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Optimising the spatial allocation of photovoltaic investments: Application to the Spanish case

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ABSTRACT

After a period of stagnation that lasted until approximately 2018, Spain has established an ambitious investment program in photovoltaics, derived from the pledge to switch to a carbon-free energy system by 2050, the sustained cost decreases of the technology, and the excellent irradiance values over its territory. This paper implements an additional criterion for the spatial allocation of these investments based on minimising the energy variability generated because of weather intermittency. The analysis is based on hourly data for the years 2005–2020 (inclusive), in various locations homogeneously spread throughout Spain. Subtracting the deterministic daily and annual irradiance cycles to estimate the variability of the random component is discussed. Failing to do that yields significantly higher and distorted values for solar energy variability, resulting in low investment proportions when combined with other energies, like wind.

The first results show that a straightforward, equally-weighted allocation of investments is suboptimal. It is also shown that investing in low-irradiance locations contributes to reducing overall variability. Secondly, the study analyses overall power variability minimisation conditional on a given wind investment weight. It is found that the impact is significant spatially, and that proportions of wind energy above 10% increase aggregated variability across all levels of aggregated power generated. Nevertheless, investment proportions in wind energy below 10% reduce the overall combined variability significantly due to the negative correlation between wind and solar irradiation. The third point addressed is the minimisation of the mismatches between renewable energy supply and aggregate electricity demand. The optimal proportion for solar and wind investments becomes close to 50% in this case. However, this proportion tilts towards solar investments if variability minimisation is also considered. Finally, the current spatial distribution of photovoltaic investments in Spain is analysed, and it is shown that there is room for improvement. It is also found that the current ratio between wind and photovoltaic energy may not be optimal, and that it would be advisable to increase proportionally more photovoltaic energy.

1. Introduction

Spain has privileged solar and wind Renewable Energy (RE) resources within Europe. However, although wind energy was developed since 1990, photovoltaic (PV) energy hardly developed until 2018. Solar energy investments focused mainly on concentrated solar power plants (CSP) with important advances and installations that have not had continuity. Two explanations are that PV costs have only recently decreased significantly, and wind investments created some inertia preventing the PV take-off [1].

To assess this situation, it is interesting to compare it with the leading economy in the European Community (EC), i.e., Germany. According to [2], the installed wind capacity in Germany in 2018 was 58.7 GW, and its theoretical onshore power potential 4050 TWh [3]. In Spain in 2018, the installed wind capacity was 23.4 GW [2], and the theoretical potential was 2780 TWh [3]. Therefore, the installed capacity to potential ratio was only slightly higher in Germany. Regarding PV, the installed capacity in Germany in 2018 was 46 GW [2] and the potential 52.92 TWh daily [4]. In Spain, the installed capacity was 4.7 GW [2], and the potential, however, is 111.6 TWh [4], implying that the installed power to potential ratio was remarkably unfavourable in Spain. This situation changed in 2019, and Spain has adopted a plan involving a significant expansion of RE, particularly PV and wind [5].

One relevant issue with these energies is their weather dependency, preventing immediate matching of demand fluctuations [6]. It has been addressed by combining them with other dispatchable energies, particularly natural gas and hydraulics. A recent example addressing the supply of electricity and seawater desalination in a small isolated island

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is [7]. They combined REs, wind and PV, with batteries, and optimised the system considering several criteria besides total life cycle cost, including human health, environmental impacts and reliability. However, given that the general objective of decarbonising the economy implies dispensing with fossil fuels altogether, alternative methods are being actively investigated.

Given that electricity is challenging to store, a major proposal has been to manage this variability by combining various types of REs; see, e.g., [8]. Another objective has been reducing the combined variability of energy prices induced by the instability of international markets for fossil energies [9]. The decreasing impact on the variability of the spatial dispersion of investments has also been long recognised [10], although fewer studies have been carried out. Another methodological approach is diversifying an investment portfolio by implementing the mean–variance (MV) methodology to minimise variability given an expected return [11].

One early study [12] criticised the engineering valuation methods for new technologies, focused on finding the least costly alternative. This omits the eventual benefits that a new technology might add to an energy portfolio, e.g., cost and risk reductions. He recommended implementing modern financial portfolio valuation methods. In a similar tack, [9] contended that adding greater shares of wind, nuclear and other RE to the European energy portfolio, would result in lower overall costs and price risks stemming from the variability and uncertainty of fossil energy prices in international markets, as well as enhanced security despite their higher costs. [13] decomposed variability into market, not diversifiable, and specific to each energy, which can be reduced by diversifying investments. Analogously, the decomposition of irradiance and wind speed volatility into cyclic and random, is crucial to obtain meaningful results. Although they considered fossil energies, it was remarked that the only way of reducing systematic risk was through incorporating RE and nuclear. [14] argued that adding nuclear and renewables would increase the reliability of the energy supply, and reduce the cut-off risks of coal-based electricity generation in China. Adding environmental and health benefits, they concluded that the overall cost and risk of the energy portfolio would be lower, even if economic costs were higher.

This idea has also been applied in many directions. [15] consider the system's Levelised Cost of Energy (LCOE), the objective being to minimise its variability. They also underscore spatial distribution for reducing variability. [16] emphasise that the complementarity between different REs is frequently disregarded in practice, resulting in suboptimal mixes. They also point out this approach's usefulness in reducing the variability induced by the price of fossil fuels. Another point underlined is that there is a wide field of research to improve spatial distribution. The variability posed by solar and wind makes them unpredictable to a certain extent, which hampers dispatchability. The idea of diversification can also be applied in this context. Thus, combining various REs in suitable proportions could reduce the variability and, therefore, the non-predictability of their generation. [8], e.g., considered the impact on the variability of the electricity supply, including a set of wind farms. They used simulated data and implemented the MV approach to derive optimal combinations of wind and hydropower.

It was also noted early that spatial diversification could reduce supply variability. Most studies in this field refer to wind energy, probably because its costs were lower in the past than those of solar. [10], e.g., study aggregate hourly data in five European countries in 2006 and 2007, and conclude that the optimisation is inapplicable because it implies high transmission costs. [17] use data every six hours over a long period in several European countries. They find that a random allocation is suboptimal, and that locations with low resources are relevant because they reduce overall variability. Like [10], they conclude that the cost of connecting networks makes this method unfeasible. Regarding the feasibility of these studies, [18] developed a technique to increase the spatial resolution of reanalysis data that bypasses the need to rely on costly and frequently unavailable meteorological data.

Spatial solar distribution analyses have developed more slowly, partly due to the absence of proper irradiance databases. With the development of Geographical Information Systems (GIS), studies are being increasingly conducted. One early study was [19], who researched the solar resource in Oman, concluding that the availability was a significant multiple of annual energy demand, and therefore was an optimal alternative to fossil fuels. [20], introduce additional criteria to estimate a map of solar resources in China relative to available land – geographical and political. [21] discuss recent methodologies to implement GIS for estimating and mapping solar resources at fine scales, concluding that Artificial Neural Networks are the most promising.

Spatial studies in the past showed that spatial dispersion could reduce average variability. [22], e.g., break down the solar power variability by spectral methods and show that spatial diversification reduces it. Interestingly, they break down variability into the regular solar cycle and weather-related, noting that only this can be diversified. [23] claim that the ability of PV energy to reduce variability is limited, although, contrarily to [22], they do not consider the high variability of the predictable component.

Studies that consider the spatial diversification of several energies are scarcer. An exception was [24], who analysed the energy expansion planning in Italy. [25] for China, analysed hourly data for fifteen years and applied the MV approach, showing that diversification between energies and space considerably reduces variability. Nevertheless, they did not remove the deterministic component and used simulated rather than actual data. A frequent hurdle is that direct observations often exist for solar energy but not so much for wind, because solar energy is measured directly by the irradiation incidence at ground level. In contrast, wind power requires the measurement of wind speeds at various heights, preferably between 80 and 100 m. Due to the high altitude of today's turbine hubs, these measurements are rarely available.

The ability to meet demand variations with REs, i.e., to combine REs so that their combined generation tracks demand variations, also deserves attention. This can be done by combining these energies with nuclear or fossil sources. It is also possible to minimise the variability of the final price, which would be another measure of discrepancies, as suggested, e.g., by [26].

One shortcoming of the MV approach may be the instability of the estimated correlations and variances [27], who found that inaccurate estimates resulted in quite different asset weights. This underlines the need for a sufficiently large and stable sample of observations to guarantee the stability of the estimates and the optimal combination of energies. Another problem is that it does not identify which risk-return combination is best. [28] propose combining cost and risk in a single function to be minimised, but the weighting of both criteria is relatively arbitrary. [29] suggest a utility function derived from economic theory to combine return and risk. It also depends on a somewhat arbitrary parameter, but theoretical information about its possible values exists. Both, [28] and [29], turn out to be similar. [30] select the best combination of wind and PV energies minimising the coefficient of variation (CV), or Sharpe's inverse ratio [31], yielding a unique solution.

The MV analysis relies on Gaussian distributions, an assumption that frequently breaks down for high-frequency data in the energy field. A criterion to solve this problem is the Conditional Value at Risk (CVaR) or Expected Shortfall (ES) [32]. Some studies in the energy field apply it [26], deriving the optimal solution by linear programming optimisation methods. For large samples, however, it becomes computationally intractable.

Another relevant issue is splitting the RE supply into systematic and random components. The problem is less relevant for wind energy because it is more difficult to detect a systematic part. However, solar variability is much greater due to the daily cycle, and studies often find that the weight in a combined wind/solar portfolio is too small for solar

[33]. The solar cycle is, however, highly predictable, being crucial to split this part from the random weather-induced part. Thus, not separating these two components implies a limited solar ability to reduce joint variability with wind power, or spatially [23]. Correcting this mistake, however, shows the strong solar capacity to reduce variability [22].

A related approach is complementarity, mainly applied to combining two energies, usually wind and solar, but sometimes wind and hydraulic. At a basic level, it refers to the fact that the variability of the two energies considered is asynchronous, i.e., at least one will likely be available. This idea applies to a specific geographical area, so spatial diversification considerations do not apply. It is particularly interesting when trying to avoid high investment in electrical distribution networks. Thus, it is very relevant currently, given the trend towards distributed generation. This has a huge advantage since it reduces the cost of the networks and increases security. [34], e.g., studied the complementarity between wind and solar in north-western Brazil with hydraulic plants used as energy storage. In this case, they obtain a combination of 40% solar and 60% wind with daily data and a negative correlation of −0.5. They also obtained that demand can be met without interruptions with only 6% of storage capacity. [35] analyse the complementarity on the Brazilian coast between wind and solar with hourly data from 1990 to 2019. On time scales ranging from one hour to one month, and depending on the location, they find complementarity between 40 and 60%.

Complementarity can be studied on various temporal and spatial scales, and, ultimately, it is always a matter of stabilising the combined supply. If the time scale is long, it is implicitly assumed that the objective is to satisfy demand, whereas if it is short, the goal is to reduce variability. Complementarity studies can also be considered as a preliminary step to study the suitability of a global plan to reduce variability, or satisfy demand in a vast territory. [36] analyse hourly wind data in Europe from 1971 to 2010 and consider 33 countries with an advanced technique of wavelets and dynamic time warping, concluding that complementarity is very low except for countries far apart. Taking advantage of this complementarity would require massive network investments, making it uneconomical. [37] analyse data from 289 meteorological stations in China and classify the regions by their degree of complementarity. They use non-parametric estimates of the wind and solar irradiation distributions and find that complementarity is greater in spring and summer than in autumn and winter. A similar methodology is implemented by [30] to map the complementarity of wind and PV with a highly detailed grid for China. They use a modern and improved database and select a cell of 15X15 squared km. The complementarity is estimated by minimising the CV, and find that variability decreases in larger areas, suggesting regional electrical grid cooperation. Since the PV daily and annual cycles are not subtracted, their results may be biased in favour of higher wind/PV ratios – they obtain values between 2 and 0.7. This criterion can also be combined with others to find the optimal location of a combined wind and PV plant with marine hydraulic storage [38].

Due to its early development, Spanish studies have focused mainly on wind energy [1]. [39], e.g., studied the optimal spatial distribution in the peninsula's south with daily data for two years. Alternatively, the studies focused on determining the optimal mix of fossil fuels [13]. underlining the need to eliminate non-diversifiable risk before applying the MV portfolio optimisation analysis – akin to subtracting the daily PV cycle.

Therefore, in this context, and given the current Renewable Energy sources (REs) expansion plans in Spain, this study aims to develop additional criteria for the spatial allocation of investments intended to reduce the variability of the power generated. It must also be noted that the study makes sense, since energy policy is broadly decided at the country level in the EC [40]. The main issues addressed are:

1) Explicit separation of the systematic and random components. This is especially relevant in the case of solar energy.
2) Considering explicitly two energies, solar and wind, in a spatially diversified portfolio. In particular, the effect of adding wind energy on the spatial optimal solar portfolio weights is analysed.
3) The adjustment to electricity demand, simultaneously reducing the random part through spatial diversification and between energies.
4) An assessment of the current Spanish PV investment spatial allocations.

2. Methods

Since the research proposed intends to minimise the variability of the combined portfolio of investments, the first required step is to estimate and subtract the broadly non-random deterministic behaviour of the series. The second step is estimating the variance–covariance matrix of the random component over the selected locations. Finally, the variance of the selected portfolio of investments can be derived, and the optimal combinations of variability/generation, and variability /cost, can be determined through optimisation.

Several optimisation settings are considered: first, just a portfolio of PV investments – hourly and daily observations; second, this portfolio conditional on existing wind investments; and finally, third, the matching of aggregate supply and demand – alone, and combined with variability minimisation.

2.1. Portfolio variance

The deterministic component has been estimated using a symmetric weighting scheme which is optimum in other contexts, and after assessing several alternatives [41]. This kernel intends to capture the deterministic non-random component of a time series of PV power generation at a given site, i, $PV^{nr}_{t,i}$, as follows,

$$PV^{nr}_{t,i} = \sum_{s=-n}^{+n} \omega_s \times PV_{t+s,i} \tag{1}$$

where ω_s is a set of symmetric weights fulfilling, $\omega_s > 0, \sum_{-n}^{+n}\omega_s = 1$.

Subtracting these estimates from the actual observations yields the random intermittent component, which allows estimating the variances and covariances at all selected locations, i.e., the variance–covariance matrix. Denoting this random component by, $\varepsilon_{t,i}$, it is given as,

$$\varepsilon_{t,i} = PV_{t,i} - PV^{nr}_{t,i} \tag{2}$$

and meets the properties, $E(\varepsilon_{t,i}) = 0$, $E(\varepsilon_{t,i})^2 = \sigma^2$, $E(\varepsilon_{t,i}\varepsilon_{t,j}) = \sigma_{ij}$, implying that the variance–covariance matrix does not depend on time. This matrix can be estimated as follows. Define first, $\varepsilon'_t = (\varepsilon_{t,1}, \varepsilon_{t,2}, \cdots, \varepsilon_{t,m})$, where m is the number of sites considered - e.g., seven in the PV implementation of this study, and eight adding wind. The variance–covariance matrix, Ω, is given by, $E(\varepsilon_t\varepsilon'_t) = \Omega$, and a straightforward optimum estimate is given by,

$$\widehat{\Omega} = \left(\sum_1^T (\varepsilon_t\varepsilon'_t)\right) \Big/ T \tag{3}$$

T being the number of observations.

The variance of a photovoltaic investment portfolio can be derived now as follows. First, the power generated by the portfolio at time t, P_t, is given by,

$$P_t = \sum_{i=I}^{m} (\lambda_i \times PV_{t,i}) \tag{4}$$

where the λ_i are the investment proportions allocated to each site fulfilling, therefore, $\sum_i^m \lambda_i = 1, \lambda_i \geq 0$, and $PV'_{t,i}s$ are the power generated over a year at location i – measured, e.g., in kWh. Note that assuming values for the rate of interest, investments maturity, and Operations and Management costs (OM) - e.g., as a percentage of capital invested -, the implied LCOE value is immediate. The expected portfolio value, $E(P_t)$, and its variance, $V(P_t)$, are immediately given by,

$$E(P_t) = \sum_{i=I}^{m} \left(\lambda_i \times PV_{t,i}^{nr}\right) \tag{5}$$

$$V(P_t) = E\left(\varepsilon_t^{'}\lambda\right)^2 = \lambda^{'} \times E\left(\varepsilon_t\varepsilon_t^{'}\right) \times \lambda = \lambda^{'}\Omega\lambda \tag{6}$$

where $\lambda^{'} = (\lambda_1, \cdots, \lambda_m)$.

2.2. Portfolio optimisation

Minimising the variance of the portfolio can now be conveniently framed in a classical minimisation set-up of a quadratic form under a set of linear equality and inequality restrictions, i.e.,

$$min.\{\lambda^{'}\Omega\lambda\}, s.t., R\lambda \geq 0 \tag{7}$$

where R embodies a set of suitable constraints, plus those on λ given in (4) - see also Appendix B. The variance can be minimised for a given value of the portfolio P^*, in which case a further constraint in R will be,

$$P^* = \sum_{i=1}^{m} (\lambda_i \times \overline{PV}_i) \tag{8}$$

where $\overline{PV}_i$ can be, e.g., the average over the sample period, i.e., $\overline{PV}_i = \sum_1^T PV_{ti}/T$. In this way, the optimum combinations that yield the lowest possible variance for a given portfolio value, i.e., power generation, or the highest portfolio value for a given variance, can be derived by solving the optimisation problem (7).

2.3. Optimisation conditional on wind investments

The optimal investment set of PV weights, given a wind investment, is considered next. This may be useful if the weight assigned to wind investments is determined with other criteria beyond variability smoothing. Denoting the wind investment weight by, λ_e, the optimisation can be set up as follows. First, the variance of the portfolio can be conveniently decomposed as,

$$Portf.Variance = \left(\lambda_s^{'}, \lambda_e\right) \times \begin{bmatrix} \Omega_s & \Omega_{se} \\ \Omega_{se}^{'} & \sigma_e^2 \end{bmatrix} \times \begin{pmatrix} \lambda_s \\ \lambda_e \end{pmatrix} \tag{9}$$

where Ω_s is the variance–covariance matrix of the PV investments, Ω_{se} the covariance of the PV and wind investments, and σ_e^2 the wind variance. Since the term $\left(\sigma_e^2\lambda_e^2\right)$ is a constant independent of λ_s it can be omitted. Thus, minimising this variance leads to,

$$min.\left\{c^{'}\lambda_s + \lambda_s^{'}\Omega_s\lambda_s\right\}, w.r.t.\lambda_s \tag{10}$$

where $c^{'} = 2\lambda_e\Omega_{se}^{'}$. In this form, the minimisation can be performed as a standard minimisation of a quadratic form under a set of linear equality and inequality restrictions, as in section 2.2.

2.4. Minimisation of the mismatch supply–demand power

Matching aggregate electricity demand with supply is the third point analysed. It turns out that the problem can also be framed as the minimisation of a quadratic form on the investment weights under a set of linear restrictions. The objective can be set up as the minimisation of the squared daily non-random supply/demand mismatches aggregated over a year, and subject to the conditions that the aggregate mismatch is zero, i.e.,

$$\min. \sum_{t=1}^{365} \{\omega^{'}X_t - D_t\}^2$$

$$s.t. \sum_{t=1}^{365} \{\omega^{'}X_t - D_t\} = 0 \tag{11}$$

where D_t is the daily electricity demand, ω is the vector of capital amounts allocated to every site, and X_t is the vector of wind and PV power in all sites – the non-random component. This can be reframed as,

$$min: \{\lambda^{'}\Sigma_{11}\lambda + 2\lambda^{'}\Sigma_{21}\}, w.r.t.\lambda \tag{12}$$

with $\lambda_i \geq 0, \sum_{i=1}^{m}\lambda_i = 1$, and where Σ is the sample variance–covariance matrix of wind and PV power supply and demand; see Appendix A. Again, the minimisation can be conducted by standard means, as noted in section 2.2.

2.5. Combined minimisation: Variability and supply–demand mismatches

Finally, both criteria, variability (7) and supply–demand matching (12), can be considered jointly, leading again to the minimisation of a quadratic form merging both, and given by,

$$min: \{\lambda^{'}\Omega\lambda + \delta(\lambda^{'}\Sigma_{11}\lambda + 2\lambda^{'}\Sigma_{21})\} \tag{13}$$

w.r.t. λ, and the conditions on λ as in (12). The weight assigned to the supply–demand mismatch is denoted by δ. A trivial rearrangement yields,

$$min: \{\lambda^{'}\Psi\lambda + 2\lambda^{'}\Sigma_{21}\} \tag{14}$$

where $\Psi = (\Omega + \delta\Sigma_{11})$, which can also be solved as the minimisation of a quadratic form under a set of linear constraints.

A measure of the agreement, or lack thereof, between the optimal weights derived under the alternatives considered in sections 2.3, 2.4 and 2.5 can be defined as follows. Denote, first, the optimal weights allocated to the sites considered by $\omega_{ij}, j = (1, \cdots, m)$, for a given volume of energy generated $E_i, i = (1, \cdots, N)$, and investing the whole portfolio in PV. The set of all weights is the vector, $\omega_i = (\omega_{i1}, \omega_{i2}, \cdots, \omega_{im})$. Second, consider allocating the portfolio proportions, $(\theta; (1-\theta))$, to wind and PV respectively, and optimising the PV allocations. Denoting the optimal weights obtained by w_i^a, where the superscript refers to the proportion allocated to wind, the correlation between $\left(\omega_i, \omega_i^a\right)$ for all $i's$ can be calculated as a measure of agreement or discrepancy between the optimal PV weights under the two scenarios. The average, maximum and minimum of these correlations in the interval $(1, \cdots, N)$ can also be calculated.

2.6. Alternative risk criteria

A further relevant issue is whether the variance is an appropriate criterion for measuring variability, and other risk criteria have been suggested. They all are equivalent under Gaussianity, but for asymmetric or/and thick-tailed distributions may yield significantly different values. The downside risk, particularly, is not adequately accounted for by the variance under asymmetry. Nevertheless, they are not easily applicable since analytical expressions for investment portfolios do not exist, preventing a standard optimisation treatment. One exception is the CVaR methodology of [32], applicable with a moderate number of vector data points. However, it becomes unmanageable for large data sets like the present case.

3. Results and discussion

The results for the several optimisation settings considered in section 2, 2.2-2.5, are reported in what follows. The data and selected locations

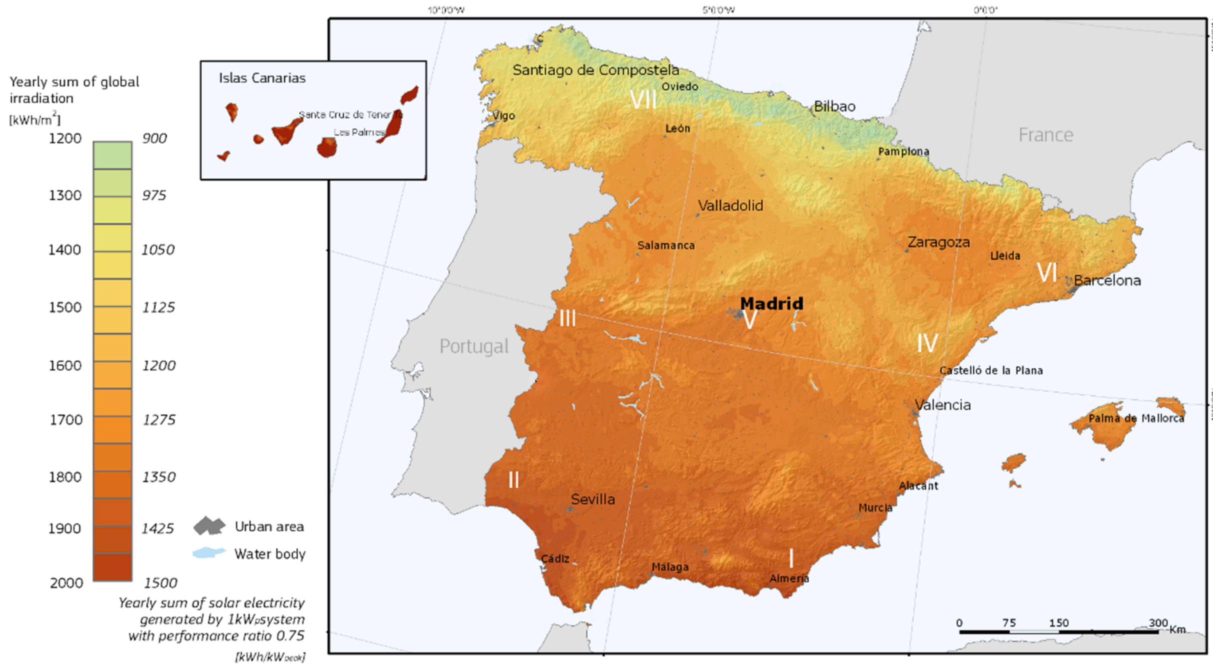


Fig. 1. Irradiation and photovoltaic electricity potential: Spain. Horizontally mounted PV modules. .
Source: [42]

Table 1
Selected locations: Latitude and longitude.

	I	II	III	IV	V	VI	VII
latitude	*36.868*	*37.245*	*39.721*	*40.084*	*40.252*	*41.440*	*42.793*
longitude	*−2.154*	*−6.856*	*−7.043*	*−0.353*	*−3.758*	*1.636*	*−6.120*
kWh$^{(1)}$	*1765.2*	*1640.8*	*1542.7*	*1410.8*	*1628.5*	*1603.6*	*1386.7*

Notes:
(1) kWh generated per 1 kW of nominal installed power over one year.
(2) Source: PVGIS-SARAH2 [42].
(3) The database reports the 'nominal' power, i.e., the nameplate (rated) capacity measured under standard test conditions.

are presented first.

3.1. Data and locations

The irradiance and power data have been taken from a highly reliable database - PVGIS-SARAH2 [42] -, funded by the European Union, which is also the reference for the World Bank in this field [43]. The database reports irradiance and PV power generated at hourly frequencies for the period spanning the years (2005;2020) at any European location. Wind and electricity data aggregated and at daily frequencies are available from official sources at [44] for the dates spanning the period (2011–1-1;2020–31-12), but without location details. Seven locations scattered homogeneously over the territory have been selected to analyse the optimal combination. Therefore, the study is based on a large set of data points -nearly 1 million.

Fig. 1 displays the location in the map of the sites selected for the analysis. It also displays visually accumulated annual irradiance values. Table 1 shows the locations specifying the latitude, longitude, and average yearly PV power potential.

3.2. Photovoltaic portfolios (daily and hourly)

Fig. 2 displays the hourly PV power generated in January 2020 at site I and the estimated cycle; see section 2.1. The Figure shows that the hourly daily cycle is very regular and well captured, increasing gradually over the month due to the annual cycle – see also Fig. B.2 in Appendix B. This allows splitting the observations between deterministic and intermittent random components, which in turn allows implementing the minimisation procedure to determine the best investment portfolio combinations of power generated and variability - similar results for daily observations are reported in Appendix B.1.

Fig. 3 displays the outcome of implementing this technique, i.e., minimising aggregate portfolio variance by appropriately selecting the investment weights at every site for all possible LCOE values; see sections 2.1 and 2.2. The minimum LCOE is attained at 34.42 kWh/kW, and lower LCOEs – or higher total output power -can be achieved at the cost of increasing the variability of the aggregated power output.

The equivalent minimisation of the investments portfolio variance with daily data yields similar results. Table 2 reports the optimum set of weights for both optimisation cases, i.e., hourly and daily frequency data, which underlines their similarity.

The first conclusion from these results is that the optimum solution implies diversified investments, i.e., investing only in the most productive places is not the best policy. This is due to the uncorrelated intermittent random components across different sites. Second, the portfolio yielding the minimum overall variability differs from the trivially equally weighted solution, implying that this procedure delivers valuable portfolio diversification insights. Finally, since the optimum weights for the frequencies analysed are close, this suggests that higher frequencies of a few minutes might yield similar results. This is useful when sufficiently disaggregated data is unavailable – as is the case here.

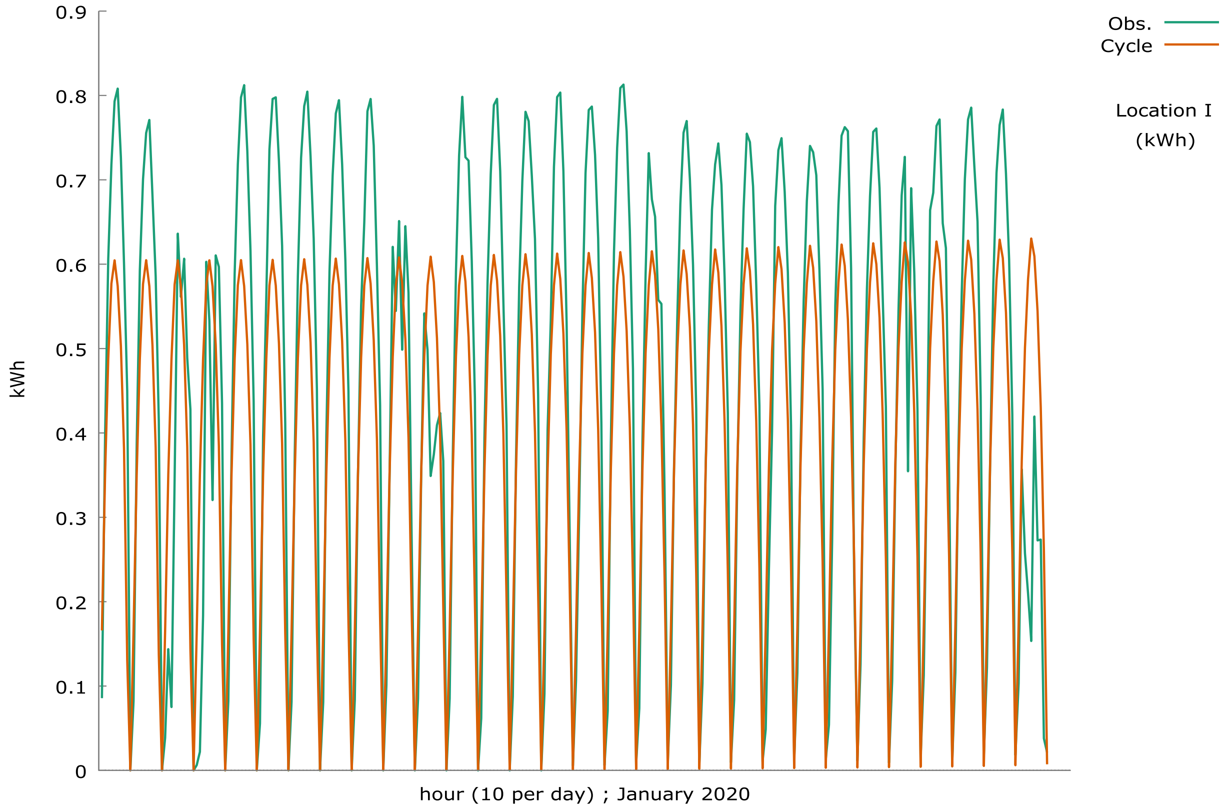


Fig. 2. Photovoltaic cycle and actual observations (Obs.).

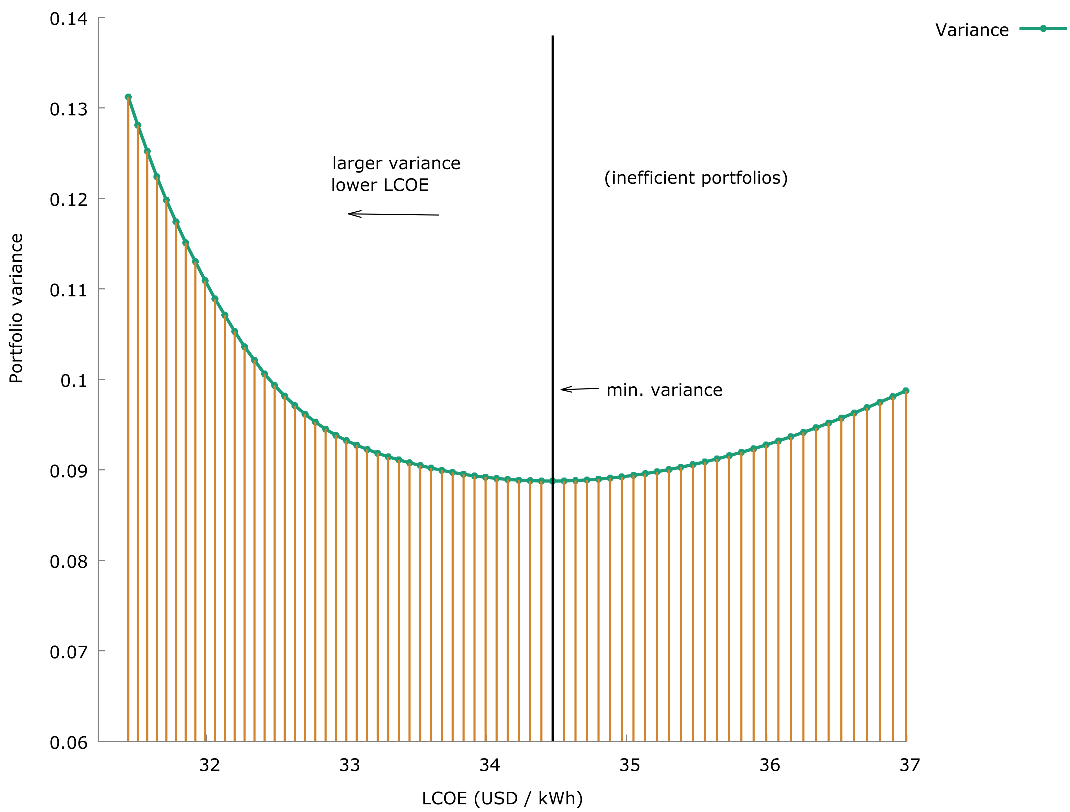


Fig. 3. Minimum variance and portfolio LCOE values.

Table 2
Minimum variance portfolio: Hourly and daily.

		weights	
Loc.	kWh	hourly freq.	daily freq.
I	1765.2	0.317	0.384
II	1640.8	0.144	0.150
III	1542.7	0.085	0.050
IV	1410.8	0.110	0.096
V	1628.5	0.074	0.018
VI	1603.6	0.153	0.155
VII	1386.7	0.113	0.145
Total portfolio (kWh)		1610.1	1617.6

Note: annual kWh (1 kW nominal power).

3.3. Photovoltaic and wind portfolios

This section considers adding wind energy to the portfolio. First, several percentages of wind energy are added, and taken as given in the optimisation of the PV portfolio – i.e., the portfolio is invested in the proportions (0.33;0.67), (0.5;0.5) and (0.66;0.34) in wind and PV energy respectively. This helps to understand the effect of including wind, and may be relevant if the wind proportion is determined outside this minimisation for other reasons. Second, optimising the whole portfolio, including wind, is analysed.

Fig. 4 displays the daily wind power generated over the available sample and the estimated cycle – see section 2.1. The Figure shows a stable and well captured annual cycle that allows splitting the deterministic from the intermittent random component – the standard deviation of the observations, cycle and residuals, are respectively, 3.134, 0.810 and 2.830.

Then, the minimisation procedure to determine the best investment portfolio combinations of power generated and variability, including wind investments, can be implemented; see section 2.3. Table 3 discusses the impact on the PV weights under these conditions. The table reports the correlation values of the vector of optimal PV weights over

Table 3
Weights Correlations (Minimum Variance Portfolios).

Optimising PV vs. (PV + Wind)			
Weight wind	Average	minimum	maximum
0.33(1)	0.688	0.406	0.857
0.5(1)	0.394	−0.196	0.857
0.66(1)	0.152	−0.623	0.856
0.091(2)	0.818	0.395	0.857

Notes: (1) Optimisation of the PV allocations, conditional on a given proportion of wind; (2) Joint optimisation of the proportions allocated to wind and PV, and the PV allocation across all sites. See section 2.5.

Table 4
Minimum variance portfolio weights: PV and (PV + Wind).

		weights	
Loc.	kWh	PV	(PV + Wind)
I	1765.2	0.384	0.333
II	1640.8	0.150	0.135
III	1542.7	0.050	0.053
IV	1410.8	0.096	0.066
V	1628.5	0.018	0.028
VI	1603.6	0.155	0.160
VII	1386.7	0.145	0.132
Wind weight			0.091
Total portfolio (kWh)		1617.6	1594.3
LCOE (USD/kWh)		34.3	34.8

Notes: a) annual kWh (1 kW nominal power). b) daily freq. both cases.

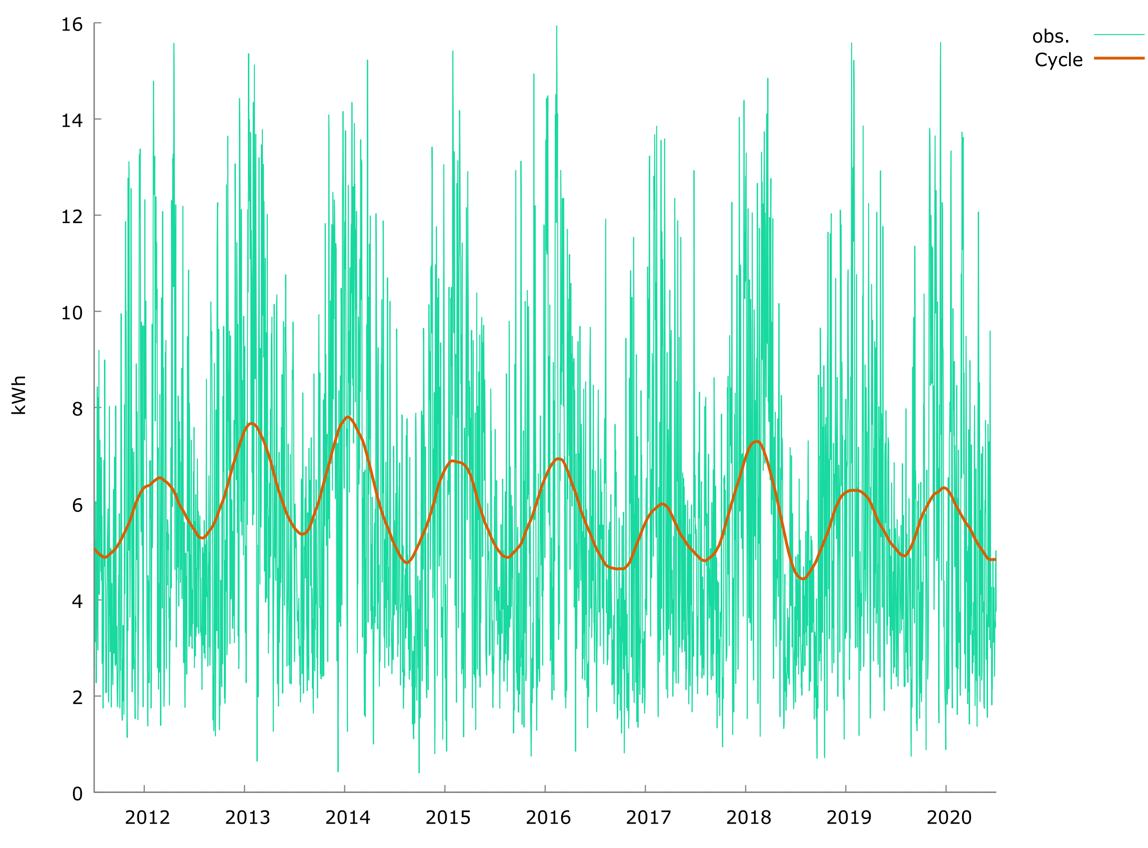


Fig. 4. Wind: Cycle and actual observations (kWh per 1 kW capacity).

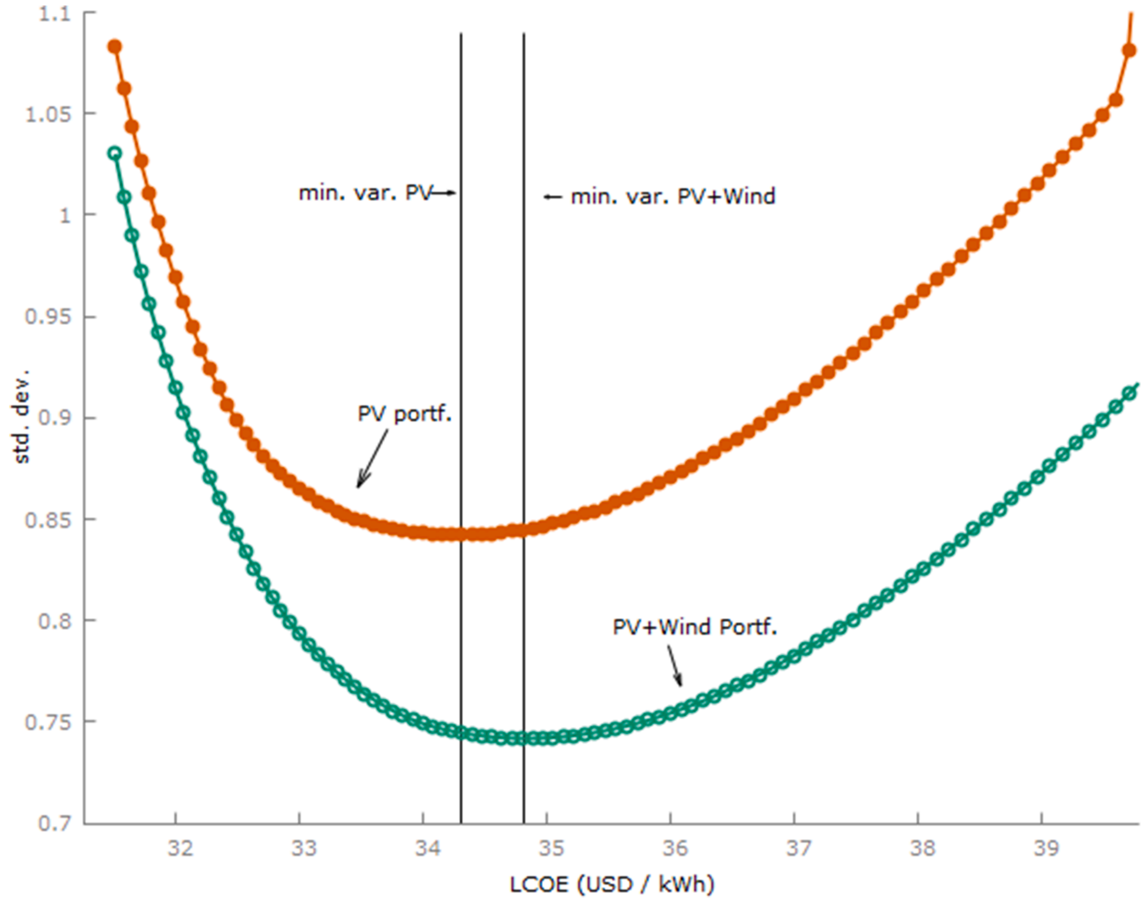


Fig. 5. Minimum variance and portfolio LCOE values. PV and (PV + Wind).

Table 5
Minimisation of the supply–demand mismatch.

	(1)	(2)	(3)
kWh[(1)]	1398	1621	1580
LCOE (USD / kWh)	39.7	34.2	35.2
Unmet Demand	3.9%	6.6%	5.4%
Capacity: (PV, Wind)	(56.5% – 43.5%)	(88.7% – 11.3%)	(85.4% – 14.6%)
Generation: (PV, Wind)	(50.6% – 49.4%)	(85.8% – 14.2%)	(74.3% – 15.7%)

Notes.
(a) annual kWh generated by 1 kW installed power.
(b) (1): min. errors (Demand – Supply); section 2.4, Appendix A.
(2): min. (1) + Variability Supply; section 2.5.
(3): min. (1) X 4 + Variability Supply; section 2.5.

the whole range of total power generation considered – see section 2.5. It is immediate that the impact is significant as the wind weight increases. Combined optimisation has a lower effect because the optimum wind proportion turns out to be low – see Table 3.

Next, the results in Table 4 report the weights optimising the whole portfolio and compare them with the PV results.

The optimal proportion for wind is moderately low, i.e., 9.1%, and the corresponding optimal portfolio power is only slightly lower – 1.5%.

Fig. 5 compares the efficient variability-LCOE frontier under both cases, i.e., PV and PV plus wind investments.

Adding wind to the portfolio decreases the implied variability for all possible portfolios and, significantly, yields a lower variance for the minimum PV portfolio - i.e., at 34.42 kWh. These results are derived from the negative and significant correlation between wind and irradiance at all sites considered. It should be noticed, too, that adding even a reduced proportion of wind decreases variability significantly.

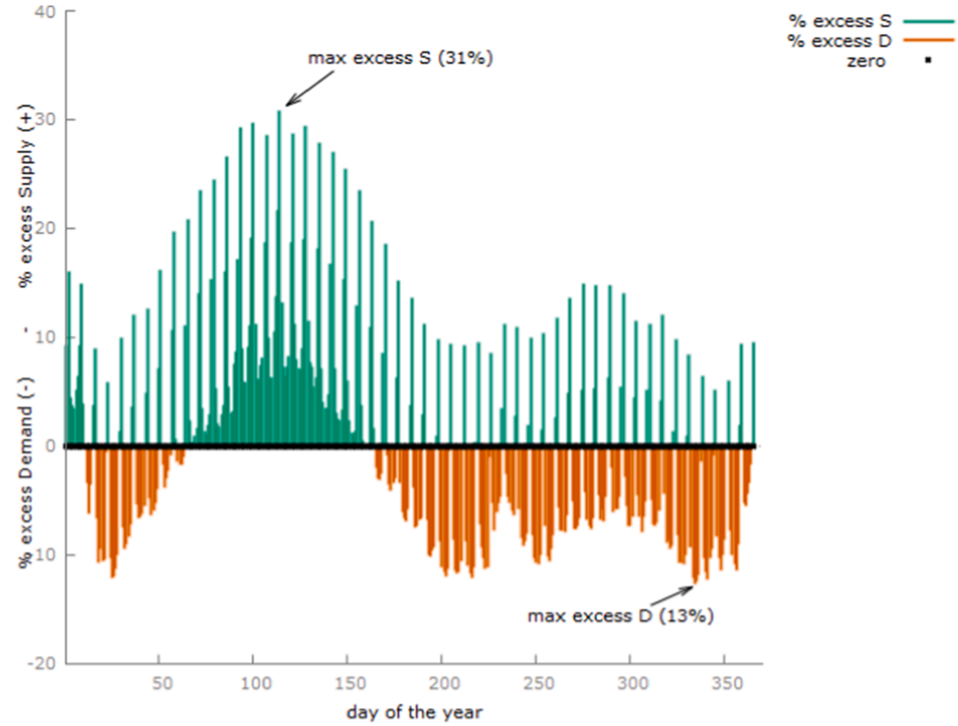
3.4. *Minimising the supply–demand mismatch*

Minimising just the variability of the random component may yield an unfavourable, i.e., low, wind power weight. An alternative approach minimises the supply–demand mismatch errors; see section 2.4 and Appendix A. Yet, a further option is to combine both approaches and jointly minimise the random variability and the mismatch; section 2.5. Table 5 reports some results for both cases.

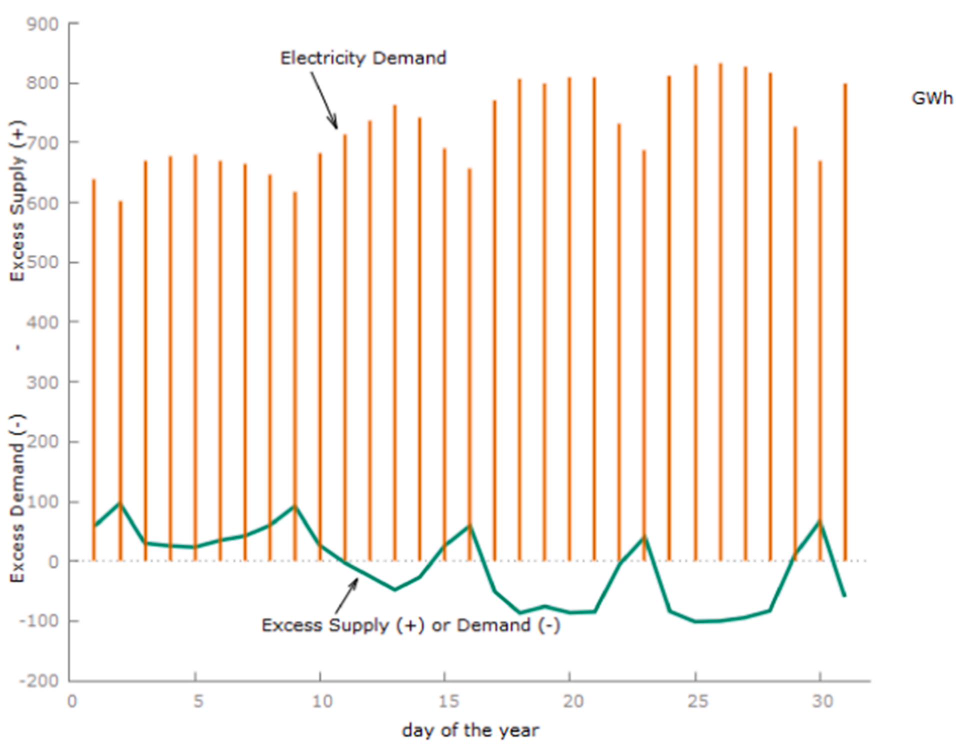
First, considering just the mismatches, total unmet demand is low – column 1, 3.9%. Note, however, that this provides a slightly distorted view, the inside-the-year daily profile giving a more nuanced interpretation – Fig. 6a. The maximum daily excess demand is 13% for a few days, although the power supply is in significant excess on several occasions, notably around the second quarter – max. 31%. This is due to the increased wind supply and lower demand in that period – see Figs. 4 and B.3 in Appendix B.

Fig. 6b displays values for the first days of the year, showing that the leading cause for mismatches is the weekly cycle, specifically, the weekends. It is also worth noting that the combined supply tracks the annual demand cycle to a significant degree. Columns 2 and 3 report results from the combined minimisation. Assigning a moderately large value to the mismatches relative to the variability decreases the LCOE significantly, with just a slight unmet demand increase – column 3. Nevertheless, the daily behaviour during the year worsens again; see Fig. B.4 in Appendix B.2. It is worth noting that the excess supply is highest in the second quarter of the year, because wind is stronger – see Fig. 4 -, and demand is lower – see Fig. B.3 in Appendix B.

Fig. 7, finally, displays the efficient frontiers for the pair LCOE/



a) % Unmatching (Supply (S)+, Demand (D)-).



b) Demand and unmatching.

Fig. 6. Minimisation unmatched Supply-Demand.

value-of-the-quadratic form (QF) related to the results in columns 1 and 3 in Table 5. Contrary to previous results in sections 3.2 and 3.3, there is no uniform best solution for all possible combinations, and, as noted in Table 5, reducing the LCOE increases the mismatch between electricity demand and supply, highlighting the implied trade-off.

3.5. Policy implications

The previous results can help assess Spain's current PV and wind energy investments. As of 2022, they amounted to 47 GW (wind) and 24.8 GW (PV), implying proportions of 0.656 and 0.344, respectively. However, the more favourable case to wind yields approximately a 0.5

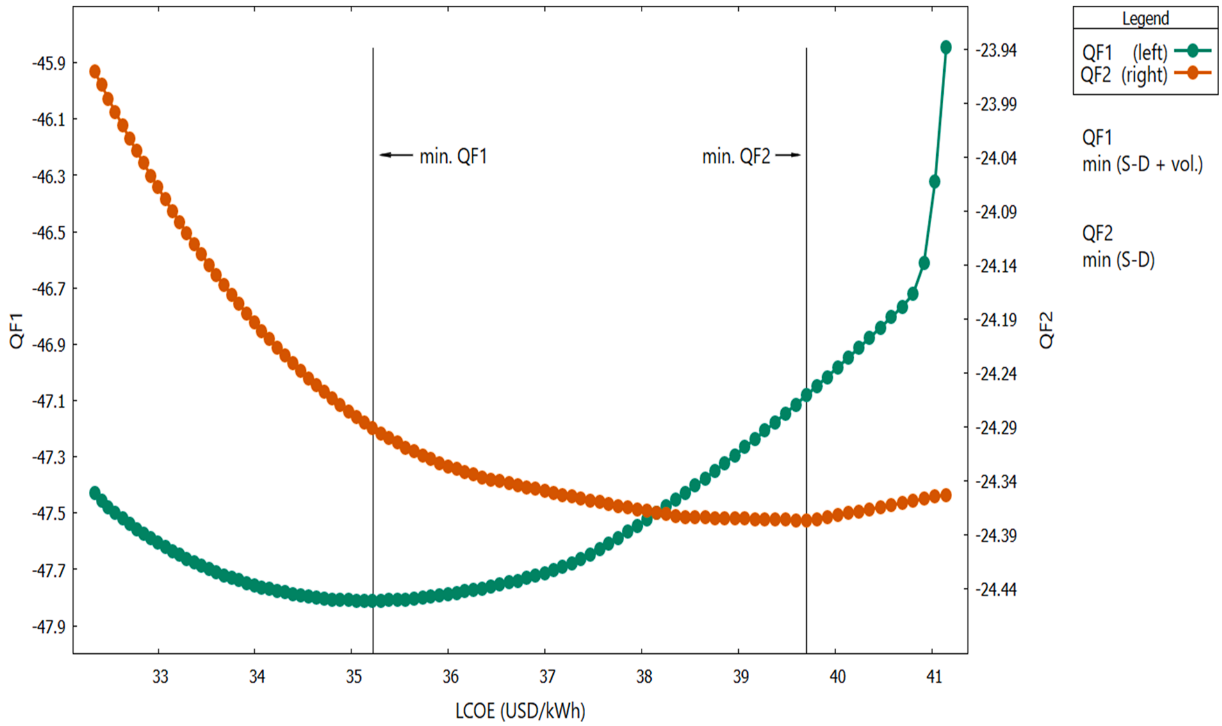


Fig. 7. Quadratic Form (QF) Minimisation Criteria and LCOE: QF2, Supply-Demand mismatch (S-D); QF1, (S-D) + Variability Supply.

Table 6
PV Weights Assessment.

location	kWh	(1)	(2)	(3)	(4)
I	1765.2	0.384	0.366	0.355	0.184
II	1640.8	0.150	0.148	0.179	0.105
III	1542.7	0.05	0.058	0	0.265
IV	1410.8	0.096	0.073	0	0.171
V	1628.5	0.018	0.031	0.106	0.157
VI	1603.6	0.155	0.176	0.359	0.065
VII	1386.7	0.145	0.145	0	0.052
Portfolio kWh		1617.6	1616.5	1670.4	1579.2

Notes:
a) minimum variance optimum portfolio (columns 1, 2, 3).
b) (1): min. PV; c) (2): min. PV and wind.
d) (3): min. II plus supply–demand mismatch (weight S/D, 4).
e) actual weights (column (4)); f) (2), (3) scaled to unit sum.

wt, decreasing to 0.1 in some cases. This may be partly because the PV costs were too high until recently.

Table 6 gathers results useful to assess the PV weights corresponding to the locations analysed. The first three columns report optimal weights under different criteria, and the last the actual values. It is immediate that there is room for improvement under all criteria considered: e.g., the power generated is higher, and therefore the LCOE is lower in all three cases.

These results suggest a reassignment of investments, both regarding the relative allocation between wind and PV energy, and the spatial PV weights. These objectives could be achieved without cost increases in an environment of increasing investments. Nevertheless, they are just another criteria to be assessed among several others – e.g., availability of proper space, social and political constraints, etc. -and should not be taken strictly.

3.6. Discussion

The size of the area to be considered is the first debatable point, and although in this study the entire territory of a country has been selected, other choices are possible. For example, in studies on wind energy, the whole of Europe has often been considered. [10], e.g., consider that restrictions on the availability of resources combined with each country's demand, make the export of electricity unfeasible in many cases. [17] also conclude that the investment in grids required to take advantage of the variability-reducing effect would be too high. This would suggest considering smaller areas to study volatility reduction through spatial diversification. Another approach that suggests focusing on local areas is the complementarity analysis [35].

These last two types of analysis point towards focusing on local areas, smaller than Europe, the first, and specific regions within a country the second. It should be underlined that this is consistent with the drive of RE investments towards distributed generation in local environments, smaller than an entire country. Accordingly, requiring as an additional restriction that all areas of the country analysed have access to a minimum percentage of investments, is another criterion to consider in future research.

A second key point is splitting both energies into deterministic and random components. A smoothing kernel method has been applied in this study, but other choices are possible. [22], e.g., break down the solar power variability by spectral methods and show that spatial diversification reduces it. Interestingly, they consider the regular solar cycle and the weather-related component. They do not provide, however, the results of their decomposition. [45] consider the clear sky cycle as the deterministic component, the remaining being the random part. However, as in the kernel method, the weather-related component has a non-zero mean that should be subtracted. Future research could also implement other possible methods – Fourier inverse, wavelets, state-space, etc.

Third, results on the optimal shares of wind and solar are another contribution of this study. Complementary studies also analyse this issue but usually omit local energy demand. Nor do they consider the systematic cyclical component of the RE analysed, primarily solar and wind. This especially penalises solar, since its daily cycle is very predictable and results in high weights for wind compared to solar - e.g. [34] obtain optimal proportions of 60% and 40% for wind and solar, respectively, and [30] give optimal values for the wind/solar ratio

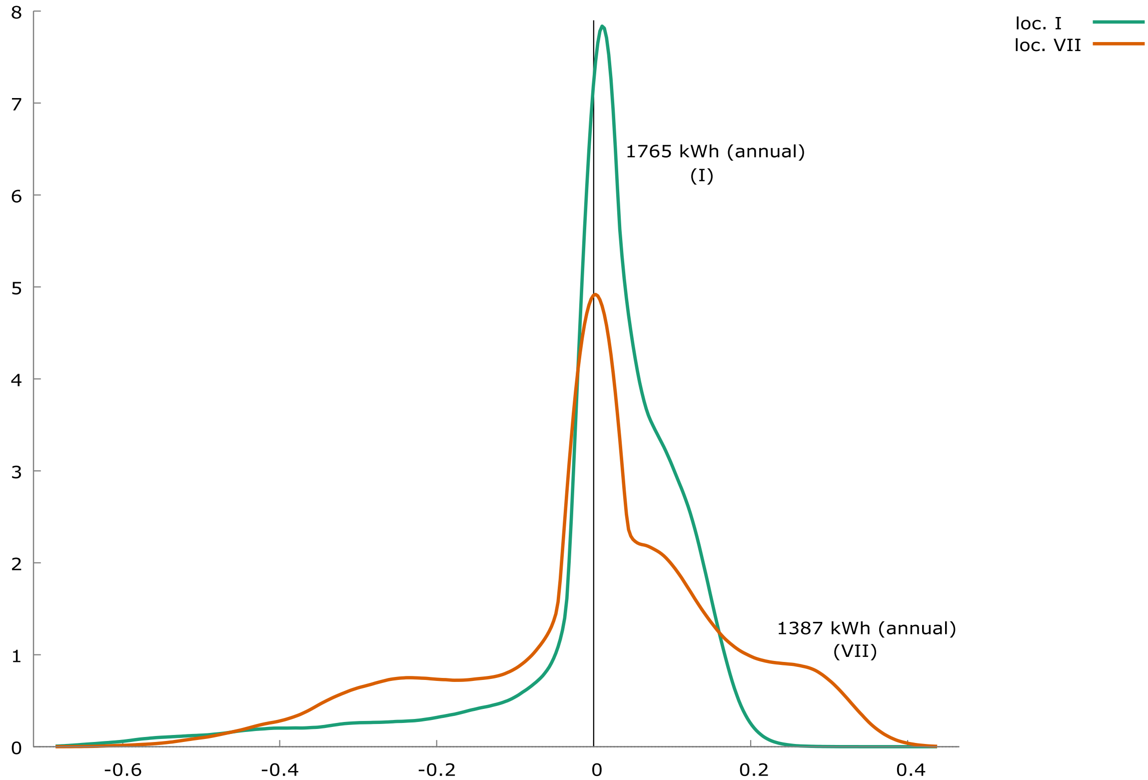


Fig. B1. Probability density of the photovoltaic intermittent random component.

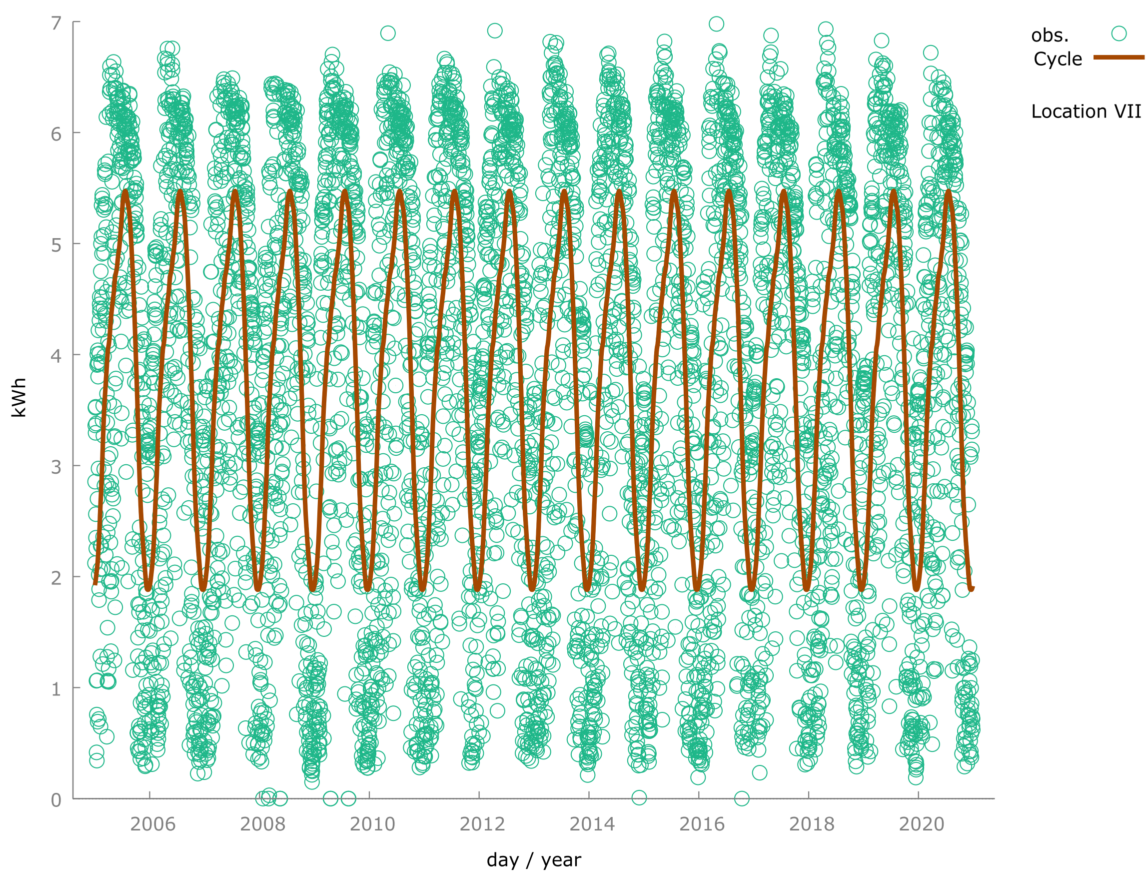


Fig. B2. Photovoltaic annual cycle and actual observations.

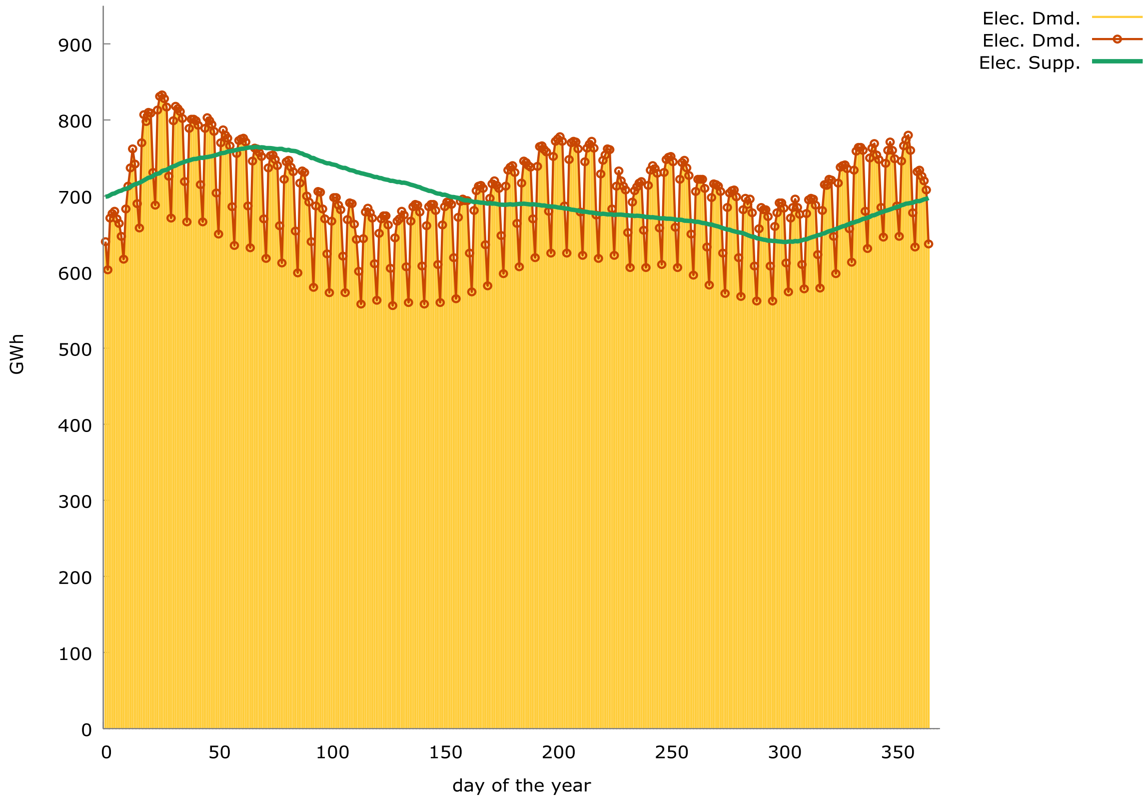


Fig. B3. Minimisation unmatched Supply-Demand: Demand and Supply.

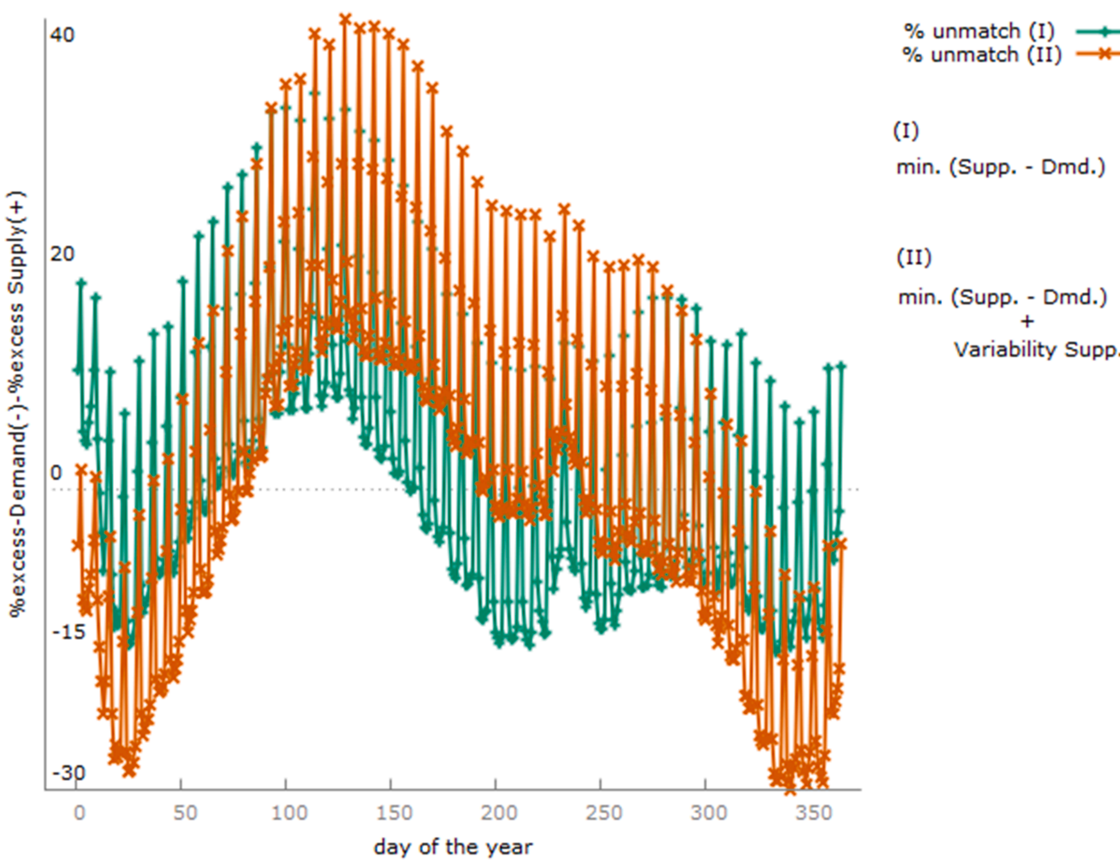


Fig. B4. Minimisation unmatched Supply-Demand (I) + Variability Supply (II). (% Unmatching (Supply +, Demand -)).

between 2 and 0.7. If, on the contrary, this is considered, the proportions for wind energy are lower, in the range (10%; 50%) depending on the cases; see section 3.

Fourth, considering energy demand explicitly, and minimising the deviations with some relevant criteria simultaneously to the supply variability, is another contribution of this research. There are only some studies in this field that address both issues simultaneously. An exception is [45], although their approach is partial and does not explicitly address the supply–demand mismatch. [26] also consider it for Chile, while additionally replacing the mean–variance method with the CVaR [32].

Fifth, regarding related results for Spain, [45] also consider optimising the distribution of PV and wind investments. A relevant aspect of their work is subtracting the systematic part of the PV daily cycle, noting that this penalises PV in the usual optimisation studies. They use a sizeable hourly database and apply the MV approach, but introduce several corrections that may explain their counterintuitive results. They recommend concentrating PV investments towards areas with scarce solar resources, and wind investments towards the south and southwest, with fewer resources than the northwest. The explanation would be that the variability of solar energy is greater in places where the resource is high, and conversely – similarly for wind. However, this is not the case, since volatility in region I with greater resources is lower; see Fig. B.1. The results obtained in the present study are more in line with what might be expected. Another related work is that of [39], who analysed the distribution of wind energy in southern Spain with daily data for two years. They did not eliminate the annual wind cycle, but still showed the ability of spatial diversification to reduce risk as measured by the variability of power generation. [13] also analyse the optimal combination of different energies in the Spanish portfolio. Although they focus on fossil energies and do not analyse the issue of spatial distribution, their work is related to the extent that they consider the Capital Asset Pricing Model (CAPM) approach to study the optimal mix of energies. In this approach, removing the non-diversifiable variability part is essential, a suggestion akin to removing the daily solar cycle.

Sixth, other criteria besides the MV implemented in this study are also possible and have been put forward, like the CV [31]. One of its advantages in this context is that it allows resolving the lack of a single solution in most risk-related approaches – including the MV and the CVaR. Other proposals for a unique solution have also been suggested in the literature, like merging mean and variance in a single function [28], and [29], who suggest a single utility function. Although both involve some degree of guessing concerning the values of some parameters, at least they are bounded. Another criterion is the CVaR [32], aiming to deal with the eventual asymmetry of climate series, which may be significant as shown, e.g., in Fig. B.1. However, it does not yield a unique solution and would have to be combined with those suggested before.

Finally, seventh, future research should also address other risks beyond variability, notably those derived from climate change. A pioneering study in this line was [46], who analysed the impact of climate risk through a series of simulations generated by Monte Carlo models and assessed their effects on the optimal combination of energies for Portugal. In this regard, the data available at the European Centre for weather forecasting [47] offer a sound basis for conducting research in this direction.

4. Conclusions

This study aimed to determine the optimal spatial combination of photovoltaic investments, currently developing rapidly in Spain. A second objective was to consider how accounting for investments in wind power might affect this optimal distribution. The optimisation criterion considered is the combination that reduces the variance of the random component of the variability in the generation of renewable energy, for each aggregate generated volume. First, the solar irradiation series have been studied, hourly and daily, regardless of wind. The main result is that combining investments in the most productive places with less productive places, can improve the risk-production pairing by reducing variability. The optimal weightings for hourly and daily frequencies are similar for all selected generation levels, suggesting that optimal combinations might also be similar at higher frequencies.

Next, the impact of wind energy has been considered – daily frequency spatially aggregated. It is shown that it conditions significantly the optimal spatial distribution of photovoltaic investments, and that simultaneous optimisation of both investments yields a small proportion for wind - around 10%. Nevertheless, it considerably reduces the variability of the total generation.

The third analysis considers minimising the supply–demand mismatch, and the contribution of wind energy increases significantly, approaching 50%. Nevertheless, joint minimisation with random variability, even with a high weighting for the supply–demand mismatch, yields a photovoltaic share above 80%. These results provide additional criteria to allocate spatial investments optimally in Spain, and for the optimal solar-wind energy mix under several settings.

CRediT authorship contribution statement

Ignacio Mauleón: Conceptualization, Methodology, Software, Data curation, Investigation, Validation.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

Acknowledgements

A preliminary version of this study was presented at the 17th Sdewes conference in Cyprus. The comments of the participants, as well as those of the editor-in-chief of this journal and two anonymous reviewers, are gratefully acknowledged without implicating them in any eventual remaining error.

Appendix A. . Minimisation of the mismatch supply–demand power

It is convenient, first, to denote the vector of PV and wind power generation at time t by,

$$X_t^{'} = \left(PV_{t,1}, \cdots, PV_{t,m-1}, E_t\right) \tag{A1}$$

where PV_{ti} are the PV generation at all seven sites, and E_t is wind generation. The $(m \times T)$ matrix of all observations is defined by,

$$X^{'} = (X_1, X_2, \cdots, X_T) \tag{A2}$$

A possible matching condition implemented in this research is given by,

$$\sum_{t=1}^{365}\sum_{i=1}^{m}(X_{ti}\times\omega_i)=\sum_{t=1}^{365}D_t \tag{A3}$$

i.e., it requires the equality of the aggregated annual supply and demand. The values of all variables considered are the deterministic component in every case, estimated through the kernel of section 2.1, and the $\omega_i^{'}s$ are the capital amounts allocated to every site. It is convenient to introduce a rescaling that will allow the joint optimisation with the variability criterion, i.e.,

$$\sum_{t=1}^{365}D_t=D\,,\ \sum_{t=1}^{365}X_{ti}=X_i\,,\ x_{ti}=X_{ti}\times\frac{D}{X_i}\,,\ \lambda_i=\omega_i\times\frac{X_i}{D} \tag{A4}$$

With this notation, the equality condition (A.3) becomes,

$$\sum_{t=1}^{365}\sum_{i=1}^{m}(x_{ti}\times\lambda_i)=\sum_{t=1}^{365}D_t \tag{A5}$$

and some straightforward algebra shows that the λ_i fulfil the conditions,$\sum_{i=1}^{m}\lambda_i=1,\lambda_i\geq 0$.

The optimisation problem can be set up now as the minimisation of the sum of the daily squared mismatches, i.e.,

$$min:\sum_{t=1}^{365}\{\lambda^{'}x_t-D_t\}^2 \tag{A6}$$

where $\lambda^{'}=(\lambda_1,\lambda_2,\cdots,\lambda_m)$, $x_t^{'}=(x_{t1},x_{t2},\cdots,x_{tm})$.

A straightforward matrix algebra development shows that this condition can be conveniently rewritten as,

$$min:\sum_{t=1}^{365}\{(\lambda^{'}x_t)-D_t\}^2=\lambda^{'}\Sigma_{11}\lambda+\Sigma_{22}+2\lambda^{'}\Sigma_{21} \tag{A7}$$

where, $z_t^{'}=(x_t^{'},-D_t)$, and,

$$Z^{'}=(z_1,z_2,\cdots,z_T)$$

$$\Sigma=(Z^{'}Z)/T \tag{A8}$$

Finally, minimising (A.7) is equivalent to,

$$min:\{\lambda^{'}\Sigma_{11}\lambda+2\lambda^{'}\Sigma_{21}\},w.r.t.\lambda$$

$$s.t.\lambda_i\geq 0,\sum_{i=1}^{m}\lambda_i=1 \tag{A9}$$

Note that, since $X_t^{'}\omega=x_t^{'}\lambda$, and the weights are constrained to match annual demand, aggregate unmet demand over the whole year is given by,

$$0.5\times\sum_{t=1}^{T}\left|\left(\lambda_{opt}^{'}x_t\right)-D_t\right| \tag{A10}$$

where λ_{opt} is the solution to (A.9). It also equals aggregate excess supply.

Appendix B. . Complementary results

The research results have been obtained with purposefully written Fortran programs [48] and R scripts by the author. The optimisations have been conducted with the routine 'solve.QP' {quadprog}, available in the R statistical software. It applies the dual method of Goldfarb and Idnani [49] – details are available in the Supplementary Material. The reliability of the routine has been tested with an '*ad-hoc* Fortran program specifically written for that purpose that simulates randomly alternative solutions in a suitable neighbourhood of the optimal solution considered.

All graphs have been implemented with the *gnuplot* software [50].

B.1. Photovoltaic portfolios (daily and hourly)

Fig. B.1 depicts the probability density function (p.d.f.) of the random intermittent PV component for two locations, as given by the decomposition applying the kernel of section 2.1. Several values for the width of the kernel have been tested, the best solution being sixteen at both sides of the hour and date considered.

The Figure shows acceptably smooth densities, though highly skewed to the left, and with thick tails. This can also be seen in the large low values shown in Fig. B.2 for daily observations. This might support the implementation of complementary risk criteria alluded to in section 2.6, notwithstanding the obstacles.

Fig. B.2 displays the estimated cycle component and the actual observations over the whole span of the available sample. The cycle is regular and stable, similar to the hourly data, showing the sample's homogeneity.

The LCOE has been calculated under a 2.5% long-run real interest rate, 25 years for investments maturity and a 10% over capital annual OM costs

[51]. This is a simplified calculation sufficient for the purposes of this research. The same method is implemented in all cases.

B.2. Combined minimisation: Variability and Supply-Demand mismatches.

Fig. B.3 shows a tight fit between overall supply and demand and highlights the leading cause of recurrent mismatches, i.e., the weekly weekend cycle. The seasonality of demand is captured to some extent, as well.

Fig. B.4 displays the daily mismatch, single mismatch, and combined minimisation in both cases. The significantly increased daily mismatch in the combined minimisation approach is apparent.

Appendix C. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enconman.2023.117292.

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