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How energy strategies are shaped by the correlation of uncertainties

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ABSTRACT

In the face of the global climate crisis, countries worldwide are striving for a shift in their energy systems from fossil fuels to renewable energy sources. This complex energy transition faces significant uncertainties, which must be addressed correctly to produce resilient and reliable investment strategies. This study systematically incorporates, for the first time, the correlation between uncertainties into a strategic energy planning model, in order to determine robust and consistent decarbonization strategies. Using the Spanish energy system as a real-size case study, we assess the impact of accounting for the correlations between primary energy prices and energy technology investment costs on strategic energy decisions. Our results reveal that decarbonization strategies significantly vary with the degree of correlation, and hence not accounting correctly for it may result in significant errors. When compared to the uncorrelated baseline scenario, a positive correlation results in increased fossil fuel use and reduced renewable deployment, whereas a negative correlation leads to higher renewable deployment and electrification.

1. Introduction

In response to the global climate crisis, numerous countries have pledged to achieve climate neutrality by 2050 as outlined in their Nationally Determined Contributions (NDC). This goal requires a profound transition from fossil fuels to renewable energy sources [1]. To meet this target, decision-makers must understand energy systems dynamics and anticipate the consequences of their actions. Strategic energy planning models are crucial for this task [2].

However, the energy transition faces significant uncertainties, including the development of key decarbonization technologies [3,4], changes in energy demand behavior [5], geopolitical instability affecting energy and material access [6], or climate change impacts [7,8]. Accounting for these uncertainties in long-term energy planning is essential to avoid wrong decisions and potential lock-ins.

Many planning exercises have tried to address these uncertainties, through different approaches. However, most consider uncertainties as independent factors, which may result in significant errors. Relevant variables in energy planning are usually correlated, making it essential to incorporate these correlations to create coherent scenarios. A significant case is the correlation between uncertain primary energy prices and uncertain investment costs for energy technologies.

On the one hand, primary energy prices, such as natural gas and crude oil, often exhibit high positive correlations due to their substitutability and market indexation [9]. Therefore, it is important to consider scenarios where fuel prices align with their historical covariance. Ignoring these correlations may lead to incoherent pathway recommendations, such as favoring CNG and LNG as transport fuel substitutes during high petroleum prices, which is unlikely to be an optimal option since crude oil prices significantly impact natural gas prices [10].

Similarly, the investment cost of energy conversion technologies is typically correlated due to shared materials or manufacturing processes. For instance, the use of steam turbines in both combined cycle and nuclear plants mean that an increase in their production costs, driven by rising steel prices, could impact investment costs for both technologies simultaneously. Conversely, technological advancements or economies of scale could reduce costs for both. This interdependency also applies to other technologies sharing components, materials, or manufacturing processes.

Lastly, cross-correlations between primary energy prices and investment costs of energy technologies mainly arise from the use of fossil fuels in various stages of technology production. Fossil fuels are involved in producing basic materials [11], high-temperature industrial

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processes [12], transporting technologies (e.g., sea transport from a Chinese factory to a photovoltaic plant site in Spain), and installation (e.g., ships and platforms for offshore wind). Including these cross-correlations provides a more comprehensive consideration of costs across supply chains, adding significant value and coherence to the analysis. Following previous examples, crude oil significantly affects natural gas prices, which in turn impacts steel production costs, affecting the investment costs for both nuclear and combined cycle plants through their reliance on steam turbines.

Thus, incorporating these correlations is crucial for capturing real market dynamics and cascading effects often ignored or treated as independent in energy planning, and hence to design consistent planning strategies.

This importance has already been recognized by several studies in the literature. For instance, Abdalla et al. [13] highlights that including correlations between uncertainties can lead to less conservative outcomes and reduced generation expansion costs. Similarly, Cao et al. [14] emphasizes that assuming independent uncertain parameters, as done in most studies, may lead to suboptimal results, underlining the need to consider correlations to ensure optimal solutions. Furthermore, Roldan et al. [15] and Wang et al. [16] also discuss the relevance of addressing correlated uncertainties in transmission network planning and the interplay between demand response and renewable energy sources, respectively. Collectively, these studies reinforce the necessity of incorporating correlations to improve the coherence and accuracy of energy planning scenarios.

Despite the importance of considering the correlation between uncertain parameters, the literature review (detailed in Appendix A[1]) shows that most existing energy-related works focusing on them address single subsectors such as electricity: generation expansion planning [13,17–20], transmission network expansion planning [15,21], demand response planning [22], and energy storage planning [14,23]. Notably, the work from Patankar et al. [24] represents the first and only attempt to introduce correlations in strategic energy planning across the entire energy sector. Despite the significant gap this work addresses and its excellent methodological development, it only considers the autocorrelation of uncertainties, i.e., the correlation of a single parameter with its historical values (e.g., natural gas actual price with its past prices). It does not account for correlations between different parameters (e.g., crude oil and natural gas prices) or their cross-correlations (e.g., natural gas prices and combined cycle plant investment costs). It is worth noting that there are also other types of analyses and techniques used in the energy sector to explore relationships and interactions between energy sectors. For example, Input-Output (IO) analysis is one of the techniques used, which helps in understanding economic trends and interdependencies across various industries, providing valuable insights into how sectors influence each other [25]. However, while these methods are effective for capturing relationships in sectoral dynamics, they do not directly apply to the optimization models typically used in long-term energy planning. Thus, no prior research has incorporated correlations between different uncertain parameters in a strategic energy planning model for multiple energy vectors. This gap likely exists due to the increased complexity of such optimization models and the traditional focus on minimizing computational complexity in energy planning.

Regarding the type of correlations considered in the literature, the vast majority considers uncertainties between (i) renewable generation and electricity demand [14–16,18–22,26–28]; and (ii.a) renewable generation from different plants (e.g., two PV plants in a different location) [17,29,30], or (ii.b) the generation of different renewable technologies (i.e. PV and wind production) [13,23,31]. However, correlations between fuel prices and energy technology investment costs have not been studied, despite their significant impact on the energy supply chain.

This study aims to address these gaps by analyzing the effects of incorporating correlations between primary energy prices and investment costs of energy technologies in energy planning. Uncertainties are incorporated in the model by a Robust Optimization (RO) approach. This technique is specifically designed to find optimal solutions that guarantee their feasibility for all possible realization of the uncertain parameters within an uncertainty set [32]. We focus on polyhedral uncertainty sets [33,34] because they are versatile enough to model correlations and uncertainties among historical data, but also because they enable the obtention of tractable deterministic counterparts. However, the most typical data-driven polyhedral uncertainty sets, either fail to capture correlations (e.g. "box" or "budget" uncertainty sets) rendering over-conservative solutions, or result in larger counterpart formulations (e.g. "convex hull" uncertainty set), which are difficult to solve. To this end, in this paper we employ the methodology proposed by Cheramin et al. [35] which proposes to reduce the dimension of the polyhedral data driven uncertainty set, and hence improving its computational performance, while keeping the maximum amount of information regarding data correlations. In particular, they propose to use Principal Component Analysis (PCA), a well stablished linear dimensionality reduction technique [36], that allows identifying the components of the data with that explain most of its variability. Moreover, Cheramin et al. [35] show how the level of conservatism in the robust solution can be adjusted by including more or less PCA components to define the polyhedral uncertainty set. A case study focused on the decarbonization of the Spanish energy system by 2030 [37] illustrates the impact of considering these correlations. This case study shows the applicability of this analysis to real-size countries or regions. Furthermore, it addresses an additional complexity arising from the long-term evolution of these correlations: while fossil fuel prices and energy technology investment costs may remain correlated, technological and market developments might allow for their decoupling over time. By modifying these correlations into three scenarios, the study aims to explore how the degree of correlation affects decision strategies, and the impact of fossil fuel prices on renewable energy deployment.

We summarize the key contributions of this paper as follows:

1. We apply an innovative robust optimization technique based on PCA to a strategic energy planning model, incorporating correlations between different uncertain parameters. According to the literature review, this research is the first to systematically incorporate these correlations within a strategic energy planning model that accounts for several energy vectors.
2. We present a case study focused on the decarbonization of the Spanish energy system in 2030, introducing for the first time the correlations between uncertain fuel prices and energy technology investment costs.
3. By varying the degree of these correlations, we assess the sensitivity of decisions to these correlations and evaluate their impact on the potential decoupling of fossil fuel prices from renewable energy costs.

2. Methods

2.1. The energy model: openMASTER

This study has been conducted within the framework of openMASTER, an open-source strategic energy planning model. This model can be used as a tool for supporting decision-making about designing public policies and investment pathways in the energy sector. It is especially useful for understanding the functioning of the energy sector as a whole, its vulnerabilities, opportunities, and trade-offs.

openMASTER is a Pyomo-based model. It operates as a dynamic (multi-stage), bottom-up, partial equilibrium, linear programming (LP)

[1] All appendices are included in the supplementary material.

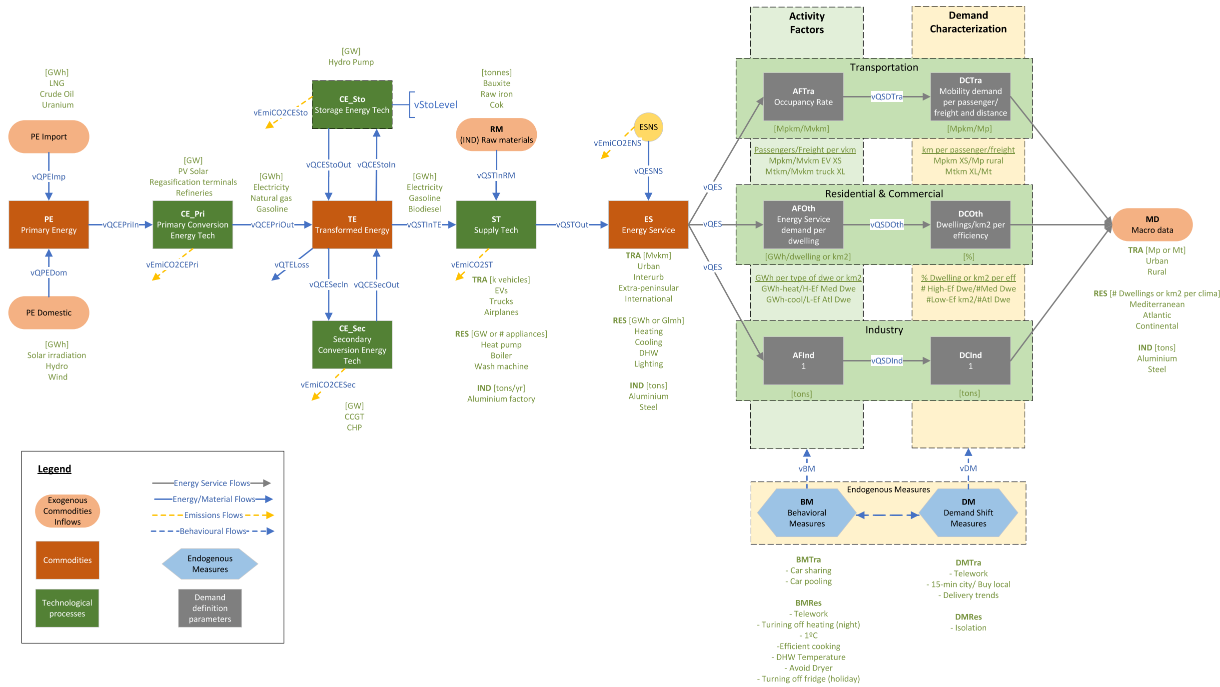

Fig. 1. openMASTER core structure. To facilitate understanding, units and some examples of various processes, commodities, and flows are shown in green. *Source:* [38].

model, aiming to meet an exogenous demand for energy services across various sectors. It achieves this by adhering to technical and policy constraints while minimizing a comprehensive objective function that includes total economic costs of energy supply, social costs of greenhouse gas emissions and pollutants, and intangible costs such as discomfort of transport.

The model is built according to a scheme of processes and flows detailed in Fig. 1 encompassing the entire energy sector, including primary energy import and domestic consumption, energy conversion and storage technologies for final energy production, and supply technologies to provide energy services. The energy services' exogenous demand is characterized using several parameters, including Activity Factors, Demand Characterization, and Macro Data.

The main equations of openMASTER include the objective function, balance equations, storage equations, capacity constraints, and electricity generation reliability constraints. Balance equations ensure the conservation of energy across all processes, while storage and capacity constraints ensure proper performance and operational functionality. The model also integrates constraints to ensure reliability in electricity generation and considers endogenous behavioral measures, capturing the impact of specific social measures across the energy value chain. Emissions accounting and constraints on emissions and carbon budgets further enhance the model's capability for comprehensive energy policy analysis. For a more comprehensive understanding of the openMASTER model, readers are encouraged to refer to [38].

For this study, a version of openMASTER that incorporates an algorithm based on robust optimization for handling uncertainties [39] has been used as a starting point. The model was then modified to include correlations based on the approach by Cheramin et al. [35], as further explained in the next subsection.

2.2. A data-driven robust optimization technique for including correlations

Historically, various methodologies have been employed to address uncertainties in energy planning models. Prominent among these is scenario analysis, which constructs narratives for qualitatively studying uncertainties [40–43]; stochastic programming, which assigns probabilities to different potential scenarios [44–46]; and robust optimization, which develops solutions based on worst-case scenarios, minimax regret, or least sensitivity [39,47–49]. Each approach, despite its merits, relies on constructing representative scenarios, or uncertainty sets, to support decisions but, in general, it is not straightforward to systematically incorporate the inherent correlations between multiple uncertainties. This often results in treating uncertainties as independent phenomena or requires manual handling, such as in scenario analysis.

The literature review shows that some studies have attempted to include correlations through various methodologies. However, none have applied these methods to different parameters in long-term energy planning models, especially in the crucial case of the correlation between fuel prices and technology costs. Popular approaches include the Cholesky Decomposition [20,27], a mathematical technique that decomposes a covariance matrix into the product of a lower triangular matrix and its transpose, allowing for the construction of a set of correlated random variables. It is mainly reserved for sensitivity analysis and statistical applications, such as Monte Carlo simulations, to explore the range of possible outcomes and assess decision robustness under different scenarios. Additionally, some works utilize Copula functions to generate a joint probability function for two uncertainties initially modeled with independent probability functions [23,26,28,29,31,50]. This approach could be applicable in models based on Distributionally Robust Optimization [51], which extends the robust optimization approach by considering the uncertainty of a parameter's distribution function rather than its specific values. However, this technique is less suitable for dealing with epistemic uncertainties found in long-term energy planning, as these involve incomplete knowledge about the future, which traditional probabilistic methods cannot capture. Epistemic uncertainties encompass fundamental gaps in understanding the evolution of complex systems, making it difficult for past behaviors to represent future outcomes accurately.

Lastly, robust optimization, based on the Wald decision criterion, prepares for the most adverse scenarios. A critical requirement within this methodology is the definition of uncertainty sets, outlining the potential range of values for uncertain parameters [52]. The challenge in incorporating correlations lies precisely in the intricate design of these uncertainty sets. The first robust optimization approach, proposed

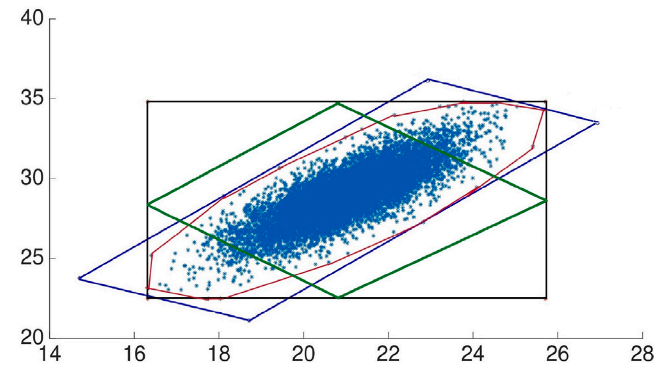

Fig. 2. Definition of uncertainty sets for two correlated uncertain parameters. Black: Box [33]; Green: Budget [34]; Red: Convex hull; Blue: PCA-based uncertainty set including correlation [35].
Source: [35].

by Soyster [33], relies on box uncertainty sets (refer to the black rectangle in Fig. 2), which represent uncertainties within a rectangular space, resulting in overly conservative outcomes due to the limited correlation space captured. Since then, various techniques have emerged, each attempting to mitigate the conservatism associated with this methodology. One widely adopted approach, proposed by Bertsimas and Sim [34], relies on budget uncertainty sets (refer to the green lozenge in Fig. 2), which introduce a control parameter to balance robustness and conservativeness, reducing the number of uncertain parameters at their worst realization, but still do not consider correlations between uncertainties. A proposal aiming to incorporate correlations involves defining convex hull uncertainty sets (refer to the red polygon in Fig. 2), which represent the smallest convex set encompassing all possible scenarios, capturing correlations but at a high computational cost, making them unsuitable for real-size strategic energy models.

A novel methodology, previously unapplied to energy models, presents an opportunity to reconcile reasonable computational costs with the integration of correlations among uncertain parameters. This innovative approach, proposed by Cheramin et al. [35], is based on Principal Component Analysis (PCA). Unlike traditional robust optimization techniques based on box or budget uncertainty sets, this approach can use historical data to capture the interdependencies among uncertainties to build a more nuanced representation of the uncertainty set (refer to the blue rectangle in Fig. 2). Data-driven techniques have gained increasing popularity across various fields, including energy systems, where they enable more precise decision-making under uncertainty [53–56]. Therefore, PCA helps develop data-driven polyhedral uncertainty sets that address the limitations of conventional polyhedral sets by capturing the correlations and allowing direct trade-offs between tractability and conservativeness: incorporating more principal components can pose additional challenges in computational complexity, but in exchange, it yields a more robust solution. Therefore, this PCA-based technique offers the potential to design robust decisions that address uncertainties while incorporating inherent correlations and maintaining computational feasibility. However, due to its novelty, it has only been used illustratively in the original work by Cheramin et al. [35] showing simple examples of the formulation for the knapsack problem and the power grid problem. It has never been applied in a real case study analysis of investment uncertainty, or in a full-scale energy model. This study aims to bridge this gap by applying it to achieve robust decisions in strategic energy planning, aligning this methodological advance with its practical application.

Applying this method to the openMASTER model involves making the necessary modifications for its implementation. These modifications involved applying the scenario-induced uncertainty set proposed by Cheramin et al. [35][2]:

$$\mathcal{U}_{\text{PCA}}(\mathcal{S}, m_1) = \Bigg\{ \boldsymbol{u} : \boldsymbol{u} = \bar{s} + \sum_{i=1}^{m_1} \left(\alpha_i \left(\frac{\overline{\omega}_i}{\|\boldsymbol{d}_i\|} \boldsymbol{d}_i \right) + (1-\alpha_i) \left(\frac{\underline{\omega}_i}{\|\boldsymbol{d}_i\|} \boldsymbol{d}_i \right) \right) + \sum_{i=m_1+1}^{m} \frac{\overline{\omega}_i + \underline{\omega}_i}{2\|\boldsymbol{d}_i\|} \boldsymbol{d}_i,\ 0 \le \alpha_i \le 1,\ \forall i \in [m_1] \Bigg\},$$

where

$$\overline{\omega}_i = \max_{j=1}^{N} \left\{ \frac{\boldsymbol{s}_{j0} \cdot \boldsymbol{d}_i}{\|\boldsymbol{d}_i\|} \right\} \in \mathbb{R}, \quad \text{and} \quad \underline{\omega}_i = \min_{j=1}^{N} \left\{ \frac{\boldsymbol{s}_{j0} \cdot \boldsymbol{d}_i}{\|\boldsymbol{d}_i\|} \right\} \in \mathbb{R},$$

meaning $(\frac{\overline{\omega}_i}{\|\boldsymbol{d}_i\|}\boldsymbol{d}_i)$ and $(\frac{\underline{\omega}_i}{\|\boldsymbol{d}_i\|}\boldsymbol{d}_i)$ are the largest and smallest projected centered scenarios onto the principal direction $\boldsymbol{d}_i$, respectively. The sample mean $\bar{s}$ is added to $\mathcal{U}_{\text{PCA}}(\mathcal{S}, m_1)$ because the scenarios have already been centered at $\bar{s}$.

This uncertainty set is applied to the uncertain parameters of primary energy prices and investment costs of energy technologies. These parameters are part of the objective function. Thus, Eq. (1) has been modified, representing the annual cost variable affected by these uncertainties. This annual cost variable is integrated into the objective function in the openMASTER model:

$$\begin{aligned} \mathbf{vUncCost}_y = pYrGap \cdot \sum_{pe,s,d,h} \mathbf{pUnc}_{pe,y} \cdot (&\mathbf{vQPEImp}_{pe,y,s,d,h} \\ &+ \mathbf{vQPEDom}_{pe,y,s,d,h}) \\ &+ \sum_{ce} \mathbf{pUnc}_{ce,y} \cdot \mathbf{vCENewCap}_{ce,y} \end{aligned} \tag{1}$$

where **pUnc** represents both the primary energy price for the subset pe (i.e., Primary Energy) and the investment cost of energy technologies ce (i.e., Conversion Energy technologies). As these two subsets are part of the same parameter, they are indicated by subscripts in the equation. The parameter $pYrGap$ is a scalar representing the year gap for which each representative year of the model is solved, and for which operating costs, including the primary energy consumed, must be summed. In this case study, the gap used is 5 years. Regarding the variables, **vQPEImp** and **vQPEDom** are the imported and domestically consumed primary energy, respectively. The variable **vCENewCap** is the newly installed capacity of energy conversion technologies. The subscripts y, s, d, and h represent the temporal subsets year, season, day, and hour, respectively, given that openMASTER has been configured to work for this case study with a temporal horizon from 2020 to 2030, with four seasons and one representative day per season with 24 h. In total, 288 time slices.

The following provides a step-by-step development of the mathematical formulation resulting from the application of the PCA-based uncertainty set (refer to Eqs. (3) and (4)) to the uncertainties in Eq. (2) of the objective function.

$$\begin{aligned} \max_{\mathbf{pUnc} \in \mathcal{U}_{pca}} \ & pYrGap \cdot \sum_{pe,s,d,h} \mathbf{pUnc}_{pe,y} \cdot (\mathbf{vQPEImp}_{pe,y,s,d,h} + \mathbf{vQPEDom}_{pe,y,s,d,h}) \\ + & \sum_{ce} \mathbf{pUnc}_{ce,y} \cdot \mathbf{vCENewCap}_{ce,y} \end{aligned} \tag{2}$$

[2] Following notation from [35], we denote scalar values by non-bold symbols, e.g., m_1, while we represent vectors by bold symbols in the column form (e.g., $\boldsymbol{u} = (u_1, \dots, u_m)^\top$). Italic subscripts represent indices, e.g., c_g, while non-italic subscripts indicate simplified specifications, e.g., $\mathcal{U}_{\text{PCA}}$. Symbol $\|\cdot\|$ denotes the Euclidean norm. The number of uncertain parameters, i.e., the size of random variable vector, is denoted by m and $\boldsymbol{u} = (u_1, \dots, u_m)^\top \in \mathbb{R}^m$ represents the random variable vector. We adopt N to denote the number of available scenarios for $\boldsymbol{u}$. Symbol $\mathcal{S}$ represents the set of the N scenarios, where each scenario is denoted by $\boldsymbol{s}_j \in \mathbb{R}^m$, i.e., $\boldsymbol{s}_j \in \mathcal{S}$, $\forall j \in [N]$. The number of utilized principal components in the scenario-induced uncertainty set is indicated by m_1.

s.t.

$$\boldsymbol{u}_m = \bar{\boldsymbol{s}}_{unc} + \sum_{m=1}^{m_1}\left(\alpha_m\gamma_{m,unc}^{up} + (1-\alpha_m)\gamma_{m,unc}^{do}\right) + \sum_{m=m_1+1}^{M}\rho_{m,unc}, unc \in (pe \cup ce) \tag{3}$$

$$0 \le \alpha_m \le 1 \tag{4}$$

where $\gamma_{m,unc}^{up} = \left(\frac{\overline{\omega}_i}{\|\boldsymbol{d}_i\|}\boldsymbol{d}_i\right)_{unc}$ and $\gamma_{m,unc}^{do} = \left(\frac{\underline{\omega}_i}{\|\boldsymbol{d}_i\|}\boldsymbol{d}_i\right)_{unc}$.

The following maximization problem is obtained by applying (3) to (2):

$$\begin{aligned}\max_{\alpha_m} pYrGap \cdot & \sum_{pe,s,d,h}(\bar{s}_{pe} + \sum_{m=1}^{m_1}\left(\alpha_m\gamma_{m,pe}^{up} + (1-\alpha_m)\gamma_{m,pe}^{do}\right) \\ & + \sum_{m=m_1+1}^{M}\rho_{m,pe}) \cdot (\mathbf{vQPEImp}_{pe,y,s,d,h} \\ & + \mathbf{vQPEDom}_{pe,y,s,d,h}) + \sum_{ce}(\bar{s}_{ce} + \sum_{m=1}^{m_1}\left(\alpha_m\gamma_{m,ce}^{up} + (1-\alpha_m)\gamma_{m,ce}^{do}\right) \\ & + \sum_{m=m_1+1}^{M}\rho_{m,ce}) \cdot \mathbf{vCENewCap}_{ce,y}\end{aligned} \tag{5}$$

Factoring out α_m, we obtain the following equation with only the elements that depend on this variable:

$$\begin{aligned}\max_{\alpha_m}\sum_{m=1}^{m_1}\alpha_m\cdot\Big(& pYrGap\cdot\sum_{pe,s,d,h}(\gamma_{m,pe}^{up}-\gamma_{m,pe}^{do})\cdot(\mathbf{vQPEImp}_{pe,y,s,d,h} \\ & + \mathbf{vQPEDom}_{pe,y,s,d,h}) \\ & + \sum_{ce}(\gamma_{m,ce}^{up} + -\gamma_{m,ce}^{do})\cdot\mathbf{vCENewCap}_{ce,y}\Big)\end{aligned} \tag{6}$$

Considering the dual problem of minimizing the negative of Eq. (6), including constraint 4, results in:

$$\max \beta_m \tag{7}$$

s.t.

$$\begin{aligned}-\beta_m \le -\Big(& pYrGap\cdot\sum_{pe,s,d,h}(\gamma_{m,pe}^{up}-\gamma_{m,pe}^{do})\cdot(\mathbf{vQPEImp}_{pe,y,s,d,h} \\ & + \mathbf{vQPEDom}_{pe,y,s,d,h}) \\ & + \sum_{ce}(\gamma_{m,ce}^{up} + -\gamma_{m,ce}^{do})\cdot\mathbf{vCENewCap}_{ce,y}\Big)\end{aligned} \tag{8}$$

$$\beta_m \ge 0 \tag{9}$$

Applying the Strong Duality Theorem:

$$\begin{aligned}\sum_{m=1}^{m_1}\beta_m = \sum_{m=1}^{m_1}\alpha_m\cdot\Big(& pYrGap\cdot\sum_{pe,s,d,h}(\gamma_{m,pe}^{up}-\gamma_{m,pe}^{do})\cdot(\mathbf{vQPEImp}_{pe,y,s,d,h} \\ & + \mathbf{vQPEDom}_{pe,y,s,d,h}) \\ & + \sum_{ce}(\gamma_{m,ce}^{up} + -\gamma_{m,ce}^{do})\cdot\mathbf{vCENewCap}_{ce,y}\Big)\end{aligned} \tag{10}$$

$$0 \le \alpha_m \le 1 \tag{11}$$

$$\begin{aligned}\beta_m \ge \Big(& pYrGap\cdot\sum_{pe,s,d,h}(\gamma_{m,pe}^{up}-\gamma_{m,pe}^{do})\cdot(\mathbf{vQPEImp}_{pe,y,s,d,h} + \mathbf{vQPEDom}_{pe,y,s,d,h}) \\ & + \sum_{ce}(\gamma_{m,ce}^{up} + -\gamma_{m,ce}^{do})\cdot\mathbf{vCENewCap}_{ce,y}\Big)\end{aligned} \tag{12}$$

Substituting into the original problem, the following equations result from applying the PCA-based uncertainty set:

$$\begin{aligned}\mathbf{vUncCost}_y = \sum_{m=1}^{m_1}\beta_m + \Big(& pYrGap\cdot\sum_{pe,s,d,h}(\bar{s}_{pe} + \sum_{m=1}^{m_1}\gamma_{m,pe}^{do} \\ & + \sum_{m=m_1+1}^{M}\rho_{m,pe})\cdot(\mathbf{vQPEImp}_{pe,y,s,d,h} \\ & + \mathbf{vQPEDom}_{pe,y,s,d,h}) + \sum_{ce}(\bar{s}_{ce} + \sum_{m=1}^{m_1}\gamma_{m,ce}^{do} \\ & + \sum_{m=m_1+1}^{M}\rho_{m,ce})\cdot\mathbf{vCENewCap}_{ce,y}\Big)\end{aligned} \tag{13}$$

s.t.

$$\begin{aligned}\beta_m \ge \Big(& pYrGap\cdot\sum_{pe,s,d,h}(\gamma_{m,pe}^{up}-\gamma_{m,pe}^{do})\cdot(\mathbf{vQPEImp}_{pe,y,s,d,h} + \mathbf{vQPEDom}_{pe,y,s,d,h}) \\ & + \sum_{ce}(\gamma_{m,ce}^{up} + -\gamma_{m,ce}^{do})\cdot\mathbf{vCENewCap}_{ce,y}\Big)\end{aligned} \tag{14}$$

$$\beta_m \ge 0 \tag{15}$$

Thus, Eq. (13) is integrated into the objective function. Additionally, Eqs. (14) and (15) are constraints that have been incorporated into the model as a result of the mathematical development stemming from the application of the PCA-based uncertainty set.

2.3. Methodological procedure to apply the PCA-based uncertainty set to an energy model

The application's steps are shown in the flowchart in Fig. 3. Starting with the correlated data, historical data must be collected and pre-processed in order to apply PCA, which reduces the dimensionality of the data matrix and generates the covariance matrix, eigenvectors, and eigenvalues. At this point, the number of principal components is determined to introduce the appropriate uncertainty set into the model. As mentioned earlier, the decision on the number of components allows the decision-maker to balance the trade-off between tractability and conservativeness: incorporating more principal components can increase computational complexity, but in return, it provides a more robust solution. This uncertainty set, with the selected number of principal components, is then incorporated into the energy model. In our case, which considers correlated uncertainties in the objective function, this equation is modified as detailed in the step-by-step formulation in the previous subsection. Once the results of applying this methodology are obtained, the analysis may prompt the decision-maker to consider increasing the number of principal components based on their conclusions. This process can be repeated, modifying the number of components as needed. In this way, a robust strategy is developed that not only protects against uncertainties but also accounts for the correlations between them.

It is important to note that during the data preprocessing stage, two key modifications can be applied to tailor the methodology to future trends. First, the correlation matrix can be adjusted to reflect updated correlation levels between pairs of uncertain parameters, allowing for the incorporation of potential changes in their relationships. Second, the mean values used to construct the uncertainty set, represented by the parameter $\bar{s}_{unc}$, can be updated based on projected trends, ensuring the methodology aligns with forward-looking scenarios.

3. Case study

The case study examines the correlations between fuel prices and investment costs in energy technologies. Although the correlations of all fuels and technologies are considered, the study places special emphasis

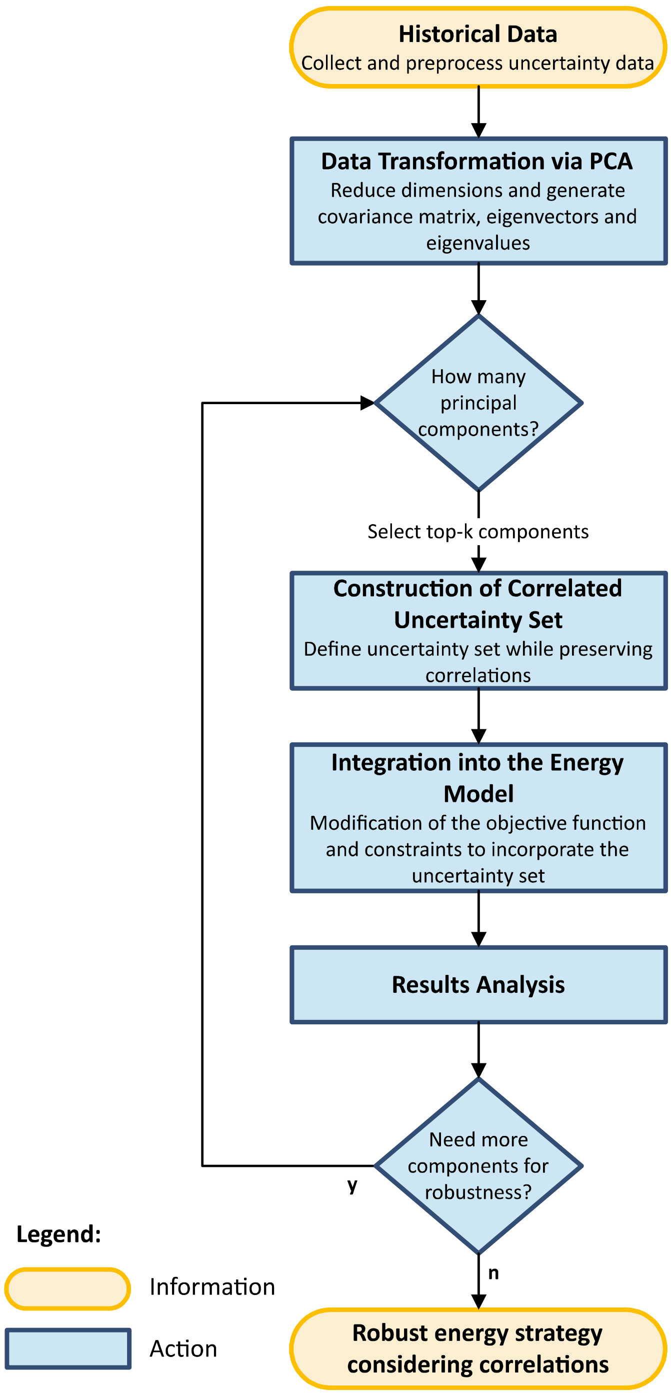

Fig. 3. Flowchart illustrating the step-by-step application of PCA-based uncertainty set in an energy model.

on fossil fuels and renewable technologies, as these are modified to create scenarios based on different levels of correlation. The objective is to understand how accounting for these correlations affects decision-making and how changes in these correlations impact the deployment of renewable energy sources.

While the analysis could be applied to any country or region, it focuses on the decarbonization of the Spanish energy system, which, in our opinion, provides a very interesting setting for this analysis. Spain features a relatively large and diverse energy system, rich in renewable resources, thus helping to show the applicability of our methodology to a real national energy planning exercise, and also showing the interactions among the many different technologies that may play a role in the energy transition. This, we believe, helps in generalizing the conclusions obtained in the study to other regions. Furthermore, Spain is already undergoing an ambitious transformation of its energy system, with a large share of renewables, and so the interactions and correlations, and their impacts, are better observed compared to other countries with lower shares of these technologies.

This case study aligns with the national CO2 emission targets for 2030 as outlined in the Spanish National Energy and Climate Plan (NECP). The base year for calibration is 2020, with detailed calibration information provided in Appendix B. As noted earlier, the data preprocessing stage allows for tailoring the methodology to future trends by updating the mean values and correlation levels. For this case study, the mean values used to construct the correlated uncertainty sets ($\bar{s}_{unc}$) have been updated to reflect the expected projections of uncertainties for 2030. The number of principal components m_1 is 10.

The correlation matrix has also been adjusted to explore three different scenarios, capturing varying levels of correlation between uncertain parameters and evaluating their impact on investment strategies (correlation values are provided in Appendix C):

- Uncorrelated scenario: This scenario uses the budget-based robust optimization technique proposed by Bertsimas and Sim [34], assuming no correlations. It serves as a baseline for comparison with other scenarios, providing a reference point to evaluate the impact of accounting for correlations.
- Positive correlation scenario: Historical data point to a positive correlation between primary energy prices and technology investment costs. In this scenario, this correlation is adjusted with a coefficient of 0.5. This scenario assumes that increases (or decreases) in fossil fuel prices lead to corresponding increases (or decreases) in renewable investment costs due to higher (or lower) costs associated with materials, production, transportation, and installation processes reliant on fossil fuels.
- Negative correlation scenario: This approach sets correlation coefficients to −0.5, indicating an inverse relationship: High (or low) fossil fuel prices accelerate (or slow down) the learning curve of renewables, reducing (or increasing) their costs and enhancing (or worsening) their competitiveness through greater (or lesser) R&D efforts.

Please note that while these scenarios offer a basic framework, real-world correlations are more nuanced, with coefficients ranging from −1 to 1. The selected correlation coefficients are designed to be representative of their corresponding scenarios and provide meaningful insights. Additionally, we ran other scenarios with different correlation levels, and the results did not show significant differences to justify their inclusion for interpreting the differences between positive, negative, and no correlation scenarios. Therefore, to facilitate the analysis and the drawing of conclusions, these additional scenarios were not included.

Therefore, these scenarios provide a comprehensive view of how different correlations can influence the deployment of renewable energy technologies for achieving the decarbonization goals of Spain by 2030.

4. Results

The uncorrelated scenario serves as a baseline for comparison, with results for positive and negative correlations presented against it. However, common elements across scenarios are worth analyzing, as they reveal consistent patterns and useful insights regardless of correlation assumptions.

On the one hand, highlights a significant reliance on gas power plants across all scenarios. This dependence on fossil fuel technologies can be attributed to reduced nuclear capacity in all scenarios, falling below 2 GW, and to the firmness and adequacy constraints of the openMASTER model, which require backup for increased variable capacity

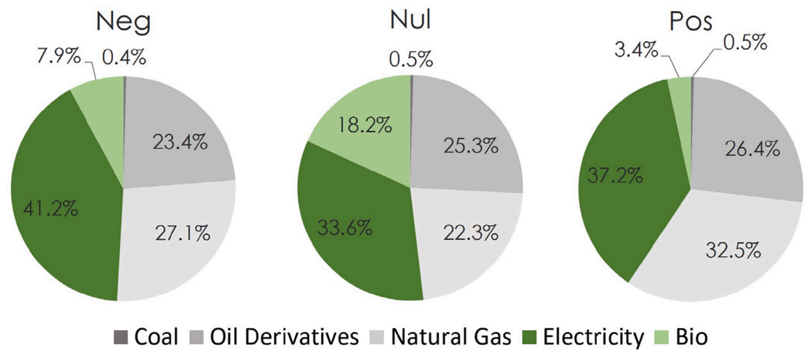

Fig. 4. Final energy mix in 2030 as a percentage of total final energy consumption. Final energy vectors are aggregated into categories.

Table 1
Capacity of installed energy conversion technologies (GW). The heatmap colors facilitate comparison between the three scenarios (Neg: Negative correlation scenario; Unc: Uncorrelation scenario; Pos: Positive correlation scenario) by highlighting the relative capacities within each technology using an orange gradient. Abbreviations: Spanish National Energy and Climate Plan (NECP), Combined Cycle Gas Turbine (CCGT), Carbon Capture and Storage (CCS), Open Cycle Gas Turbine (OCGT), Photovoltaic (PV), Thermosolar (Th), Power Plant (PP), Combined Heat and Power (CHP), Total electricity generation capacity (TOTAL ELECT).

Conversion energy capacity [GW]	2020	2030		
		Neg	Unc	Pos
Nuclear	7.4	1.9	1.9	1.9
Coal	10.2	0	0	0
CCGT	26.6	18.8	16.4	13.1
CCGT+CCS	–	14	7.7	12.1
OCGT	–	8.7	6	9.5
OCGT+CCS	–	0	0	0
Fuel Oil	3.7	0	0	0
Hydro	14	14	14	14
Wind Onshore	26.7	90.8	67.6	75.7
Wind Offshore	–	3	3	0
Solar PV	11	40.3	30.7	18.7
Solar Th	2.3	0	0	0.6
Biomass PP	1.4	0	0	0
Pumping storage	6.4	6.5	6.5	6.5
CHP	5.5	0	0	0
TOTAL ELECT	**115**	**198**	**153.7**	**152**
Oil Refinery	28	24	24.5	26.1
Biofuel	7	4.4	14.3	0.1
Regasification	76	81.5	48.2	75.2

from wind and solar sources. To mitigate emissions from the electric mix, Carbon Capture and Storage (CCS) technologies play a notable role in reducing emissions from gas-based technologies in all scenarios.

Regarding renewable energies, hydroelectric capacity shows minimal expansion due to geographical constraints on maximum capacity. Pumped hydro also increases marginally across all scenarios, likely due to high costs of new capacity, which reduce its competitiveness compared to gas power plants, a trend expected to continue through 2030. Additionally, all three scenarios show a clear preference for wind power over solar. This preference may stem from the better adaptation of wind power's generation profile to demand, hence reducing the need for backup.

Concerning CO2 emissions in 2030, total emissions are nearly identical across scenarios, around 100 Mt, complying with the emission cap set, as depicted in Fig. 6. However, significant differences exist in the sectoral distribution of these emissions, particularly affecting the energy generation and transportation sectors.

Under the scenario in which we assume a **positive correlation**, the strategy varies notably from the uncorrelated baseline. It exhibits higher crude oil refinery capacity and minimal biofuel refining capacity, indicating a greater reliance on oil derivatives. This is supported by higher consumption of oil derivatives and natural gas, which together account for nearly 60% of the final energy mix, as depicted in Fig. 4. In contrast, the uncorrelated baseline scenario relies more on biofuels, displacing both fossil fuels and conventional electricity generation.

In the transportation sector, which accounts for the highest greenhouse gas emissions in Spain, the total final energy consumption indicates a strong preference for emission reduction through natural gas and electrification over biofuels, as shown in Fig. 5. However, it exhibits around 10 TWh higher consumption of oil derivatives compared to the uncorrelated baseline, as well as the highest natural gas consumption, leading to the highest emissions in this sector. This underscores the greater competitiveness of fossil fuels in a scenario where the costs of renewables increase in tandem with them: EVs become more expensive to operate if the renewable electricity mix also becomes costlier, transmitting these costs and giving fossil fuels a competitive advantage. This translates directly to the car fleet, with a preference for PHEVs to electrify part of the mobility and greater use of natural gas in ICEVs. On the contrary, the reliance on biofuels in the uncorrelated baseline scenario represents a clear preference for ICEV (see Table 3).

Renewable energy deployment in this scenario is the lowest, with a combined wind and solar capacity of 94.4 GW, compared to 101.3 GW in the uncorrelated baseline, as observed in . Paradoxically, it accounts for the lowest emissions in the energy generation sector. This can be attributed to the electricity consumption being approximately 45 TWh lower than in the negative correlation scenario, reducing overall emissions despite a lower renewable share. Additionally, a greater share of CCS provides lower-emission electricity backup, especially important given the reduced nuclear capacity and minimal hydropower growth. This adjustment in the electricity sector compensates for higher emissions in the transportation sector, which heavily relies on fossil fuels, thus meeting the 2030 emissions target.

An interesting phenomenon when assuming a positive correlation is the absence of offshore wind, in contrast to the other two scenarios where the maximum allowed capacity of 3 GW is installed, aligned with NECP planning due to licensing constraints [37]. This can be explained by the significant correlation between offshore wind deployment and crude oil prices [57]: offshore wind and oil industries compete for vessels, oil majors' investments in offshore wind are negatively driven by the price of oil, and the price of oil influences the cost of transport fuel, steel, and copper. This, again, underscores the importance of considering correlations and their impact on decision-making.

If a **negative correlation** scenario is assumed, the investment strategy contrasts sharply with both the uncorrelated and positive correlation scenarios. It features the highest level of electrification, approaching nearly 300 TWh annually, as observed in . This electrification strategy is strongly complemented by the highest deployment of wind and solar at 134.1 GW aggregated, marking a nearly 40 GW difference compared to the other scenarios, as presented in . However, higher capacity in combined cycle gas turbines enhances firm capacity and

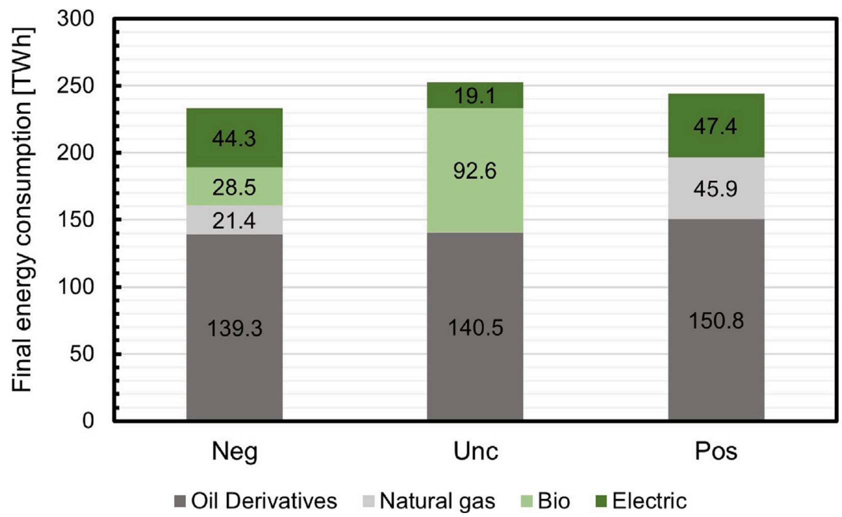

Fig. 5. Annual consumption of final aggregated energy vectors in the transportation demand sector for 2030 (TWh).

Table 2
Total annual consumption detailed for final energy vectors for 2030 (TWh). The heatmap colors facilitate comparison between the three scenarios (Neg: Negative correlation scenario; Unc: Uncorrelation scenario; Pos: Positive correlation scenario) by highlighting the relative capacities within each technology using an orange gradient. Abbreviations: Liquified Petroleum Gas (LPG), Other petroleum derivatives (Oil Others).

Final energy [TWh]	2030		
	Neg	Unc	Pos
Coal	3.0	3.0	3.0
Fuel Oil	2.6	2.9	2.9
Diesel	101.2	112.2	109.5
Gasoline	39.6	27.4	39.2
Kerosene	11.5	13.6	12.4
LPG	1.0	1.1	1.1
Oil Others	9.5	10.4	10.2
Natural Gas	191.4	147.8	215.9
Biomass	54.7	27.4	22.2
Biofuel	1.0	93.1	0.4
Electricity	291.6	222.5	247.0

Table 3
Car fleet in 2030 (Millions of Vehicles). The heatmap colors facilitate comparison between the three scenarios (Neg: Negative correlation scenario; Unc: Uncorrelation scenario; Pos: Positive correlation scenario) by highlighting the relative number of vehicles within each row using an orange gradient. Abbreviations: Internal Combustion Engine Vehicle (ICEV), Plug-In Hybrid Electric Vehicle (PHEV), Electric Vehicle (EV).

Car fleet [Million vehicles]	2030		
	Neg	Unc	Pos
ICEV	11.7	18.1	11.7
PHEV	0.3	0.0	2.3
EV	5.6	0.0	3.5

supports increased variable installed capacity, resulting in the highest total installed capacity in the electricity sector among the scenarios. This is consistent with the greater electrification of demand in this scenario. Nevertheless, this scenario exhibits the highest emissions in the energy generation sector, primarily due to the lower capacity of CCS for backup and significantly higher electricity consumption: despite having the largest share of renewables in the electricity mix, it is not enough to offset the increased generation.

This electrification, when assuming this negative correlation scenario, primarily occurs in the transportation sector, resulting in a more diversified mix of energy vectors. Specifically, natural gas and biofuels, though less prevalent than in other scenarios, play significant roles. The car fleet predominantly favors EVs over PHEVs. Additionally, ICEVs increase the use of natural gas and biofuels, which is consistent with the overall energy consumption patterns of the transportation sector.

5. Conclusions and future work

This study is the first to incorporate correlations between uncertain parameters into a strategic energy planning model. Using a novel PCA-based methodology, correlations between fuel prices and energy technology investment costs are examined in a case study on the decarbonization of the Spanish energy system, aligned with the 2030 CO2 emission reduction targets. By developing scenarios with varying levels of correlation between fossil fuel prices and renewable energy costs, the impact on decision-making processes and the deployment of renewable energy technologies is assessed.

The case study results reveal that decarbonization strategies vary significantly with the level of correlation. When assuming an uncorrelated scenario, a key finding is that greater decarbonization in the transportation sector is achieved by heavily investing in biofuels rather than electrification. This outcome can largely be attributed to vehicle fleet inertia, where only vehicles at the end of their life cycle are replaced. Consequently, while electric vehicle adoption is slow by 2030, the existing ICEV fleet can still reduce emissions through biofuels. This underscores the potential role of biofuels in the transitional decarbonization of transportation as EVs gradually replace ICEVs under this assumption.

If the correlation between fossil fuel prices and renewable energy costs is positive, and beyond initial adoption barriers of EVs, such as investment cost, home-based charging, and vehicle range, higher renewable electricity costs make EV operation more expensive, hindering this transition. This finding could be transferable to other electrifiable demands, such as those using heat pumps or electrified industrial processes, which are key contributors to emissions reduction. A particularly sensible technology in this regard is offshore wind energy, which is deeply linked with the fossil fuel industry, and hence subject to its fluctuations.

Our results have significant policy implications for the energy transition. First, it shows the relevance of including these correlations into energy planning and the design of transition strategies. Policymakers,

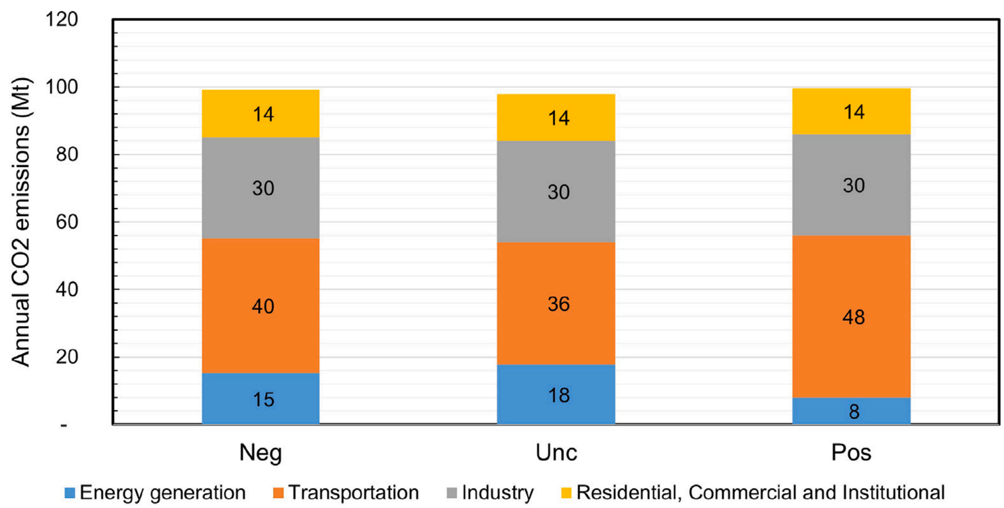

Fig. 6. Annual sectorial CO2 emissions for 2030 (Mt).

when deciding upon decarbonization strategies, should take into account the correlation between uncertain parameters in order to produce robust and consistent pathways. The energy mix changes markedly across scenarios, suggesting that strategies based on wrong correlation assumptions may lead to inefficient investments and potential lock-ins. Therefore, introducing correlations into energy planning, and accurately understanding the expected sign and value of those correlations, is crucial to produce robust and consistent strategies and to minimize costly mistakes.

Second, policymakers should deploy policies that may help in decoupling unwanted correlations. For example, decoupling renewable energy costs and fossil fuel prices can be done by investing in R&D to reduce the dependence of renewable energy technologies on fossil fuels (e.g., by developing green steel or concrete). Promoting a circular economy for materials can also help achieve the same goal.

Additionally, faster green electrification of the production processes through which transition technologies (renewables, batteries, etc.) are produced can also help decouple their costs from fossil fuel prices. This electrification should then be given priority in the decarbonization of industry. Another policy that would help reduce the unwanted impacts of correlations would be to use alternative fuels, not that dependent on fossil fuels for their manufacturing: biofuels may play an important role in making decarbonization strategies more robust in the presence of uncertain correlations.

Third, our results show that a positive correlation between fossil fuel prices and renewable energy costs makes it more difficult to electrify transportation, residential, or industrial demands. Therefore, support policies may be needed to address this reduced competitiveness (unless this positive correlation has been minimized through other policies, as mentioned above). This may call for a larger use of carbon pricing (which separates further the fossil fuel price and renewable energy cost), or for stronger support systems for low-carbon technologies (such as subsidies for electric vehicles or renewable energy generation).

In this regard, it is worth noting that carbon prices, when determined in emissions markets, are typically set by fossil fuel prices (typically the opportunity cost of shifting to natural gas). Therefore, there is also a correlation between fossil fuel prices and carbon prices in markets, which must be taken into account, and which generally goes against the original sign of the correlation. Emissions markets can, therefore, play an interesting role as “mitigators” of the correlations analyzed in the study.

Finally, the existence of a correlation (positive or negative) between fossil fuel prices and renewable energy costs should be accounted for by designing support systems for renewables which are indexed to fossil fuel prices, as has already been done in some countries (e.g. Germany).

Moreover, this methodology has potential applications beyond the energy sector and can be extended to explore interdependencies in other contexts. For instance, the approach could be adapted to assess correlations in sectors such as water or agriculture, where similar dynamics of resource dependencies exist [58]. Additionally, it could support integrated planning across interdependent systems, such as those with water-energy-food, by capturing cross-sectoral correlations. From a regional perspective, the methodology can provide insights into localized correlation dynamics, informing tailored policies for regions with distinct economic structures, resource dependencies, or decarbonization challenges.

Despite its contributions, the study has limitations that suggest directions for future research. The methodology considers the level of correlation during the data preprocessing phase, using these correlations to generate the necessary parameters, such as eigenvalues and eigenvectors, for constructing the uncertainty set. Consequently, modifying the level of correlation dynamically over time is not directly feasible within the current optimization framework. However, a potential avenue for future research could involve combining this methodology with adaptive optimization techniques. For example, implementing a rolling horizon approach could enable the consecutive optimization of subperiods, where the uncertainty set would be updated to reflect varying levels of correlation over time. Although it would represent a challenge both computationally and methodologically, this could provide a more flexible framework for addressing evolving trends driven by market transformations, policy shifts, and technological innovation, particularly in analyses that extend toward long-term horizons. Furthermore, future work could also explore correlations and interdependencies beyond fuel prices and technology costs, expanding the applicability of the methodology to capture broader interdependencies.

CRediT authorship contribution statement

Antonio F. Rodriguez-Matas: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Carlos Ruiz:** Methodology, Conceptualization. **Pedro Linares:** Writing – review & editing, Supervision, Formal analysis. **Manuel Perez-Bravo:** Visualization, Methodology.

Code availability

The open-source code for the openMASTER model is available at https://github.com/IIT-EnergySystemModels/openMASTER Further information related to the openMASTER model, data and assumptions is available in [38].

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.apenergy.2024.125257.

Data availability

The data used are included in the Supplementary Material. The model code is open source and can be found in GitHub (link shared in the Manuscript)

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