of each plant in terms of its generation capacity within the optimized mix. This optimization model aimed to construct an optimal portfolio of power plants while considering their similarity in weather and climate risk profiles. The objective was to maximize the overall similarity while controlling the size of the portfolio and ensuring that each original plant was represented by one of the selected plants. The weights w_j provided information on the contribution of each plant to the portfolio based on its generation capacity.

Our current optimization model focused on preserving the climate risk configuration by selecting power plants with similar climate profiles. However, we recognized that this approach did not directly consider the need to balance generation with system demand at all times. To address this limitation, it was essential to include the analysis of the demand diagram and its daily and seasonal evolution. Energy demand varies significantly throughout the day and year, and these variations needed to be considered to ensure that the system could meet demand at all times. Clearly, the incorporation of generation demand would completely change the model used, which is currently based on analyzing climate correlations. In future research, we propose to extend our model to integrate these critical factors. This will include the analysis of the hourly and seasonal demand profile, allowing a selection of plants that not only maintains climatic stability, but also ensures a continuous and balanced supply of energy according to the needs of the system.

By incorporating these additional dimensions, we aimed to develop a more comprehensive and applicable methodology for planning resilient and sustainable energy systems, which could effectively adapt to variations in demand and ensure a robust balance between generation and consumption.

Value at risk (VaR)

VaR is a widely adopted measure used to evaluate the risk associated with a portfolio of financial assets. In the context of our study, VaR served as a powerful tool for assessing the risk related to the generation of electricity from renewable sources, particularly in the face of variable weather conditions. In [29], VaR can be defined as a quantification of the maximum potential loss in the value of a portfolio that may occur over a predefined time horizon and within a specified level of confidence. In statistical terms, VaR represents an extreme percentile of the distribution of changes observed in the series being analyzed. In our case, we applied VaR to estimate the risk associated with the logarithmic variation of weather factors used in electricity generation.

We employed two fundamental approaches to estimate VaR in our application. The first was historical VaR, which calculates VaR by analyzing historical data. Specifically, it quantifies the α empirical percentile of the historical distribution of the data series. This approach provides insights into the potential loss scenarios based on past observations of weather conditions. It is a valuable tool for assessing risk in situations where historical data are rich and relevant to the current context. Parametric VaR, the parametric approach, on the other hand, assumes that the changes in the weather series follows a Gaussian (normal) distribution. This distribution is characterized by two key parameters: the mean (μ_t) and the standard deviation (σ_t) of the changes. The parametric VaR is then determined by combining these parameters with the desired confidence level α. Mathematically, it is expressed as:

$$VaR_{(\alpha,t)} = \mu_t + Z_{(\alpha)}\sigma_t, \tag{2}$$

where $VaR_{(\alpha,t)}$ represents the value at risk at a given time horizon t and confidence level α. In addition, μ_t is the mean of the changes in the weather factors. σ_t is the standard deviation of the changes in the weather factors. $Z_{(\alpha)}$ corresponds to the α percentile associated with the normal distribution. The parametric VaR approach provides a valuable tool for estimating risk in situations where historical data may be limited or where there is a need to project potential losses into the future based on the statistical characteristics of the data. In our analysis, we applied both historical and parametric VaR methodologies to comprehensively assess the risk associated with electricity generation from renewable sources.

VaR calculations for weather-related series in renewable energy generation brought significant relevance and innovation to our study. These calculations played a pivotal role in quantifying and managing the inherent risks associated with renewable energy sources, particularly those dependent on variable weather conditions. VaR serves as a powerful tool to assess potential financial and operational risks, aiding decision-makers in energy planning and policy formulation. What set our approach apart was the use of logarithmic variations in the VaR analysis. Logarithmic transformations not only stabilized data variance, but also provided results that were highly interpretable in terms of percentage changes. This enhanced the practicality and applicability of our risk assessment, making it an essential component for stakeholders and policymakers in understanding, prioritizing, and addressing the challenges posed by weather-related variability in renewable energy generation.

Furthermore, we extended our risk analysis beyond VaR by incorporating expected shortfall (ES), also known as conditional VaR (CVaR). ES, as defined by [30], represents the conditional loss expectation given that the loss exceeds the VaR for a specified significance level α. Mathematically, ES is expressed as $ES_\alpha(X) = E[X|X \geq VaR_\alpha(X)]$, where X represents the weather-related series. This addition allowed us to delve deeper into understanding the potential consequences of extreme weather conditions on renewable energy generation and provided an even more comprehensive risk assessment for our study.

We introduced VaR as a fundamental tool to assess and manage the risk associated with electricity generation from renewable sources, specifically in the context of variable climate conditions. This measure becomes relevant when addressing volume risk, which is manifested through significant deviations in energy generation forecasts due to climate variability. The uncertainty introduced by changes in temperature, extreme weather events, and other unpredictable conditions can have a considerable impact on renewable energy production. The applicability of VaR in our study rested in its ability to quantify the probability and magnitude of possible losses associated with volume risk. By considering fluctuations in power generation related to climate factors, VaR provides a valuable measure that helps decision-makers better understand the potential financial and operational implications amid climate uncertainty. This tool becomes an essential component for effective risk management, supporting the transition toward a more sustainable energy matrix.

We can confirm that the preservation of the climate risk configuration is justified by its role in the stability, predictability and security of energy generation. This aligns with the need to minimize economic and social impacts associated with extreme weather events. Furthermore, we will highlight how this preservation supports energy security and contributes to a more controlled transition toward sustainable energy sources.

Data

For our empirical application, we selected the country of Argentina and used 106 main power generation plants that utilize different production technologies associated with wind, solar and hydraulic sources. We included a total of 38 wind plants, 34 solar plants, and 34 hydraulic plants in our sample. These plants represented an installed power capacity of more than 16,747 MW. Figure 1 shows the geolocation of the 106 plants. The wind plants are located mainly on the coast of the country, while the solar plants are located in the north of the country and the hydraulic plants are distributed in the center and north of the country. Of the 16,746 MW generated from the plants in the sample, 74.7% was produced by hydroelectric plants, 16.3% by wind parks, and 9% by solar parks.

From the georeferencing of each plant, we determined the latitude and longitude. Using NASA's POWER Project tool [31], we extracted for each coordinate according to its type of generation, information on wind speed at 2 m, solar irradiation (JM/m2), and precipitation (mm). Climate information was extracted from 01/01/2000 to 01/01/2022 with a daily frequency.

The climate variability in Argentina is notable due to its extensive geography and the interaction of various atmospheric currents. This unique climate component adds an additional layer of challenges and opportunities in optimizing renewable energy generation. The geographical and climatic diversity of the country makes it an exemplary case to analyze strategies that address climate variability in the energy sector. We highlighted the relevance of Argentina as a significant study model to understand how countries can successfully manage the transition toward renewable sources and address climate variability in the electricity sector. We developed an interactive application that provides an innovative tool to visualize and explore these aspects in a detailed and accessible way. It can be consulted at https://juniorjb5.shinyapps.io/AppBeta.

Our current optimization model focuses on preserving climate risk settings using historical climate statistics. However, for a medium and long-term analysis, it is essential to consider not only these statistics, but also projections of climate evolution. In a climate change environment, incorporating climate trends and projections is critical to ensuring that proposed solutions are resilient and sustainable over time. Future research can extend our model to include climate projections, should data become available. This will enable a selection of power plants that not only preserves the current climate risk configuration, but also considers future trends, thereby ensuring robust and adaptive energy planning in the face of changing climate conditions.

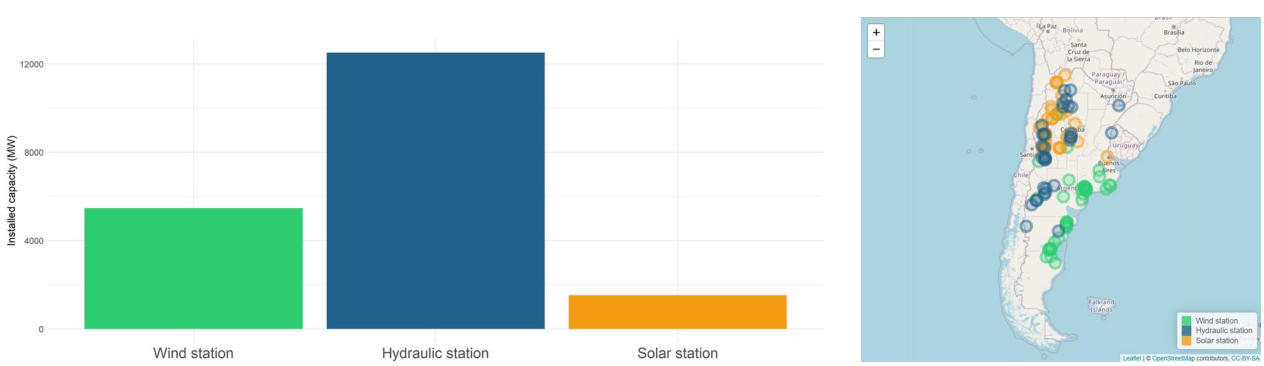

Fig. 1 Sources of energy generation in Argentina. The panel on the left shows the installed capacity in MW according to the source of power generation. The panel on the right shows the georeferencing of the generation sources, the green color represents the wind plants; the blue color represents the hydro plants, and the orange color represents the solar plants

In our study, we used the NASA POWER portal database because of its high reliability and precision. This NASA project was designed to improve renewable energy data sets and create new data from satellite systems. In addition to NASA POWER, we recommend considering other reliable databases such as WorldClim, the Copernicus Climate Change Service's Climate Data Store (CDS), NOAA's National Centers for Environmental Information (NCEI), and the European Climate Data and Assessment Set (ECA&D). These sources can complement future analyses depending on the context of the required variables.

Results

Optimization and risk

Figure 2 shows the number of plants according to their technology within each optimal portfolio of q specialized plants. We progressively show, from $q = 1$ to $q = n = 106$, how the portfolio of plants that preserve the weather risk structure of actual generation in Argentina, as much as possible in each step, can be constructed. For instance, when $q = 71$, the model discards 35 non-optimal plants in the sense that these 35 plants are the ones that contribute the least to preserving the weather risk configuration observed in the portfolio of the 106 original plants. That is, considering all the existing plants, our model discards 13 wind plants, 17 hydraulic plants, and 5 solar plants that do not contribute the most to preserving the weather risk configuration in the country. This can be due to variability of the meteorological series, the installed capacity, or a combination of both. This means that with a smaller number (71 plants) we achieved satisfactory similarity with respect to the original weather risk structure (see Fig. 2).

With our approach, we could identify progressive optimal subsets of plants. We were able to observe greater participation of solar plants at the beginning, followed by wind plants and, lastly, we could observe the incorporation of hydropower plants. This result was certainly linked to the installed capacity of each of the existing technologies (i.e., a greater number of solar plants was needed because they had less installed capacity). On the contrary, a small number of hydraulic plants sufficed, because they had greater installed capacity. Figure 3 shows the same information using percentage shares.

Figure 4 shows the optimal weights assigned by our optimization model to each source at each step. Due to the dominance of hydropower in the generation mix of Argentina, it was natural that our model assigned large optimal weights within each portfolio to hydraulic plants.

In Table 1, we present summary statistics of the meteorological series and of the installed energy capacity in our optimal portfolios for different values of q. As q increased, we generally observed greater variability in the installed capacity of hydro plants, while wind and solar plants exhibited relatively stable characteristics in terms of mean values and variability. The total installed capacity of all plant types naturally increased with higher q values, reflecting the inclusion of more power generation plants in the portfolio. These patterns provided insights into how portfolio composition impacts the distribution of weather-related variables and installed capacity as q varies. The climatic variables, specifically wind speed and solar irradiation, exhibited relatively stable

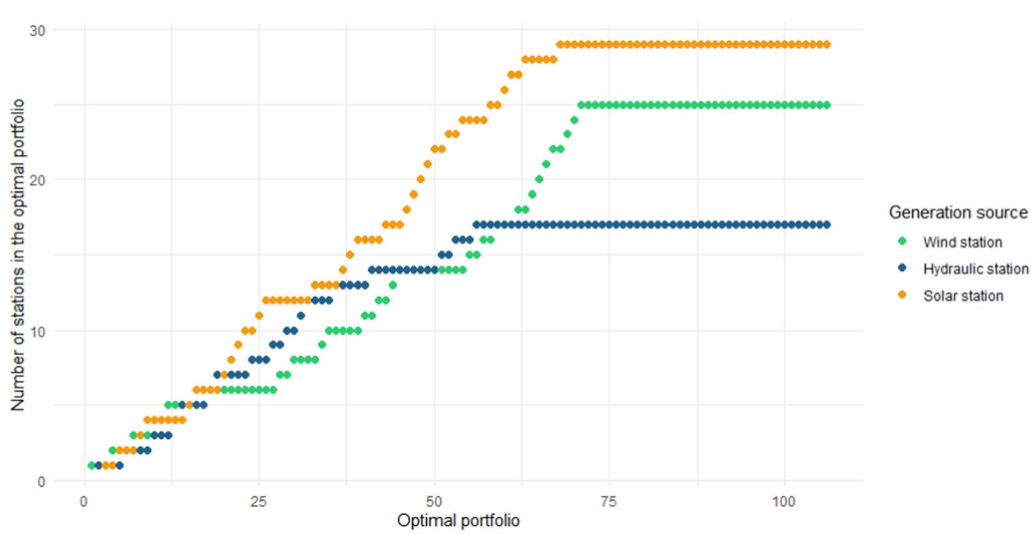

Fig. 2 Distribution of the number of plants for each optimal portfolio. The axis of the optimal portfolio represents the number q of plants specialized in preserving the correlation structure of the energy network

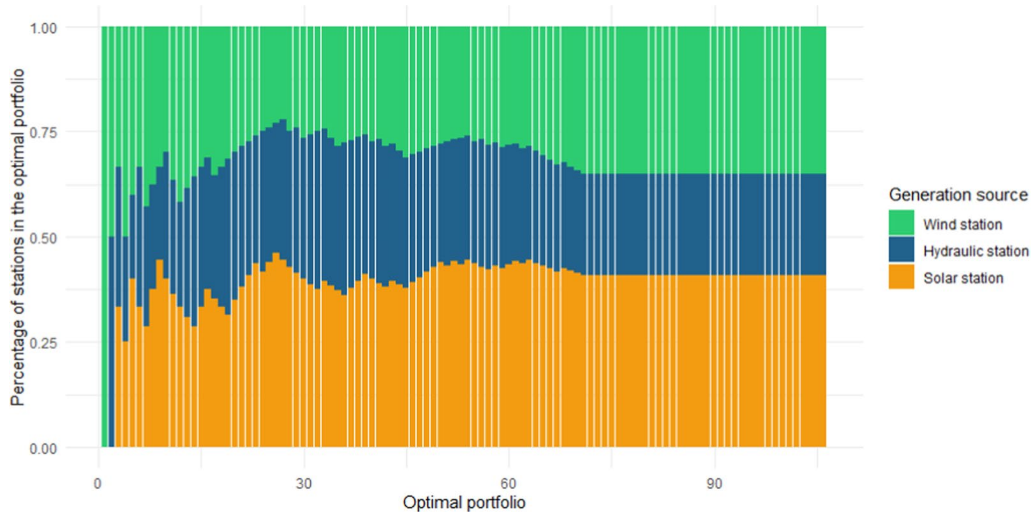

Fig. 3 Distribution of the percentage of plants for each optimal portfolio. The axis of the optimal portfolio represents the number q of plants specialized in preserving the correlation structure of the energy network

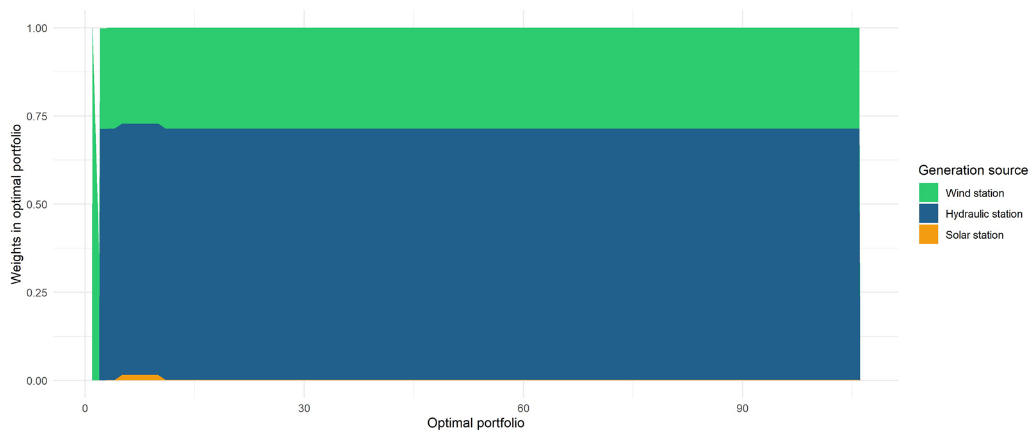

Fig. 4 Optimal composition of each portfolio. This figure shows how the compositions in each portfolio manage to preserve the correlation structure and the current allocation of the energy network

characteristics in terms of mean values, variability, and distribution shapes as q varied. These patterns suggest that increasing the number of power generation plants in the portfolio does not significantly alter the climate-related characteristics. Table 1 presents the distribution of plants assigned for different values of q. For q = 100, the table shows a total of 71 assigned plants (25 wind, 17 hydroelectric and 29 solar). This distribution may seem confusing, since it does not reach the indicated value of q. This is because our optimization model was designed to identify the minimum number of plants necessary to preserve the country's climatic structure. Although the model was iterated until q = 106, our results indicated that the climate risk structure remains constant from q = 71. This means that it is not necessary to increase the number of plants beyond this point to maintain such a climate structure. Consequently, the table reflects that, although the value of q could be increased to 100, only 71 plants are required to achieve the model objective.

Figure 5 provides insights into the risk dynamics associated with different portfolio sizes (q) for the estimated VaR and ES. This analysis was conducted using two distinct methodologies: historical and parametric (Gaussian). In the left panel, one can see how the VaR and CVaR change as we incremented the number of plants (q) in our optimal portfolio. Both VaR and CVaR exhibited a noteworthy decreasing trend, indicating a reduction in risk exposure as the portfolio diversified. The substantial differences between the parametric VaR and the historical VaR in Fig. 5 are due to contrasting estimation

Table 1 Summary of optimal portfolio statistics

		Climate information							Installed capacity (MW)					
Source	n	Mean	Standard deviation	Coef. variation	Median	Min	Max	Total	Mean	Standard deviation	Coef. variation	Median	Min	Max
							q = 5							
Wind	2	6.2	2.5	39.9%	6.1	0.5	17.3	254.4	127.2	72.8	57.2%	127.2	54.4	200.0
Hydro	1	1.3	1.8	135.9%	0.7	0.0	20.9	184.4	184.4	0.0	0.0%	184.4	184.4	184.4
Solar	2	9.1	8.7	95.7%	6.3	0.0	41.6	140.0	70.0	30.0	42.9%	70.0	40.0	100.0
							q = 30							
Wind	8	6.4	2.5	39.2%	6.3	0.3	17.6	538.0	67.3	30.8	45.8%	66.0	6.3	100.0
Hydro	10	1.5	1.9	133.6%	0.7	0.0	26.6	699.0	69.9	80.5	115.0%	35.0	4.0	261.0
Solar	12	9.0	8.8	98.1%	6.2	0.0	41.6	515.0	42.9	38.2	88.8%	23.4	1.0	100.0
							q = 60							
Wind	17	6.3	2.5	39.7%	6.1	0.3	17.6	1080.0	63.5	34.5	54.3%	50.4	3.0	120.0
Hydro	17	1.6	2.1	133.8%	0.8	0.0	34.5	6524.0	383.8	791.6	206.3%	26.0	2.0	3200.0
Solar	26	9.0	9.0	99.3%	6.1	0.0	41.8	1176.0	45.2	61.8	136.7%	22.0	0.0	300.0
							q = 100							
Wind	25	6.3	2.5	39.9%	6.1	0.3	17.6	1610.0	64.4	33.6	52.1%	53.0	3.0	121.8
Hydro	17	1.5	2.1	134.1%	0.8	0.0	34.5	7133.0	419.6	789.5	188.2%	44.0	2.0	3200.0
Solar	29	9.0	9.0	99.7%	6.1	0.0	41.8	1310.0	45.2	60.2	133.3%	22.0	0.0	300.0

This table shows the summary statistics within each optimal portfolio when q = 5, q = 30, q = 60, and q = 100. On the left side is the climatic information, and on the right side is the installed capacity. Wind: meters per second (m/s). Hydroelectricity (hydro): precipitation in millimeters (mm). Solar: joules per square meter (J/m^2)

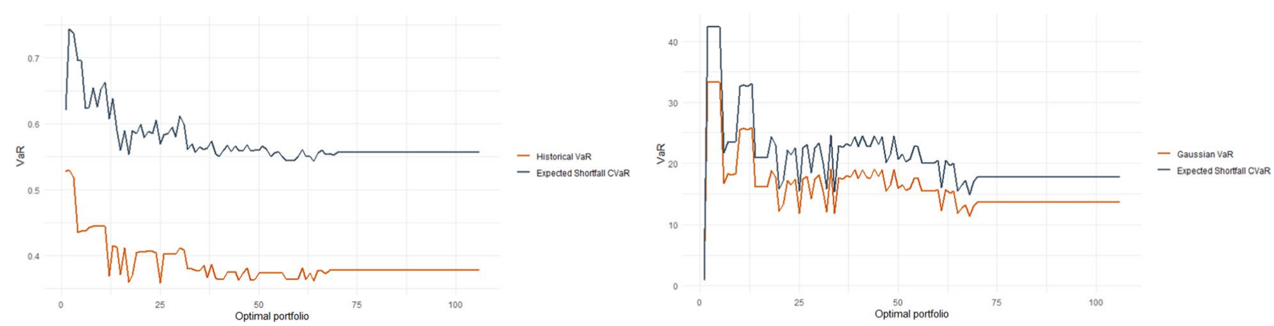

Fig. 5 Value at risk for each optimal portfolio. Left panel: historical method. Right panel: Gaussian method

methodologies. Climate variability introduces complexities that impact the empirical distribution in the historical method, while the parametric VaR, by assuming a normal distribution, can underestimate extreme events associated with exceptional climatic conditions. These discrepancies highlight the importance of considering the non-linear and non-normal nature of volumetric risks in the context of renewable energy generation.

Initially, there was some volatility in the risk measures, but this stabilized, notably around $q = 71$. It is crucial to highlight that the blue line, representing CVaR, consistently remains higher than the red line (VaR). This divergence signifies that while VaR provides a valuable measure of risk, CVaR considers the conditional loss expectation beyond VaR, making it a more comprehensive risk-assessment metric. This difference underscores the importance of considering the tail end of the risk distribution, particularly in scenarios where extreme events might have substantial consequences. In the right panel, one can find a similar analysis, but this time using the parametric (Gaussian) method for estimating VaR. Interestingly, the gap between the red and blue lines is notably narrower compared to the left panel. This suggests that the parametric approach results in a more aligned VaR and CVaR. The decreasing trend in risk as the portfolio size increased was a positive finding, indicating that diversification across a larger number of plants effectively mitigates weather-related risk. The stabilization of risk metrics around $q = 71$ suggests an optimal portfolio size for balancing risk and return in the context of renewable energy generation. The risk tends to stabilize once the share of the number of hydroelectric plants within the optimal portfolio stabilizes. It is crucial to note that the choice to assume a normal distribution for changes in the meteorological series is a necessary simplification to apply parametric methods such as value at risk (VaR). However, in reality, climatic conditions can show non-normal behavior, with extreme events more frequent than expected under a Gaussian distribution. Additionally, weather patterns are altering due to climate change, which may increase the frequency and severity of these extreme events. This simplification allows the application of analytical tools, but the inherent limitation of modeling climate variability and the effects of climate change must be considered.

Furthermore, the consistently higher values of CVaR compared to VaR emphasize the significance of considering not only the likelihood of extreme events (VaR), but also their potential severity (CVaR). This insight underscores the importance of robust risk management strategies, especially in the renewable energy sector, where weather-related events can have a substantial impact on energy generation.

The expectation of agreement between the historical and Gaussian methods would assume that the historical data fit a normal distribution. However, the complexity of climate variability introduces non-linear dynamics that may affect this assumption. While the historical method directly uses information from the observed data, the Gaussian method imposes the restriction of a normal distribution. The observed differences highlight the need to consider the idiosyncrasies of climate data in the assessment of volumetric risk in renewable energy generation.

In the realm of finance, index funds are typically constructed to track the financial returns of selected assets. In our context, we drew an analogy by defining our own equivalent of return series, denoted as G, which represented the logarithmic variation in meteorological factors such as wind, irradiation, and precipitation. The left panel of Fig. 6 illustrates that as we progressively built our portfolios (from $q = 1$ to $q = 30$), the average growth rate of these portfolios increased. Beyond $q = 30$, portfolios exhibited a substantial contribution from hydroelectric sources. Importantly, G consistently maintained positive values, indicating a strengthening of the meteorological phenomena in question. In Fig. 6, one can see that some portfolios with around 25 plants had a lower generation risk ratio compared to larger portfolios. This is because some of these first portfolios contained hydroelectric plants, which provided risk minimization due to the controllability and storage capacity of these plants. However, these initial portfolios showed very unstable behavior due to variability and lower diversity in generation sources. As the number of plants in the portfolio increased, a stabilization was observed in the generation risk ratio, indicating a reduction in volumetric risk and greater resilience to climate variations. The optimal portfolio of 71 plants was selected not only for its low generation risk ratio, but also for stability and consistency in risk minimization over time. Although some smaller portfolios may show lower risk ratios at certain times, their lack of stability and diversity makes them less reliable in the long term.

Now, we can draw parallels between financial concepts and our energy-climate framework. The right panel of Fig. 6 introduces the "generation risk ratio", akin to the Sharpe ratio in finance. This ratio reflects the relationship between mean growth rates and the historical volatility of the meteorological series associated with our optimal plant portfolios. *Increasing Growth Rates:* The left panel demonstrates that as we diversify our plant portfolios, represented by q, the average growth rate of energy generation rises. This increase suggests that a broader mix of energy sources tends to capture more favorable meteorological conditions. Just as diversified financial portfolios aim to maximize returns, our energy portfolios seek to

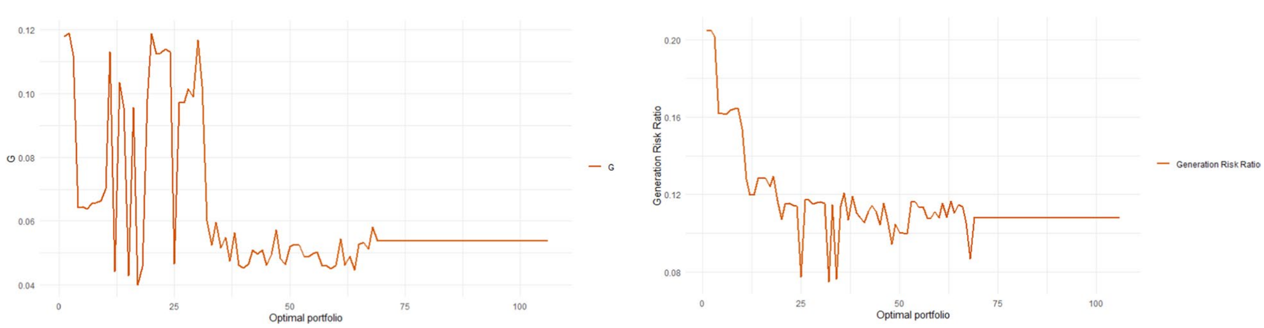

Fig. 6 Comparison between average growth rates of climatic sources (left panel) and generation risk ratio (right panel)

maximize energy generation. *Strengthening Meteorological Phenomena:* the consistently positive values of G highlight a pronounced intensification of meteorological factors. This aligns with our understanding that renewable energy generation relies on these weather-related variables, which are becoming more prominent and predictable as we diversify our energy sources. *Generation Risk Ratio:* in financial terms, the Sharpe ratio helps assess the risk-adjusted returns of an investment. In our context, the generation risk ratio serves a similar purpose. It's noteworthy that this ratio consistently remains below 1 across all q values. As q increases, signifying a more diversified portfolio, the ratio declines and stabilizes. This indicates that while the growth rates intensify with diversification, so does the associated risk.

In essence, just as diversified financial portfolios aim to balance returns and risk, our approach aimed to optimize energy generation while recognizing the evolving and intensified meteorological conditions that influence it. This nuanced understanding can guide effective energy portfolio management, ultimately contributing to a sustainable and reliable energy transition.

Figure 7 shows the relationship between growth rates and risk (measured as the volatility of the series) for each set of optimal plants, similar to the "efficient frontier" in finance. We can see that as q increases, the risk decreases. We have that for smaller values of q, there are associated higher growth rates and greater risk. Here, hydraulic sources play an important role in stabilizing the risk of power generation.

Weather risk diversification

Our results show that the optimization process helps to diversify the weather risk through a variety of geographical coordinates. Figure 8 shows the geographical distribution of the plants that better preserve the actual weather risk configuration in Argentina. As the value of q increases, the new plants appear, which are dispersed throughout the territory. Each plant selected in a portfolio q is the plant that best represents the set of plants correlated with it, which is naturally related to the closest plants, owning to the fact that weather configurations are mainly determined by geographical locations. This allows the distribution of power generating plants to be optimized in geographical terms. Additionally, our results show that much less than 106 plants are enough to capture the actual weather risk configuration of renewable energy generation in the country.

Figure 8 provides a visualization of the geographic distribution of plants that optimally preserve the current configuration of climate risk in Argentina. Exploring the results in more detail for different values of q reveals significant patterns in relation to installed capacity and geographic location.

As we increased the value of q, we observed the inclusion of new plants that contributed to geographic diversification. Specifically, for q = 3, strategically selected plants effectively represented the various climatic regions of the country. When considering the installed capacity of these plants, a balance between wind, solar, and hydroelectric sources was highlighted, with a total installed capacity of 282 MW, reflecting the current technological

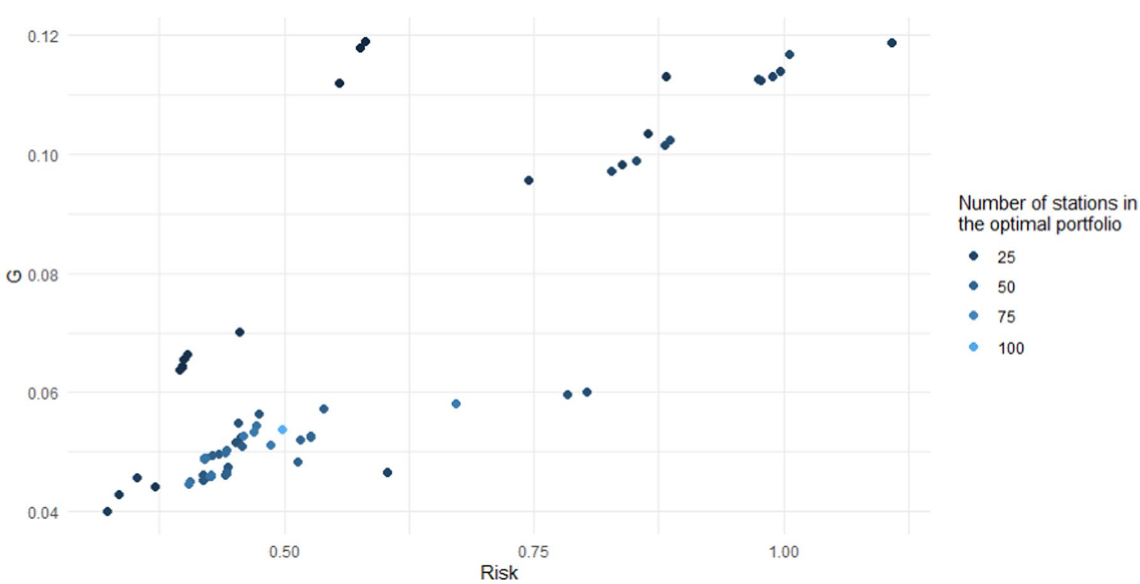

Fig. 7 Average growth rates of climatic sources vs risk for each optimal portfolio. G is simply the logarithmic variation of the meteorological series of wind, irradiation and precipitation. We define it like the analogous of the series returns

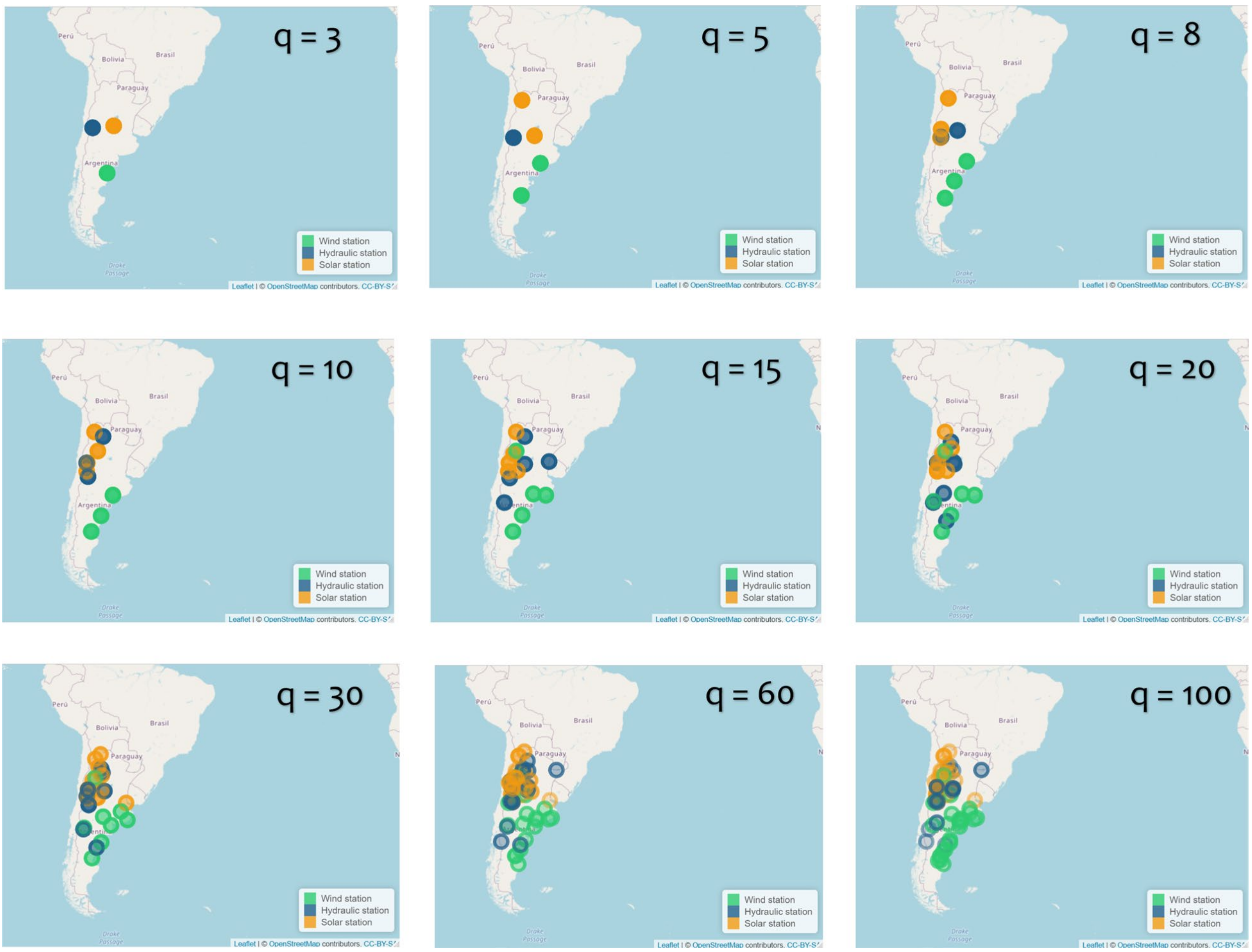

Fig. 8 Geographic distribution of plants optimally selected. We selected a number of values of q to identify diversified climatic variability from a geographic perspective

diversity in Argentina. Increasing to q = 5, the selection of additional plants further expanded both geographic diversification and the distribution of installed capacity, totaling 578 MW. It is interesting to note how the inclusion of solar plants, such as the Arroyo del Cabral Photovoltaic Solar Park, contributed to a greater representation of regions with specific latitudes. This approach not only balanced installed capacity, but also considered geographic location to preserve the structure of climate risk.

In the case of q = 8, the optimization strategy continued to focus on geographic diversification, utilizing both wind and solar sources in different regions of the country. The choice of plants such as the Chubut Norte III and IV Wind Park and the La Puna Solar Park highlights the importance of considering latitude and longitude to maintain climatic stability. In this group, the total installed capacity reached 459 MW. These results reinforce the idea that geographic diversification and balanced installed capacity are crucial in the transition to a more specialized electricity market. Optimization not only seeks to maintain the structure of climate risk, but also considers geography as a key factor in the strategic selection of plants for renewable energy generation. This approach ensured optimal adaptation to variable climatic conditions throughout the country.

Figure 9 shows the time dynamics of the meteorological series of wind speed, precipitation, and solar irradiation for the optimal portfolio of $q = 30$. This figure illustrates the variability of weather series due to each kind of generation technology, which present marked seasonal patterns, as expected. As q increased, the dynamics remained similar; hence, we did not include a figure showing other values of q.

Figure 10 shows a moving average of 12 months for each meteorological series, changing the number $q = 5, 30, 60, 100$. It can be seen that as q increased, the diversification between wind (green line) and solar

Fig. 9 Averages of the meteorological series. This figure shows the behavior of all the climatic series associated with an optimal portfolio with q = 30. We used this value of q to exemplify the climatic variability of each type of source. Wind speed: meters per second (m/s); precipitation: millimeters (mm); solar irradiation: Joules per square meter (J/m.^{2})

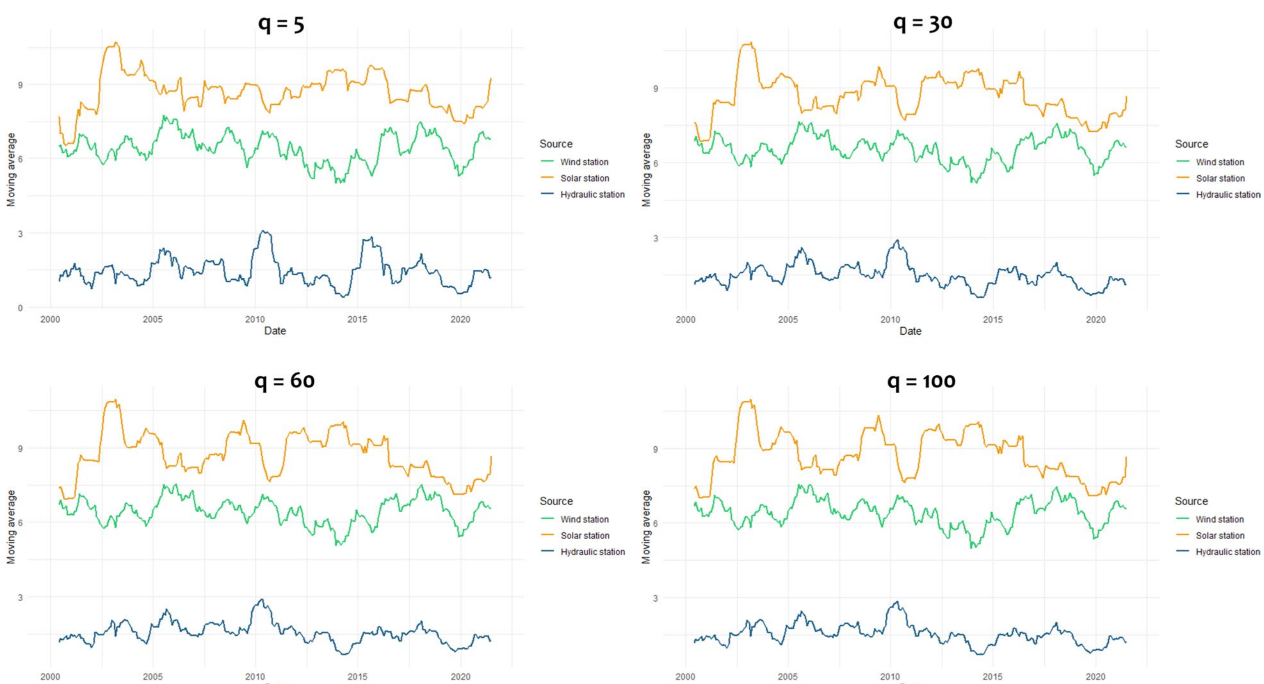

Fig. 10 12-month moving average for meteorological series. This figure shows optimal portfolios for q = 5, 30, 60, 100, where each series is the moving average of the set of meteorological series by generation source

Table 2 Correlation matrix for climatic series and moving average (MA) processes for different optimal portfolios

q = 5 **Wind**	**Wind**	**Wind**	**Wind**	**Wind**	**Wind**	**Wind**
Wind	1.00	0.37***	– 0.12.	0.34***	0.11.	– 0.07
Hydro		1.00	0.05	0.13**	0.33***	0.03
Solar			1.00	– 0.01	0.03	0.08
Wind (MA)				1.00	0.40***	– 0.19**
Hydro (MA)					1.00	0.10
Solar (MA)						1.00
q = 30						
Wind	1.00	0.51***	– 0.20**	0.33***	0.14*	– 0.12.
Hydro		1.00	0.02	0.17**	0.34***	0.05
Solar			1.00	– 0.03	0.04	0.09
Wind (MA)				1.00	0.51***	– 0.36***
Hydro (MA)					1.00	0.12.
Solar (MA)						1.00
q = 60						
Wind	1.00	0.52***	– 0.19**	0.33***	0.14*	– 0.12.
Hydro		1.00	0.00	0.18**	0.34***	0.04
Solar			1.00	– 0.03	0.04	0.10
Wind (MA)				1.00	0.52***	– 0.34***
Hydro (MA)					1.00	0.11.
Solar (MA)						1.00
q = 100						
Wind	1.00	0.52***	– 0.19**	0.33***	0.14*	– 0.11.
Hydro		1.00	– 0.01	0.18**	0.34***	0.05
Solar			1.00	– 0.03	0.04	0.11.
Wind (MA)				1.00	0.53***	– 0.33***
Hydro (MA)					1.00	0.12.
Solar (MA)						1.00

p-values (0, 0.001 = ***, 0.01 = **, 0.05 = *, 0.1 = .)

irradiation (yellow line) increased too. That is, the two series decoupled. This indicates that, at each step, our optimal plant portfolios strategically leveraged and enhanced the natural negative correlation between the two meteorological sources. In addition, in Table 2 we show that the negative correlation intensified when there was a larger number of selected plants. Table 2 shows these correlations alongside their associated significance levels. In addition to the negative correlation between wind and solar generation, there was a high correlation between wind and hydro generation. This latter point emphasizes that optimal portfolios of plants need to consider the three generation technologies when solving the sequential problem.

Discussion

Our study demonstrates how we can effectively leverage integer-portfolio-optimization tools from the realm of finance to address the complexities of transitioning toward a more specialized electricity market, particularly one heavily reliant on renewable energy sources. The significance of our findings spans various critical domains.

We recognize the challenges associated with the shift toward liberalized markets in the majority of economies. Nonetheless, even within liberal environments, governments and regulators play pivotal roles in strategic decision-making to ensure the stability and efficiency of the electrical system. Our approach does not aim to supplant the market, but rather, it offers a methodology for authorities to make well-informed decisions in specific circumstances. This includes scenarios where maintaining a particular climate risk profile is imperative.

The optimization for preserving the current climate-risk environment is rooted in the idea that some countries may seek to protect their electricity generation from climatic factors. This stability is essential for energy security and resilience, especially in cases where sudden shifts in generation due to climatic events can have detrimental economic and societal consequences. We do not propose that this should be the objective for all markets, but rather, we believe it should be an option for certain countries to consider, particularly those in regions with unpredictable climatic conditions. By maintaining a climate-risk profile akin to the current state, the risk of excessive dependence on highly climatically volatile energy sources can be mitigated, especially in regions with erratic weather conditions.

The transition to a higher share of renewable energy can be a gradual and controlled process rather than an abrupt one. By preserving a climate-risk environment similar to the present, we can strategically plan the transition to more sustainable energy sources while ensuring reliability. Our methodology does not focus primarily on reducing the number of power plants; instead, it prioritizes the selection of a subset of plants that maintain a desired climate-risk profile. This does not guarantee that the electricity system will meet all power demands, but instead, it ensures optimal adaptation to climatic conditions in line with government objectives. We recognize the importance of meeting energy demand as a fundamental priority of the electrical system. Although our approach focused on maintaining a desired climate-risk profile by selecting a subset of plants, we understand that this does not automatically guarantee that an electrical system can meet all energy demands. Considering total capacity rather than the number of plants could provide a more direct assessment of capacity security under current climate conditions. This approach would allow governments to assess what capacity is needed given current climate risk conditions and better prepare for climate variabilities. We consider our methodology to be a mechanism that can be used in conjunction with a full-capacity analysis to offer a more comprehensive view, thus helping policymakers to make informed decisions that balance climate resilience with energy security.

The "specialization" discussed in this paper addresses the need for certain countries or companies to emphasize energy generation that aligns with their climatic conditions and available resources. This entails certain energy market participants focusing on generating power from specific renewable sources, such as solar or wind, rather than relying heavily on a diversified mix of energy sources. This specialization can optimize the efficiency and profitability of electricity generation, provided a reliable supply is ensured, and risks associated with variable climatic conditions are managed effectively. However, it is crucial to underscore that the energy transition does not necessarily necessitate extreme specialization but rather intelligent and strategic diversification of the energy mix. In this context, specialization refers to the capacity of specific energy-market participants to adapt and efficiently use energy sources that best suit their environment and resources, thereby contributing to diversified, resilient, and flexible energy systems. The adoption of technologies like distributed energy resources (DERs) also plays a pivotal role in this diversification and resilience, enabling greater flexibility in energy generation and distribution.

The central question of our study focused on determining which companies the Argentinian government should support to preserve the current configuration of climate-related generation risk, if it were necessary to rely on only a subset of already existing companies. In this sense, it was imperative to examine the benefits and disadvantages of depending on a limited number of companies in the context of the transition toward renewable energy sources and climate specialization in electricity generation.

Concentration on a select set of companies could provide opportunities to optimize power generation and appropriately adapt to the country's specific climatic conditions. This could result in greater operational efficiency and profitability for selected companies, better aligning them with renewable energy transition goals. However, it is crucial to address the potential risks associated with this strategy, such as system vulnerability to unexpected events or technical failures in the selected companies, which could have significant implications on the country's energy security.

Limiting the number of companies could potentially lead to greater specialization in the implementation of specific renewable technologies. By assigning each company a more precise approach based on the particular climatic conditions of its region, operational efficiency could be optimized. Close collaboration between a few entities could facilitate more efficient coordination in the implementation of sustainable policies and practices, thus simplifying decision-making and the implementation of measures to address climate challenges. Additionally, by working with a limited number of companies, technical risk management can be more effective, allowing for the standardization of mitigation strategies and emergency response protocols.

However, this approach poses significant challenges and potential risks. Dependency on a small group of companies increases the vulnerability of the electrical system to unexpected events, such as technical failures or internal crises in one of the key companies. Diversification, which may be limited in this approach, is often considered a strategy to reduce these types of risks. Furthermore, the concentration of generation in a small group of companies raises questions about the country's energy security. Disruptions to power generation by these companies could have significant consequences for the national electricity supply. Furthermore, dependence on a limited number of companies could limit the power system's ability to adapt to changing climate conditions, since geographical and technological diversification, associated with a wide range of companies, often offers greater flexibility. Ultimately, the critical evaluation of these positive and negative aspects will help inform strategic decision-making in the design of energy policies that seek to balance operational efficiency with the resilience and security of electricity supply in the specific context of Argentina.

It is essential to recognize the limitations of our study. We have not explicitly incorporated temporal dimensions, such as seasonal variability, nor have we comprehensively evaluated energy transmission and storage capabilities. The absence of temporal considerations could limit the complete understanding of climate dynamics over time. Furthermore, transmission capacity and storage infrastructure have not been addressed in detail, which could affect the practical implementation of our approach in real-world conditions. Future research can address these limitations to offer an even more complete view of the real challenges of the energy sector.

In this study, we focused on the optimization of power generation during the transition to renewable energy sources and regional specialization. Although the demand profile, the daily profiles, and the different consumption sectors (industrial, residential, commercial) are relevant to understand the electrical system comprehensively, these aspects were not specifically addressed in this work. We recognize the importance of these factors and suggest that future research delve deeper into this aspect to obtain a more complete view of the energy transition.

Conclusions

We adapted integer-portfolio-optimization tools from finance to show how a government could move to electricity generation based on renewable energy sources using fewer power plants than those already operating within its borders. Such transitions may be necessary in the future if energy markets become more globalized than they currently are, and a nation's electricity generating needs are impacted by diverse weather patterns across various regions of its territory. During such a transition, the main objective of the government would be to preserve the configuration of weather risks (a determinant for variable renewable energy technologies) to stabilize it as much as possible.

We used data for Argentina, which consisted of several meteorological irradiation patterns recorded on the earth's surface along with wind speed and precipitation associated with each of the 106 power plants in the country. We resorted to these fundamental weather factors and showed that our model was able to provide the path that could be utilized optimally during the transition to a more specialized electricity market in Argentina.

Two natural extensions of our study would be exploring the impacts on the results after changing the optimal correlation matrix and examining the original generation mix that the optimization targets. For instance, future research might use an electricity-generation mix unobserved in the data but which is directly associated to optimal generation scenarios for a particular country. In such a case, the overall goal of that country's government would likely be different. Accordingly, its leaders probably would not be interested in research focused on current weather risks to electricity generation, but instead, they would want studies to focus on future, hypothetical scenarios. A second extension would be to incorporate more than one country into the model. Doing so would directly target the problem of globalized markets from a supranational perspective instead of focusing on a restricted optimization problem that only concerns a single nation.

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Author contributions
OJB: methodology, software, data curation, writing—original draft, visualization. DFMD: conceptualization, investigation, supervision. JMU: conceptualization, methodology, validation, supervision. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

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Not applicable.

Consent for publication
All the authors read and agree to publish the article.

Competing interests
The authors declare no competing interests.

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References

1. Huber M, Dimkova D, Hamacher T (2014) Integration of wind and solar power in Europe: assessment of flexibility requirements. Energy 69:234–241. https://doi.org/10.1016/j.energy.2014.02.109

2. Santos-Alamillos FJ, Brayshaw DJ, Methven J, Thomaidis NS, Ruiz-Arias JA, Pozo-Vázquez D (2017) Exploring the meteorological potential for planning a high performance European electricity super-grid: Optimal power capacity distribution among countries. Environ Res Lett 12:110–115. https://doi.org/10.1088/1748-9326/aa8f18
3. Anaya KL, Pollitt MG (2017) Using stochastic frontier analysis to measure the impact of weather on the efficiency of electricity distribution businesses in developing economies. Eur J Oper Res 263:1078–1088. https://doi.org/10.1016/j.ejor.2017.05.054
4. Sauter R, Awerbuch S (2007) Book reviews. Energy Policy 35:756–759
5. Schrattenholzer L, Miketa A, Riahi K, Roehrl R (2013) Achieving a sustainable global energy system. Edward Elgar Publishing. https://doi.org/10.4337/9781845423582
6. Awerbuch S, Yang S (2008) Efficient electricity generating portfolios for Europe: Maximizing energy security and climate change mitigation. Elsevier, Amsterdam
7. Ferreira RS, Barroso LA, Carvalho MM, Pereira MVF (2014) A mean-variance optimization approach to the development of portfolios of renewable generation in transmission-constrained systems. In: Proceedings - 2014 Power Systems Computation Conference, PSCC 2014. IEEE, Wroclaw. https://doi.org/10.1109/PSCC.2014.7038322
8. Mohan V, Singh JG, Ongsakul W (2017) Sortino ratio based portfolio optimization considering EVs and renewable energy in microgrid power market. IEEE Trans Sustain Energy 8:39–50. https://doi.org/10.1109/TSTE.2016.2593713
9. Yu S, Zhou S, Zheng S, Li Z, Liu L (2019) Developing an optimal renewable electricity generation mix for China using a fuzzy multi-objective approach. Renew Energy 139:1049–1061. https://doi.org/10.1016/j.renene.2019.03.011
10. Awerbuch S, Yang S (2008) Using Portfolio Theory to Value Power Generation Investments. Elsevier, Amsterdam
11. Matosovic M, Tomsic Z (2014) Power generation mix optimization using mean-lower partial moments (LPM) portfolio theory. In: ENERGYCON 2014 - IEEE International Energy Conference. IEEE, Dubrovnik. https://doi.org/10.1109/ENERGYCON.2014.6850448
12. Pinheiro Neto D, Domingues EG, Coimbra AP, de Almeida AT, Alves AJ, Calixto WP (2017) Portfolio optimization of renewable energy assets: Hydro, wind, and photovoltaic energy in the regulated market in Brazil. Energy Econ 64:524–538. https://doi.org/10.1016/j.eneco.2017.03.020
13. Unni AC, Ongsakul W, Madhu M (2020) Fuzzy-based novel risk and reward definition applied for optimal generation-mix estimation. Renew Energy 148:234–245. https://doi.org/10.1016/j.renene.2019.10.154
14. Zhang M, Tang Y, Liu L, Zhou D (2022) Optimal investment portfolio strategies for power enterprises under multi-policy scenarios of renewable energy. Renew Sustain Energy Rev 154:111879. https://doi.org/10.1016/j.rser.2021.111879
15. Han C, Vinel A (2022) Reducing forecasting error by optimally pooling wind energy generation sources through portfolio optimization. Energy 239:122099. https://doi.org/10.1016/j.energy.2021.122099
16. Jacobson MZ (2021) On the correlation between building heat demand and wind energy supply and how it helps to avoid blackouts. Smart Energy 1:100009. https://doi.org/10.1016/j.segy.2021.100009
17. Aghahosseini A, Bogdanov D, Breyer C (2020) Towards sustainable development in the MENA region: analysing the feasibility of a 100% renewable electricity system in 2030. Energy Strateg Rev 28:100466. https://doi.org/10.1016/j.esr.2020.100466
18. Hansen K, Mathiesen BV, Skov IR (2019) Full energy system transition towards 100% renewable energy in Germany in 2050. Renew Sustain Energy Rev 102:1–13. https://doi.org/10.1016/j.rser.2018.11.038
19. Kiwan S, Al-Gharibeh E (2020) Jordan toward a 100% renewable electricity system. Renew Energy 147:1–11. https://doi.org/10.1016/j.renene.2019.09.004
20. Oyewo AS, Aghahosseini A, Ram M, Breyer C (2020) Transition towards decarbonised power systems and its socio-economic impacts in West Africa. Renew Energy 154:1092–1112. https://doi.org/10.1016/j.renene.2020.03.085
21. Zozmann E, Göke L, Kendziorski M, Del Angel CR, von Hirschhausen C, Winkler J (2021) 100% renewable energy scenarios for North America—spatial distribution and network constraints. Energies 14:651. https://doi.org/10.3390/en14030658
22. Jacobson MZ, Delucchi MA, Cameron MA, Mathiesen BV (2018) Matching demand with supply at low cost in 139 countries among 20 world regions with 100% intermittent wind, water, and sunlight (WWS) for all purposes. Renew Energy 123:236–248. https://doi.org/10.1016/j.renene.2018.02.009
23. Jacobson MZ, von Krauland AK, Coughlin SJ, Dukas E, Nelson AJH, Palmer FC et al (2022) Low-cost solutions to global warming, air pollution, and energy insecurity for 145 countries. Energy Environ Sci 15:2678–2694. https://doi.org/10.1039/d2ee00722c
24. Thomaidis NS, Moukas AI (2022) Designing efficient renewable energy portfolios for optimal coverage of European power demand under transmission constraints. Energies 15:3493. https://doi.org/10.3390/en15249375
25. Maimó-Far A, Homar V, Tantet A, Drobinski P (2022) The effect of spatial granularity on optimal renewable energy portfolios in an integrated climate-energy assessment model. Sustain Energy Technol Assessments 54:102827. https://doi.org/10.1016/j.seta.2022.102827
26. Wohland J, Brayshaw D, Pfenninger S (2021) Mitigating a century of European renewable variability with transmission and informed siting. Environ Res Lett 16:065004. https://doi.org/10.1088/1748-9326/abff89
27. Strub O, Baumann P (2018) Optimal construction and rebalancing of index-tracking portfolios. Eur J Oper Res 264:370–380. https://doi.org/10.1016/j.ejor.2017.06.055
28. Cornuejols G, Tütüncü R (2006) Optimization methods in finance. Cambridge University Press. https://doi.org/10.1017/CBO9780511753886
29. Morgan JP (1996) RiskMetrics - Technical Document. Morgan Guaranty Trust.
30. Patra S (2021) Revisiting value-at-risk and expected shortfall in oil markets under structural breaks: the role of fat-tailed distributions. Energy Econ 101:105452. https://doi.org/10.1016/j.eneco.2021.105452
31. Sparks A (2018) nasapower: a NASA POWER global meteorology, surface solar energy and climatology data client for R. J Open Source Softw 3:30. https://doi.org/10.21105/joss.01035

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