Energy planning and modern portfolio theory: A review

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ABSTRACT

Modern portfolio theory (MPT) stands as a widely accepted methodology to meet the challenges associated with the definition of energy planning for a particular territory or region. Energy planning is thus framed as an investment selection problem. MPT is characterized by having a wider capacity and conceptual richness than the other previously used methodologies, such as the individual least cost alternative. The portfolio approach is based on solving for an objective function that seeks to minimize either the cost or the risk of the portfolio, subject to different constraints, considering that real electricity generation assets can be defined in terms of cost or return and economic risk for each alternative technology. The relevant portfolios are the result of solving the optimization model, to determine the efficient cost-risk frontier. The work presented here consists of an exhaustive review of the literature in relation to the application of MPT methodology to the field of energy planning and electricity production. A new classification is proposed from a financial perspective of the selection of investments from the preceding studies. It delves deeper into the explanation of the limits to the methodology and into the concept of risk, which is key from both a financial and an energy perspective. The main methodological contributions found in the literature are examined that are aimed at improving the capacity of the model and adjusting it to the reality of the electricity market, Finally, conclusions are provided from the works analyzed in terms of renewable technologies and the policy implications derived from them. In most studies, a preference has been shown for the inclusion of renewable technologies in the efficient portfolios. However, in order to implement the decision to increase the share of renewable technologies, greater flexibility in the interconnection capacity between states and in storage capacity is needed.

KEY WORDS:
Modern portfolio theory, Energy planning, Portfolio efficiency, Renewable energy sources Externalities Diversification

1. Introduction

The design of the portfolio of technologies used to generate electricity takes on special importance in the context of energy and environmental planning. It is a matter of defining the *how* electricity should be produced over the medium-long term in a territory. The production cost is not the only consideration; also important are the level of outside dependence on resources, the corresponding energy security and efficiency of the territory and the social and environmental impact that the use of the available technologies might entail [1–3]. The aim is to form a diversified portfolio in terms of not only non- renewable and renewable energy sources (hereinafter, RES), but also combinations of the latter. Diversification even applies to the optimal location of RES plants, in order to maximize efficiency [4–6].

Energy planning, understood as a problem of investment selection [7], facilitates the long-term design of the electricity generation mix that best reconciles security of supply, sustainability (economic, social and environmental) and competitiveness [8,9]. The horizon subject to analysis is conditioned by the long service life of the power generation assets and by a high level of uncertainty, which affects the different variables of the selection problem, which are a combination of technological, economic, regulatory and environmental variables. In this sense, the planning process makes it possible to reduce the uncertainty associated with the required assets in the future and favors the laying of a foundation for increased energy supply security, access to the lowest possible cost (economic, social and environmental), the efficient use of resources and environmental sustainability.

This work reviews the application of Markowitz's modern portfolio

Abbreviations: CAPM, Capital Asset Pricing Model; CCS, Carbon Capture and Storage; CHP, Combined Heat and Power; CO_2, Dioxide Carbon emission; EIA, Energy Information Administration; EU, European Union; IEA, International Energy Agency; IPCC, Intergovernmental Panel on Climate Change; IRR, Internal Rate of Return; kW h, Kilowatt per hour; LCOE, Levelized Cost of Electricity; MPT, Modern Portfolio Theory; MW h, Megawatts per hour; NPV, Net Present Value; O & M, Operation and Maintenance; RES, Renewable Energy Sources; Solar PV, Solar Photovoltaic; TSO, Transmission System Operator; U.S., United States of America; WACC, Weighted Average Cost of Capital

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theory (hereinafter, MPT) [10] to energy planning. This methodology attempts to solve the long-term investment selection problem by defining the share of each of the real power generation assets (technologies) found in a territory's energy portfolio. To achieve this, MPT assesses both the cost (or return) and the economic risk (defined as variability of cost) of each technology and set of technologies (portfolio). The quadratic optimization approach with restrictions makes it possible to formulate the problem with the prime objective of either maximizing the return or minimizing the cost of the portfolio, subject to a given risk level; or secondarily, with the objective of minimizing the risk of the portfolio, subject to a set level of return or cost. In this manner, the efficient portfolio obtained would fulfill the requirements of optimization of the cost-risk pair. The set of the different efficient portfolios that can be obtained by solving the optimization equation for the different levels of restriction are found on what is known as the efficient portfolio frontier.

This work represents an exhaustive review of the previous studies based on the application of MPT to energy planning on a regional level. This review intends to help readers understand the state of the art in terms of this methodology, originally applied in the financial sector. It has now also been widely accepted in the field of energy planning, as this is understood to be a long-term investment selection problem.

In this sense, the objectives sought by this study are the following:

- To conduct an in-depth analysis of the MPT methodology in the context of energy planning, including its limitations when applied to power generation assets.
- To propose a new classification for the grouping of the different approaches based on MPT, from the perspective of selecting long-term financial investments. An attempt has also been made to provide a compendium of relevant information in relation to the data sources, the regions studied, the technologies analyzed and the restrictions contemplated in the proposed models.
- To examine the concept of risk in greater depth, as a key component of any portfolio theory approach and energy planning. To this end, the concept of portfolio diversification will be reviewed, highlighting the important role of the renewable technologies in reducing the risk of the energy portfolio.
- To highlight the most relevant conclusions in terms of policy implications for renewable energies, taken from the studies reviewed.

The work is organized as follows: the following section presents an explanation of why portfolio theory is preferred over the previous widely used methodology, i.e., the least cost alternative. The third section examines in greater depth the different approaches proposed by the many works that apply MPT to the problem of power generation assets. In order to facilitate the comprehension of the review, the analysis is based on the study of two different types of approaches: those using economic criteria and those using power production criteria. The fourth section presents and discusses the main limitations to the model, the concept of risk in terms of MPT and energy, the main methodological contributions and the main results of the works analyzed, particularly those related to renewable energies. Finally, some conclusions are presented.

2. Mean-variance portfolio theory vs. the least-cost alternative

In the field of energy planning, the least-cost alternative approach stands out as the methodology most commonly used to select power generation assets in the energy sector from the perspective of a single criterion [7]. This methodology is based on evaluating each alternative technology according to its levelized cost of electricity (hereinafter, LCOE). The chosen technology would be that with the lowest value for the cost and production coefficient. In spite of its widespread application, this methodology has been called into question. The criticisms are centered around the fact that the selection of the technology focuses solely on the criterion of lowest individual cost. Therefore, this methodology would give preference to those technologies that use fossil fuels over RES[1] [11–14]. This circumstance is seen in those cases in which externalities [18], such as environmental costs, were not included in the technology cost structure, resulting in an underestima- tion of the total costs for conventional pollutant technologies as compared to RES [19–21].

Modern portfolio theory makes it possible to analyze the technological alternatives from the two-part perspective of either cost-risk or return-risk. In this manner, when risk was considered, RES were favored over non-RES. Awerbuch and Berger [11] define these as technologies with fixed costs that are invariable and uncorrelated with fossil fuel prices; this leads to a much lower risk than that associated with the cost of non-RES [22,23].

With the change in portfolio methodology, the "individual technology" focus is abandoned in favor of another that is focused on the "alternative resource portfolio" as a whole. A vision focused solely on the investor side (lowest cost alternative) is also abandoned. Another long-term vision is adopted that includes both the investor and the regulator (since the efficient mix allows for the diversification of risk) [12,24–26], as well as society, thanks to a perspective that minimizes the assumed power generation costs or risks [9,11,19,26].

Among the strengths of MPT is the fact that the approach has a greater ability and conceptual richness than that provided by the perspective of the simple individual lowest cost of each technology, thanks to the double analysis of both cost and risk. Likewise, the portfolio model enables the incorporation of characteristic elements of energy analysis: the risk related to the variability of the cost of electricity generating technologies, the benefits of the portfolio effect in mitigating risk, and the risks of intermittency that are associated with RES production.

3. Review of the literature on modern portfolio theory, as applied to power generation

The application of MPT to energy planning was first proposed in the study by Bar-Lev and Katz [27], who analyze the relationship between the U.S. Power generation industry and fossil fuel resources. The studies by Humphreys and McClain [28] and Awerbuch [7,11,12,29,30] later served as a basis for numerous subsequent works that provide great diversity in terms of the definitions of the objective function and efficient frontiers, the types of restrictions addressed, variables studied and time horizons analyzed [20,25,31–34].

When undertaking a review of the literature, it is mandatory to acknowledge those reviews that already exist, such as those found in the works by Roques et al. [32], Allan et al. [14], Delarue et al. [33] and Janollo and Crawford [35], as they are particularly exhaustive and complete. These are supplemented by the works by Awerbuch and Berger [11], Awerbuch and Yang [30], Gökgöz and Atmaca [36], Bhattacharya and Kojima [37], Kumar et al. [38], which provide an accurate explanation of portfolio theory methodology.

We personally found it interesting to consider a classification of the different works from a financial perspective, which furthermore, is characteristic of MPT. This proposal is based on the understanding of energy planning as a problem of long-term investment selection [7,11,21,30]. Below is a comprehensive review of the works found in

[1] In this regard, authors like Jäger-Waldau [15] and Cuixia et al. [16] opt for a certain reduction of renewable energy costs in the case that learning curves and scale economies are considered. Along with this, we must also consider the indications of Del Río and Mir-Artigues [17], who opt for the application of corrective measures in the European Union until 2030, according to which the system promoting renewable technologies would increase the cost-effectiveness of these energies and mitigate the distortions affecting competition among power generation technologies.

the literature, based on the study of two different types of approaches: those based on economic criteria or on power production criteria.

3.1. Approaches based on economic criteria

3.1.1. Return as the inverse of generation cost

Awerbuch [11,29] provides the theoretical bases for this perspective. This approach, similar to that proposed by Humphreys and McClain [28][2], considers the overall profitability of the portfolio as the weighted sum of the profitability of each generation technology, according to MPT proposal.

The expected return for each technology is obtained based on the sum of the inverse of each type of cost. The expected return on the portfolio, $E(r_p)$, is estimated based on the mathematical calculation of the expected return on each technology share in the portfolio. This is determined by the following expression (Eq. (1)):

$$E(r_p) = x_1E(r_1)+x_2\,E(r_2) + \ldots + x_nE(r_n)= \sum_{i=1}^{n} x_i\,E(r_i) \tag{1}$$

where x_i is the share of each of the technologies i in the portfolio p and $E(r_i)$ is the expected return for each technology i. The authors opt for a definition of return as the amount of generation output produced (in kW h) per monetary unit spent. This thus can be interpreted as the inverse of a cost measured according to monetary units spent per unit of energy generated. As a result, a lower cost would equal better return. Awerbuch and Berger [11] measure the risk of each technology by means of the standard deviation of the relative variations in its cost per period.[3] These changes per period correspond to a measure similar to that of the calculation of the per period return. This calculation considers historical data for the different generation costs per technol- ogy, for which normality is assumed. This is determined by the following expression (Eq. (2)):

$$\textit{Holding Period Returns} = \frac{(cost_{t_1} - cost_{t_0})}{cost_{t_0}} \tag{2}$$

The risk of each technology would be calculated based on the standard deviation (or variance) of the time series that results from applying Eq. (2) to each cost component of the technology. Specifically, they propose the calculation of the technology risk as the sum of the risks for each cost component, weighted by the share that each component has in the total cost of the technology.

Portfolio risk (σ_p) is a function of the individual risks of each technology and any relationship that may exist between the costs of the different technologies considered (Eq. (3)):

$$\sigma_p = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \sigma_{ij}} = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \rho_{ij} \sigma_i \sigma_j} = \sqrt{\sum_{i=1}^{n} x_i^2 \sigma_i^2 + \sum_{i=1}^{n}\sum_{\substack{j=1\\ i\neq j}}^{n} x_i x_j \rho_{ij} \sigma_i \sigma_j} \tag{3}$$

Where x_i represents the share as a percentage of the technology i in the portfolio, σ_i the risk of technology i calculated as explained above and ρ_{ij} is the linear correlation coefficient between the costs of the technologies i and j. A normal distribution of the calculated percent changes is assumed [11].

The model thus generates an efficient portfolio frontier according to the return-risk pair. Other authors who have also opted for this pair include [13,31,39,40] (Table 1).

Hickey et al. [9], Jansen et al. [19], Roques et al. [26] and Delarue et al. [33] frame this proposal within the perspective of maximizing social welfare. This qualification owes to the aim of the approach, which is based on obtaining the efficient technology portfolio that implies exposing society to the minimum level of cost and risk necessary that are associated with the generation of electricity.

There are different points of view on how to handle the economic risk associated with RES. For instance, Awerbuch and Berger [11] identify the RES technologies as being risk-free. They would assimilate them into the behavior of risk-free assets in portfolio theory, as they have no fuel costs (except for biomass) that are subject to high price volatility [4,14,16,35,41,42]. In general, RES technologies use freely available natural resources [22,43] and have zero availability cost (wind, sea currents, precipitation or solar radiation). Furthermore, they do not incur costs related to CO_2 emissions, as they are not sources of emissions – except in the case of biomass technology and RES, which are only subject to investment and O & M costs. It is for this reason that a lack of correlation is assumed between fuel costs and fuel CO_2 emissions [14,30,38], something which reinforces the positive role of RES in the portfolio, reducing the risk if there are technologies that use fossil fuels. Awerbuch and Berger [11] indicate that since the potential year-on-year variation experienced by these costs can be considered null, these technologies present no risk. Escribano et al. [4] follows this same consideration of free-risk assets for RES.

Alternatively, Arnesano et al. [39] opt to characterize RES as technologies with an economic risk (Table 1). Accordingly, they link the capacity factor of the technologies to the real availability of the natural wind or solar PV "fuel". They thus equate the value of the capacity factor for each technology with the variability in the price of fuel for the RES.

The unlikely availability of series of historical data on the different types of generation costs in relation to the different technologies conditions most of the studies in this field. The real costs of the different electric companies is a very sensitive subject, and thus difficult to access. To make up for the lack of data, many authors turn to those collected in previously published works, international agencies, such as the IEA, or simulations (Table 1; Tables 2–4).

3.1.2. Earnings calculated based on NPV and IRR values

In the literature, we find works based on the calculation of the expected mean value and standard deviation (risk) of the net present value (NPV) and the internal rate of return (IRR) associated with each power generation asset or technology (Table 2). These analyses propose the estimation of the free cash flows for each power generation asset as receipts (from the sale of the electricity produced) minus payments (costs). In particular, NPV is obtained by discounting free cash flows at a discount rate, usually the *weighted average cost of capital (WACC)*[4].

Roques et al. [26] propose an approach based on the risks associated with plant performance. Investments in new base-load plants are evaluated from the perspective of private investors and their incentives. The goal is to obtain maximization of the financial returns of the investors, given determined risk levels (in relation to the variability in the price of electricity, certain fuels and CO_2 emissions). The authors propose the function of average utility-variance as a standard model of balance between risk and return. Its expression would be defined by: $U = E(r_p) - \frac{1}{2}\lambda\sigma_p^2$, where U is the generation utility of the portfolio being considered; $E(r_p)$, the expected return in terms of

[2] They propose the dynamic selection of portfolios with the aim of reducing the impact of energy price volatility on the generation portfolio and reducing the impact of sudden changes in energy prices.

[3] The *Holding Period Return* [11] does not express return, as it is not based on the variation in asset prices, but rather on their costs. It therefore offers information about the percent changes in the cost, but not the return. For this reason, Jansen et al. [19] propose that the measure of risk should contain a monetary value dimension, in which the production costs are expressed (instead of their inverse, as an expression of profitability), and should consider cost-risk instead of return-risk frontiers.

[4] Roques et al. [26] use a discount rate of 10%, as they consider that it is the most representative of the investment conditions on the free markets; they also present a sensitivity analysis using the discount rate of 5%. Muñoz et al. [45] propose a lower discount rate of 4%, however.

Table 1
Studies based on profitability as the inverse of generation cost.

Author	Objective function	Constraints	Horizon	Territory	Data origin-source	Analyzed technologies
Awerbuch and Berger [11]	Return maximization	Technologies limit shares	2000 and 2010	European Union (EU-15)	IEA	Coal, Nuclear Energy, Natural Gas, Oil and Wind Energy
Kienzle et al. [31]	Return maximization	Inexistent	2007	BKW Company (Switzerland)	IEA; BKW Company Data	Nuclear Energy, Hydro, Pump Hydro, Natural Gas and Coal
Rodoulis [13]	Return Maximization	Technologies Limit Shares	2010	Cyprus	IEA; Awerbuch and Berger [11]; Awerbuch and Yang [30]	Oil, Coal, Natural Gas and Wind
Arnesano et al. [39]	Return Maximization (inverse of the cost)	Technology Limit Shares	2009, 2020 and 2030	Italy	Centro Elettrotecnico Sperimentale Italiano; European Commission; Awerbuch and Yang [30]	Natural Gas, Coal, Hydro, Wind, Solar PV, Biomass and Nuclear Energy
Cuixia et al. [16]	Return Maximization (inverse of the cost)	N/A	2020 and 2030	China	*British Petroleum; China National Petroleum Corporation; Zhu and Fan* [25]*; Natural Development and Reform Commission for China*	Oil, Natural Gas, Coal, Wind energy, Biomass, Solar power

Table 2
Studies that propose the definition of earnings based on the NPV and IRR values of the technologies.

Author	Objective function	Horizon	Territory	Data origin-source	Analyzed technologies
Roques et al. [26]	Utility maximization/ Performance maximization	N/A	Liberalized Markets (United Kingdom)	IEA	Base Load Plants: Nuclear Energy, Coal and Natural Gas.
Muñoz et al. [45]	Sharpe Index Maximization	2005 and 2010	Spain	Spain-Portuguese Energy Market Operator (OMEL)	RES: Wind, Solar PV, Small Hydro and Thermoelectric
Westner and Madlener [46]	Return Maximization (NPV)	2010 and 2020	Germany, Italy, United Kingdom and France	European Energy Exchange (EEX) and Energy exchange of the respective countries.	Combined-cycle gas turbines and engine Combined Heat and Power technologies
Lynch et al. [44]	Return Maximization (NPV)	N/A	Single Electricity Market (SEM) -Republic of Ireland and Northern Ireland	EIA; IEA; Roques et al., 2008; NREL; SEMI	Coal (Sub-Super and Advanced Super Critical Coal), Combined Cycle Gas Turbine, Advanced Combined Cycle Gas Turbine, Aero-derivate Gas Turbine and Open Cycle Gas Turbine.
Cuchiella et al. [47]	Sharpe Ratio Maximization (NPV)	N/A	Italy	Awerbuch and Yang, 2007 [30]; GSE (Energy Services Operator) and other own authors sources.	RES (Biomass, Hydro, PV and Wind)

Table 3
Studies considering the profitability based on prices and costs of electricity generation.

Author	Objective function	Constraints	Horizon	Territory	Data origin-source	Analyzed technologies
Gökgöz and Atmaca [36]	Utility maximization	Investment capacity in spot market	2006 and 2011	Turkey	Turkish Electricity Market	Hydro, Coal and Natural Gas
Gökgöz and Atmaca [50]	Utility maximization	N/A	2009 and 2012	Turkey	Turkish Electricity Market	Hydro and thermal power plants (lignite fired thermal, natural gas combined cycle)

the NPV of the portfolio p containing assets i; λ the risk aversion coefficient; and $\sigma_{r_p}^2$ is the variance of the portfolio return.

The process starts with an estimate made through a Monte Carlo simulation of the mean and variance of the NPV for each technology in a cash flow discount model. The NPV distributions are obtained for the plants based on their free cash flows and their correlations, which are the calculation basis for portfolio optimization. The efficient frontier corresponds to the NPV-risk pair. These authors propose the study of three scenarios: the absence/existence of a correlation between the fuel, CO_2 emissions and electricity prices, and where fixed prices are linked to long-term contracts. They conclude that the model is very sensitive to the degree of risk aversion considered, due to the strong correlation among the prices on the free markets. One of the limitations of this study indicated by Lynch et al. [44] is that the proposed model cannot be used to evaluate mid-merit and peaking technologies or for systems that include the penetration of renewable energy generation.

Muñoz et al. [45] propose a portfolio model based on maximizing the IRR value of a portfolio consisting solely of RES technologies (Table 2). The expected IRR is calculated as the sum of the average IRR for each technology, weighted by the share of each technology in the portfolio. The cash flows from which the IRR is obtained would consist of receipts (annual production, average market price, reactive energy supplement, regulated price, deviation in production and premiums) and payments (O & M, service costs, fuel, etc.). The risk would be defined by the standard deviation of the IRR, depending on the variability of each of the aforementioned elements (receipts and payments). The authors use the simulation to generate the data on the mean and standard deviation of the variables, thus calculating the stochastic distribution of the IRR. Janczura [48] presents a study on the composition of the U.S. Portfolio, based on a proposal similar to that of Muñoz et al. [45], considering the minimization of the portfolio risk and the maximization of the Sharpe Ratio for technologies in the U.S. portfolio (Oil, coal, natural gas, nuclear energy and RES). The cost structure includes external costs derived from carbon intensity.

They establish the Sharpe index as the measurement of return in relation to risk. With this, they jointly achieve the minimization of risk and the maximization of return for a portfolio consisting of RES in Spain. The model has the following objective function (Eq. (4)):

$$\mathbf{Max}\,[(\overline{IRR_P} - r_f)/\sigma_P] \tag{4}$$

where $\overline{IRR_P}$ is the internal rate of return expected from the portfolio p (average profitability), r_f the rate offered by a risk-free asset and where σ_P expresses the portfolio risk in terms of standard deviation of the IRR.

Westner and Madlener [46] find support in the study by Roques et al. [26] to defend the applicability of their approach. The assets subject to analysis are different Combined Heat and Power technologies (hereinafter, CHP). The proposed NPV calculation includes the flow of investments throughout the construction phase and the annual free cash flows during the plant operation phase. They provide the NPV distribution through a Monte Carlo simulation and define electricity, fuel and CO_2 prices as random variables. In order to calculate the flows, the financial model incorporates the price of the products, the operating and technical costs and the costs of CO_2 emissions according to the permits obtained by the plants for the years 2012 and 2013, among others. The return measurement is defined by the sum of the expected NPV for the assets considered, weighted according to their portfolio share, and the risk defined by the standard deviation of the portfolio NPV.

Different cogeneration (CHP) technologies are compared to create better, more robust portfolios for 2010 and 2020. Westner and Madlener [46] seek portfolios capable of generating steady incomes, independently of the behavior of external elements, such as electricity prices, regulatory changes, technical changes, etc. The correlation coefficients are calculated based on the econometric model of regression analysis, which includes the prices for electricity, natural gas and CO_2 emission permits from the different member states.

3.1.3. Return based on prices and costs of power generation

Gökgöz and Atmaca [36] present a model of mean-variance optimization that incorporates restrictions related to the non-congestion of the electric system (Table 3). The objective focuses on the efficient assignment of electricity generation assets (plants), taking into account both generation costs and spot[5] and contract prices. These are used to calculate the return value, which is determined by the following expression, previously used by Liu and Wu [49]:

$$\textit{Rate of return} = \frac{(\textit{spot price}_t - \textit{generation cost}_t)}{\textit{generation cost}_t} \tag{5}$$

The risk would affect both the costs and the prices per hour[6] on the spot market. The electricity sales prices through bilateral contracts are assumed to be risk-free, as they have fixed or non-variable values for specific periods of time and are guaranteed by the regulating body.

The authors propose the existence of a single hourly behavior pattern for the demand on standard working days and for daily spot schedule prices, with a normal distribution of the mean. Based on this pattern, they define a total of 24 assets with a risk, one for each hourly spot price. The vectors obtained ($a_{n,m}$) include 1710 prices (days from 57 months) for each of the 24 h in relation to marginal prices from the system and "day-ahead" prices.

The authors obtain data on the average return rate and its standard deviation. They propose three models in which the objective function is the maximization of the utility[7] (similar to Roques et al. [26]). The first considers the existence of the aforementioned 24 assets (hourly sales alternatives) associated with risk, while the second includes restrictions related to the real sale of electricity,[8] and the third would incorporate the possibility of contracting the risk-free asset.

In a recent study, Gökgöz and Atmaca [50] demonstrate the applicability of the portfolio optimization techniques based on the mean-variance and the lower partial moments on the Turkish Electricity Market. They also observe the impact of the degree of risk aversion by the investors on the composition of efficient portfolios. They conclude that the mean-variance methodology presents less

[5] In Turkey, spot prices are used as the sole market prices. The authors rely on historical data regarding the Turkish marginal market system schedules, as well as the "day-ahead hourly" data between 2006 and 2011.

[6] The generating agents have 24 sales alternatives (one per hour), and they can opt to either sell their production at different hours or sell it through bilateral contracts that avoid risk.

[7] $U = E(r_p) - \frac{1}{2}\lambda\sigma_p^2$, with λ as the risk aversion coefficient, which has a value of 3.

[8] It adopts the form of maximum investment constraint on the same asset (hourly price).

Table 4
Studies with a cost-risk approach.

Author	Objective function	Constraints	Horizon	Territory	Data origin-source	Analyzed technologies
Delaquil et al. [55]	Risk Minimization	Technology Limit shares	2015	Common-wealth of Virginia	EIA, Electric Power Research Institute, Department of Energy; Awerbuch and Berger, 2003 [11].	Coal, Oil, Natural Gas, Nuclear, Hydro, Wood Residue, MSW, Landfill Gas, Other Biomass, Wind, Solar PV
Doherty et al. [52,53]	Least-Cost Optimization	Net-Load Duration, Plant utilization and generation adequacy criteria	2020	Ireland	Commission for Energy Regulation; European Commission; ESB National Grid	Coal, Natural Gas, Wind Energy, Biomass and Biogas.
Jansen et al. [19]	Risk and Cost minimization	Technology Limit Shares	2030	The Netherlands	Energy Research Center of The Netherlands; Awerbuch and Berger [11]	Coal, Nuclear Energy, Natural Gas, Biomass, Wind Energy and other RES
White et al. [54]	Risk and Cost minimization	Technology Limit Shares	2020	California (U.S.)	EIA (U.S.); California Energy Commission	Coal, Hydro, Natural Gas, Nuclear Energy, Wind Energy, Biomass, Solar Thermic and PV, Biogas and Geothermal
Awerbuch and Yang [30]	Risk and Cost minimization	Technology Limit Shares	2020	EU-27	European Commission; EIA (U.S.); California Energy Commission; TECHPOLE	Coal, Natural Gas, Nuclear Energy, Hydro, On-shore and Off-shore Wind Energy, Biomass, Solar PV and Geothermal
Awerbuch et al. [12]	Cost Minimization	Technologies Limit Shares	2010	Scotland	Airtricity	Nuclear Energy, Coal, Natural Gas, Hydro, On-shore and Off-shore Wind
Krey and Zweifel [20]	Cost Minimization	Risk Level	2003	U.S. and Switzerland	EIA (U.S.)	Coal, Nuclear Energy, Natural Gas, Oil and Wind Energy (U.S.) Nuclear Energy, Hydro (run of river), Pump Hydro and Solar PV (Switzerland)
Huang and Wu [56]	Cost minimization balanced by risk	Installed capacity related to demand side	2006 and 2025	Taiwan	Taiwan Power Company	Coal, Nuclear Energy, Natural Gas, Oil, Wind Energy, Hydro, Solar PV, Biomass and Geothermal
Zhu and Fan [25]	Risk Minimization	Technology Limit Shares	2005 and 2020	China	EIA (U.S.)	Coal, Hydro, Natural Gas, Nuclear Energy and Wind Energy
Marrero and Ramos [23]	Cost Minimization	Technical	2006	Canary Islands (Spain)	Spain Government, IEA, OECD	Oil, Diesel, Natural Gas, Solar PV and Wind
Allan et al. [14]	Risk and Cost minimization	Technology Limit Shares	2020	Scotland	Awerbuch and Yang [30]; Digest of United Kingdom Energy Statistics, Eurotom	Coal, Natural Gas (with/without CCS), Nuclear Energy, On-shore and Off-shore Wind, Hydro, Marine (Wave and Tidal) and Biomass
Delarue et al. [33]	Risk and Cost minimization	Load Factors (Power) Technology Production Ramp Rates	N/A	N/A	IEA; Danish Operator; Belgian TSO; Awerbuch and Berger [11]; White et al. [54]	Nuclear Energy, Coal, Natural Gas, Oil and Wind
De Jonghe et al. [40]	Cost Minimization	Load Factors and Wind Power reduction. Technology Production Ramp Rates	N/A	N/A	TSO Energinet	Base Load, Mid Load, Peak Load, High Peak Load
Bhattacharya and Kojima [37]	Risk Minimization (with cost and return perspective)	Technology Limit Shares and Carbon Price	2020–2030	Japan	Awerbuch and Yang [30] and Simulation techniques	Oil, Coal, Natural Gas, Nuclear Energy, Wind Energy, Large Hydro, Small Hydro, Solar PV, Biomass and Waste
Guerrero-Lemus et al. [57]	Volatility minimization for a given level of the average cost	Feasibility constraints according to short and long-term scenarios (bound restrictions-share limits)	2011; 2050	Road transport sector EU-27	IEA, EIA (U.S.), OECD, United Kingdom, Government Department, Joint Research Center	Gaso-diesel, Sugar cane ethanol, Rapeseed biodiesel, Cellulosic ethanol, Blt biodiesel and Electricity
Peerapat Vithayasrichareon and MacGill [58]	Cost minimization	Installed capacity related to demand side	2030	Thailand	IEA, Electricity Generating Authority of Thailand, Thailand's Energy Policy and Planning Office, Massachusetts Institute of Technology	Coal, Nuclear Energy and Natural Gas. Hydro, small power producers –RES- and foreign power purchases are considered fixed.
DeLlano et al. [42]	Risk Minimization	Technology Limit Shares and Pollutant Emissions Limit (CO_2, SO_2, NO_x, Particulates Matter).	2030	EU-27	Awerbuch and Yang [30]; Jansen et al. [19]; Awerbuch et al. [12]; IEA; IPCC.	Nuclear Energy, Natural gas, Natural Gas with Carbon Capture and Storage (CCS), Coal, Coal with CCS, Oil, On-shore wind, Off-shore wind, Large Hydro, Small Hydro, Biomass, Solar PV
Marrero et al. [59]	Risk Minimization	Technology Limit Shares	N/A	N/A	IEA, Guerrero-Lemus et al. [57], Lazard, World Bank Commodity Price Data and IMF Commodities Unit Research Department.	Technologies: Base Load (Coal, Combined Cycle Gas, Nuclear, Gas peak); RES (on-shore wind, Solar PV, Solar-Thermal). Road transport fuels: (Gasoline-diesel, Sugar cane ethanol, rapeseed biodiesel).

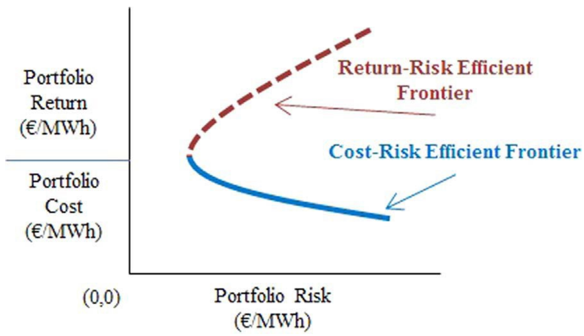

Fig. 1. Efficient portfolio frontiers.

aggressive optimal solutions (lower profitability and less risk) than those of the lower partial moments (down-side and semi-variance) methods. Furthermore, they also find that, even with a low level of risk aversion, these solutions are divergent, with greater aversion levels that tend to converge.

3.1.4. *Cost-risk models*

The authors of numerous works have opted to define models based on the costs of the technologies and the risks associated with them (Table 4). This is why the efficient portfolio frontier they generate is cost-risk [12–14,25,30,37,51–54]. Fig. 1 below shows the two different types of efficient portfolio frontiers, depending on whether a return- risk or cost-risk approach is followed.

In the cost-risk approach, the expected cost value of the portfolio is obtained as the sum of the total cost per technology, weighted by the share of each technology in the portfolio. The risk value of the portfolio is a function of the risk for each technology, the share of each technology and the correlation factors among the different types of cost (investment, O & M, fuel, etc.) associated with the different technologies.

Doherty et al. [52,53] propose a minimum cost algorithm that optimizes both the installed capacity for each technology in the portfolio and the mode of plant use, according to the load needs in Ireland. The main technology analyzed is wind energy. A previous study [51] also analyzes the diversification of the portfolio through MPT and the Shannon-Wiener index. By not requiring any forecast of the future in terms of probability, the latter index enriches the robustness of the model, in the opinion of the authors.

Krey and Zweifel [20] and Kienzle et al. [31], drawing from a proposal focused on MPT similar to that of Awerbuch and Berger [11], propose different approaches. Accordingly, Krey and Zweifel [20] establish the alternative objectives of minimizing the expected rate of cost increase per unit of electricity generated, expressed as c$/kW h,[9] and minimizing risk. They apply Seemingly Unrelated Regression estimation to the systematic components of the covariance matrix for the returns of the technologies in the United States and Switzerland. The estimation errors of the variances-covariances are studied through the degree of correlation among the regression errors for the expected return. In other words, those correlations between unexpected changes (e.g. those related to the weather) were examined for the returns of the technologies in order to improve the estimates. In turn, Kienzle et al. [31] seek to maximize the expected return, calculated as the least increase in cost per unit of electricity generated.

Huang and Wu [56] propose the aim of minimizing the current value of the total generation costs, plus their risk, weighted by the aversion factor. This measurement maximizes the utility, in this case, applied to costs (Eq. (6)):

$$WR_{(C_g)} = PVC_g + \lambda\sigma^2_{PVC_g} \tag{6}$$

Where WR is the weighted risk of the generation cost (C_g), PV is the Present Value and λ is the parameter that expresses the risk aversion. If this has a value of 0, the risk associated with the generation costs would not be incorporated in the analysis. The greater the value, the greater the risk aversion is for the investor (according to the proposal by Van Zon and Fuss [60]). The intent is to obtain the total cost value by considering the costs along with the risk weighted by an aversion factor.

The authors used a load curve to establish different packages of demand, studying the impact of different levels of risk on the portfolio. Delarue et al. [33] based their proposal on one by Jansen et al. [19] and present a quadratic programming optimization model with built-in restrictions. They consider two objective functions: minimum cost and minimum risk. They seek to determine the optimal technology portfolio (installed power) for a specified production and cost. The impact of including wind technology[10] in the portfolio is contemplated, along with restrictions on imbalances in terms of non-RES technology plants for an hourly load profile of one year (8760 h). The objective function would be (Eq. (7)):

$$\textit{Cost Minimization} = \sum_i F_i\, cap_i + \sum_{i,j} g_{ij}\, v_i \tag{7}$$

where cap_i expresses the optimal installed capacity of the technology i, g_{ij} expresses the electricity generation of technology i during the period j, and thus $\sum_{i,j} g_{ij} = d_j$, where d_j represents the electricity demand during the period j. F_i represents the fixed cost of technology i and $_i$ is the variable cost of technology i. Technical restrictions are also included in the form of limits (coefficients) for each technology.

De Jonghe et al. [40] apply two methodologies for portfolio optimization: projection of the load duration curve and linear programming. The objective is to attain the maximum return for the different types of load plants by minimizing costs and the maintenance of the optimal number of generation units. By using the curve projection methodology, they are able to determine the optimal mix of technologies over the long-term. As part of this methodology, they calculate the optimal number of operating hours in terms of costs, and combine these with the shape of the load duration curve. This provides the shares of the different technologies in the portfolio. These authors also propose using linear programming methodology to obtain a second result for the technology shares in the portfolio. They start with the assumption of a heavy future weight for wind technology in the portfolio to justify the need for incorporating restrictions in the model related to system flexibility, which include restrictions on regular maintenance operations, generation fluctuations and balance requirements. In its basic definition, this model is similar to that proposed by Delarue et al. [33] and Jansen et al. [19]. With this focus, they are able to incorporate both the variability on the net demand side[11] and operational restrictions on the offer side, within the scope of long-term planning.

3.2. *Approaches based on electricity production criteria*

The literature includes an alternative proposal that differs from the others by focusing on the maximization of the electricity generated, subject to a specified level of variability. The model goes from being focused on a value measured in monetary units to using physical units of production. The analyzed portfolio still consists of production

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[9] *Return* $= -\frac{(Y_t - Y_{t-1})}{Y_{t-1}}$. This is a negative index of change in production costs. An increase in them would represent a negative return. The objective is to minimize said increase.

[10] The unmanageable nature of wind energy would cause it to be considered a negative load factor, and one to be subtracted from the total demand. Once subtracted, we would have the net demand, which must be covered by non-renewable energy plants.

[11] Net demand: total demand minus wind generation. They follow the proposal by Delarue et al. [33] and consider wind production as a negative demand, due to the fact that it has zero marginal costs of generation. Wind energy has a negative load. Variability passes from the offer side to the demand side.

Table 5
Approaches based on electricity production criteria.

Author	Objective function	Constraints	Horizon	Territory	Data origin-source	Analyzed technologies
Roques et al. [32]	Return of production Maximization	National wind resources: potential and transmission	2020	Austria, Denmark, France, Germany and Spain	OeMAG; REE; ERDF; TSO Energinet; TSO ENBW; TSO RWE; TSO EON; TSO Vattenfall	Wind Energy
Rombauts et al. [34]	Return Maximization and Risk Minimization	Cross-border transmission-capacity	N/A	N/A	KNMI (Danish Operator)	

technologies, and the studies usually incorporate restrictions related to the amount of production generated and the production that can be assimilated by the system. One of the earliest works in this line is that by Dunlop [61], who studies the possible diversification of a wind farm portfolio for the European Union and the United States. There are two recent studies that stand out in this category: one by Roques et al. [32] and another by Rombauts et al. [34], both linked to wind energy production (Table 5).

The model proposed by Roques et al. [32] seeks to identify the portfolio consisting of those European plants (inter-State[12]) that minimize the variability of the wind production output for a specific production level. They propose an alternative definition for return, referring to it as the mean capacity factor for the different locations. Risk is defined as the hourly variability of production [34].

The proposal lies in optimizing the balance between maximizing wind energy production (the capacity factor) and minimizing the variability of production associated with this type of technology through geographical diversification. The authors suggest two objective functions: one minimizing the variability of electricity production or a certain level of production, and another maximizing the contribution made by wind energy to system reliability (per unit of installed capacity), only minimizing variability during peak hours of demand.

Both propositions incorporate the correlations between countries in relation to wind energy production, which makes it possible to diversify the portfolio by combining wind energy production locations with a weak positive and/or negative correlation.[13] For each of the two models, two alternatives are established: one without restrictions and another with restrictions on capacity per country (the member state's technical wind energy potential) and grid interconnection limitations. They propose an improvement based on the work of Drake and Hubacek [62], contemplating the variability of hourly wind production instead of obtaining this from data time series directly.

The authors draw from the important problem of intermittency costs to propose a focus centered on geographical diversification as a tool to find the portfolio that maximizes electricity production through the inclusion of wind energy and minimizes the variability of the production, thus attaining the least intermittency of production.

Rombauts et al. [34] attempt to explicitly measure[14] the effect of the restrictions derived from the *Cross-border transmission (capacity constraints),* exclusively available for wind energy flows. The objective focuses on the definition of efficient wind energy locations that reduce variability to minimal levels. They propose three models of inter-state wind energy transmission capacity: unlimited, zero and limited. Each model is applied to three sample member states. They base their model on the proposal made by Roques et al. [32], according to which the expression of production is determined by the mean capacity factor for each of the countries and the risk is the function of the variability in hourly production. They expand the capacity of the model by Roques et al. [32] based on the inclusion of cross-border transmission capacity constraints in order to better assess the management of electricity derived from wind energy. The portfolio risk is calculated according to the different shares of the countries, along with their respective standard deviations and the correlation coefficients of their produc- tions. An attempt is made to find the combination of shares from the countries that minimize the risk of the hourly differences in output.

4. Discussion

The intent of this section is to examine in greater depth the contributions made by the literature reviewed, through the analysis of the following aspects of interest: the main limitations to the application of MPT methodology to the energy planning problem; the concept of risk and its definition as an essential part of all MPT planning; the most salient methodological contributions and the most relevant conclusions from the studies in relation to the importance and the positive impacts of including RES technologies in the portfolio, such as the reduction of risk; and the system requirements in order to incorporate them.

4.1. Limitations to the application of MPT methodology to energy planning

The limitations of this type of methodology, as applied to energy planning, lie in the different nature of the assets: real assets (power plants), as opposed to financial assets. The definition of the energy asset selection problem as seen through Markowitz's [10] original approach requires certain conceptual adaptations to be made. The portfolio model requires less-than-strict compliance with the portfolio theory hypotheses regarding market efficiency [9,11,14,16,19,29,30,38,63–65]. It is thus assumed that there are discontinuities in the power generation markets, problems with the liquidity of generation assets and the length of time required to recover the investment. There are also difficulties related to the different degrees of replacement in terms of the fuels and technol- ogies, the divisibility of the investments in the field of energy, the inefficient operation of the electricity markets, the indivisibility of the assets, the non-existence of taxes and commissions for transactions and the failure to incorporate the costs related to changing over from an inefficient portfolio to an efficient one. In spite of the existence of the aforementioned limitations, a proper definition of the problem, the restrictions or objective functions considered by the model, and the processing of data from quality, internationally relevant sources, govern- mental bodies and system operators could partially overcome the aforementioned limitations.

Hickey et al. [9], Kruyt et al. [63] and Kumar et al. [38] refer to the critique of the portfolio approach by Stirling [64,66]. According to Stirling [64–66] in an environment predominated by a lack of knowl- edge that affects the diversification and security of supply, using only historical data to support the portfolio model might lead to erroneous results. Portfolio theory, a probabilistic technique, is based on the capacity of the numeric model to explain future events. However,

[12] The entire set of generation plants in the Member States constitute a single wind park.

[13] They point out the decisive role played by the inter-state wind energy production correlations previously identified by Drake and Hubacek [62]. Accordingly, a lower or negative degree of correlation among states would lead to a reduction in the variability of the portfolio, as the result of the production balance provided by the different geographical regions. The counterpart would be the increase in system maintenance- reliability costs.

[14] It differs from the proposal made by Roques et al. [32] in that the limitation is included in the form of a restriction.

Stirling defines the energy problem based on two elements: the lack of knowledge (regarding possible benefits) and uncertainty. Both ele- ments are indications of a situation in which it is impossible to assign probabilities or to establish future collections. This is the reason why portfolio theory is only accepted by Stirling in the context of risk mitigation in which the probabilities and returns are defined and known and all the information available would be used to identify the optimum portfolio. Based on Stirling's indications, Hickey et al. [9] propose evaluating the reliability, security and flexibility of the electricity offer portfolio based on three possible methodologies: portfolio theory, real options theory and diversity measurements (Shannon-Wiener and Herfindahl-Hirschman indexes). The authors defend the application of portfolio theory for its capacity to mitigate the risk of the portfolio, which leads to greater reliability, minimizing the possibility of supply disruptions. The real options methodology, in turn, is contemplated as a financial tool that complements the evaluation of the energy asset investment problem, based on dis- counted cash-flows. It could provide flexibility in the case of invest- ments in capital-intensive infrastructures. Roques et al. [26], however, see less potential for this methodology, ensuring that the flexibility that it provides is less (in terms of an asset) than that which comes from applying portfolio theory (a set of assets) and an optimum portfolio approach. Kumar et al. [38] later define a proposal focused on the total risk of power generation, assuming the limitation that the probabilistic model does not take into account possible negative events that cause interruptions in the system. In spite of these conditioning factors indicated for MPT, which uses past events to explain the future when defining the expected return-risk pair, it stands out as a relevant methodology in the literature.

It has also been observed that Portfolio Theory has a certain limitation when it comes to assessing the impact of the inclusion of renewable technologies in the portfolio. Even though RES are char- acterized within the portfolio approach according to their economic cost-risk, there are other relevant attributes that must also be included. Among them are the environmental contribution, job stimulation and the economic development of rural areas and improved energy independence of the region [2,4,42,43,55,67]. The difficulty in model- ing cash-flows for the environmental and energy security dimensions makes it difficult to include them in the models [2,42,68].

One of the options to overcome this limitation could be the inclusion of externalities in the technology cost structure. This would permit reducing part of the cost distance between polluting technologies and renewable energies [3,21,39,42]. Numerous articles have included both carbon dioxide emissions costs [16,19,25,26,35,37–39,42,44,46,48,52,53,57,58,69–71] and externalities [20,21,28,39,42]. In particular, Arnesano et al. [39] distinguish between direct emissions costs linked to power generation and indirect costs incurred during the construction process and the elaboration of the materials used for the installation. In addition, there are studies that propose considering the CO_2 emission limits for the portfolio [35,38] and those of this and other pollutant gases and particles (SO_2, NOx, PM) [42]. Lucheroni et al. [71] define a portfolio CO_2 emission rate in order to compare the emission levels of the portfolios. It has thus been confirmed that by introducing cost or quantity variables related to CO_2 emissions and externalities, renewable technologies become more attractive through the approximation of costs to those of non-renewable sources and the non-polluting nature when meeting emissions reduction objectives.

When calculating the risk of a technology or portfolio, it is necessary to estimate the standard deviation, variance and covariance values. This can be done based on historical data from statistical series related to asset performance, assuming future representativeness based on past events. This way, the means, variances and covariances for the population will be estimated based on available sample values. However, the application of portfolio theory to real power generation assets encounters certain limitations in terms of the availability of series of historical data on the types of costs for each technology [11,21]. To remedy this, some authors opt to set proxy variables [11], while others [14,21,33,39] choose to assume the data proposed by Awerbuch and Yang [30] related to correlations between O & M cost types. Yet another group of authors turn to simulation to infer the subjective probability distributions of the asset costs [71], returns [26,44] and power production [33,34,40], as well as the set of variables considered in the model [37].

4.2. *Risk management in energy portfolios*

The agents who participate in the electricity market are subject to uncertain factors that determine their situation (costs, demand func- tion, prices, system operation, regulatory measures, etc.). From the perspective of investors (electrical companies), the risks affect different elements in the form of uncertainty and variability, including financial and regulatory aspects, those related to climate change, the social acceptance of certain technologies, conditioning factors related to energy security and transaction costs [35]. Allan et al. [14] point to the existence of other types of risk, such as those related to uncertainty in relation to demand management when incorporating electricity generated in a non-manageable, intermittent manner through renew- able sources, the high costs of incorporating renewable energy into the system and the risk derived from regulatory or policy changes. Along these lines, Hernández-Escobedo et al. [72] indicate the presence of risk in relation to the difficulty to make short and long-term predictions with regard to RES. Other authors like Huang and Wu [56] opt for a more reduced classification of the risk, consisting of only three elements: fuel price volatility, the uncertainty of technological change and capital cost cuts. Cuixia et al. [16] opt to present a double definition of risk for technology portfolios: in the traditional sense, derived from cost and price fluctuations and that corresponding to new technologies defined based on the fluctuation in the volatility of the feed-in tariffs for RES technologies. Van Zon and Fuss [60] indicate that the elements determining the risk (cost volatility) of the portfolio in the electricity sector are the price of the energy resources and the uncertainty regarding technological evolution. Escribano et al. [4] propose an interesting diagram divided into three overarching concepts to define energy risk: primary risks (geopolitical and technological), secondary risks (price variability, supply disruptions, environmental risk and the risk to society) and vulnerabilities that affect the energy intensity, the energy mix, suppliers, users, etc. These proposals go beyond that initially made by Awerbuch and Berger [11], which was based solely on the variability of the technology costs (investment, fuel and O & M).

Risk management consists of reaching the desired equilibrium between return and risk through a negotiation strategy Liu and Wu [73]. In light of these risks, agents may opt for one of two types of actions when it comes to risk management: *risk control* and *risk assessment* [73]. Risk control is achieved by taking coverage actions that permit compensating for or hedging the risk in the event of a possible loss (with forward or future contracts) or through an optimization of the portfolio that achieves better diversification [21,30,35,36,42,47,73,74]. The optimization problem, in turn, can be solved using the Decision Analysis or Modern Portfolio Theory technique. Alternatively, risk assessment can be carried out through *Asset Valuation* (financial option model and real options model) and *Risk measurement* measures, such as Value at Risk (VaR), which measures the expected value of the loss for the portfolio, taking into account a certain level of confidence for a set time horizon.

As indicated, the MPT methodology allows the risk of the portfolio of power generation assets to be controlled based on the maximization of return or the minimization of risk or cost. Authors such as White et al. [54] and McLoughlin and Bazilian [75] choose to include MPT methodology in the long-term energy planning of the resources in order to control the overall risk of the portfolio.

Portfolio analysis is based on the individual study of each financial asset and ends with the selection of the portfolio that best matches the profile of the investor (characterized by differing levels of risk aversion) from among all the portfolios proposed by the model. The study of the assets is based on the analysis of the past behavior of each asset in the market and on the estimated future behavior performed by analysts and experts. This analysis is characterized by the uncertainty regarding the future behavior in the market of each asset, as well as the correlation between assets. Both aspects make up the portfolio risk, which can be reduced, thus achieving greater diversification.

The initial approach of portfolio theory analyzes the financial assets, characterized by the ease of exchange, through the prism of profitability and risk. In the latter case, the correlations between the profitability of the assets are especially relevant. In the area of financial investment, portfolio theory considers the historical behavior of the variables to be a useful indicator of future volatility. Therefore, in its application to the field of energy, risk would be determined by the variability in the expected values for the parameters considered to define each technology and is expressed through the variance σ_p^2 or standard deviation σ_p of the returns or past periodic costs of the technologies [11,19,75]. The inclusion of the relationships among the different parameters of alternatives through the covariance matrix results in an improvement in the model estimate, which increases the robustness of the solutions as compared to the arbitrary combination of alternative technologies [7]. This is demonstrated in the variance formula for the portfolio return shown below:

$$\sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} X_i X_j \sigma_{ij} \tag{8}$$

Where σ_{ij} represents the covariance of the returns of the assets i and j, and ρ_{ij} (Eq. (8)) is the linear correlation coefficient for the returns of the assets i and j. This correlation coefficient has a value between −1 and , with intercorrelated variables having the value 0. Accordingly, the investor will be able to diversify the risk of its portfolio more effectively if the expected returns of the assets of which it consists are not highly correlated with one another.

Recently, some authors [50,59] have opted to approach the study of technology portfolio risk based on the proposal made by Sharpe [76] and his market model. According to Sharpe's [76] proposal, the variance formula (Eq. (9)) for the return of a financial asset with a risk (σ_i^2) would be determined by two risk components: the systematic component ($\beta_i^2 \sigma_M^2$), determined by the market in which the asset is traded, and the non-systematic or specific component of the asset, which is influenced by fluctuations from outside the system and specifically related to each of the assets that makes up the portfolio:

$$\sigma_i^2 = \beta_i^2 \sigma_M^2 + \sigma_{\varepsilon i}^2 = \textit{systematic risk} + \textit{specific risk} \tag{9}$$

The specific risk can be reduced or eliminated through diversifica- tion based on the distribution of the investment budget among several assets instead of dedicating it to a single asset [76]. The reduction in the case of the systematic component, in turn, is lower and cannot be canceled out. For this reason, the relevant risk to evaluate is no longer the overall risk, rather the non-diversifiable or systematic risk. This is a move away from the perspective of a portfolio composition based on a single asset and opts for its combination with other securities.

In this context, according to [24,37,59], it would be possible to propose a classification of the different risks related to the investment in power generation assets according to the MPT proposal regarding systematic and specific risks. In this regard, systematic risk is understood to be that derived from economic growth and regulatory-political factors, as well as those associated with electricity market operations and technological factors associated with the systems supporting the development of certain technologies. Specific risk, on the other hand, refers to those factors related to the size of the portfolio and the diversity of the technologies present in it, with control over the costs and cost overruns derived from power generation. In this sense, Marrero *et al.* [59] propose an approach intended to provide better management of systematic risk. Although they present a mean-variance model of optimization, they also base it on CAPM, a model according to which the market only compensates for the systematic risk assumed by the investor, as measured by the portfolio beta, β_p [15]. The authors determine the systematic risk, taking into account time varying betas. This allows them to analyze the trade-offs in risk management from an energy policy perspective.

Alternatively, Gökgöz and Atmaca [50] indicate the suitability of opting for methods with lower partial moments to measure risk, which contemplate only negative deviations from the objective (variance also takes into account positive deviations). They observe that the mean-variance methodology presents less aggressive optimal solutions (lower profitability and less risk) than those using lower partial moments (downside and semi-variance) methods.

As previously mentioned, diversification of the technology portfolio will make it possible to minimize its non-systemic risk as a means to prevent or minimize the negative consequences derived from it [11,14,19,21,30,38,58]. This comes from the idea that a diversified portfolio would lead to more robust solutions and a greater level of supply security, and with this, to a lower risk of supply disruption [22,37,38,42]. Bhattacharya and Kojima [37] stress the positive effect of diversification over the short term in the form of a lower risk of supply disruption, and in the long term, as a facilitator of greater macroeconomic stability, if the region is highly dependent on fossil fuels (as in the case of Japan).

Stirling [65] defines diversification as an "irreducible property of a system" or as "a system attribute that can be divided into categories". There are three properties to characterize the diversification of a system: variety –the number of different categories that the system being analyzed divides in–, balance –the number of different elements in each one of those categories– and disparity *–the number of differentiated elements–*. Each one of these categories is necessary but not sufficient [66] and they are interrelated.

When measuring portfolio diversification, some authors [20,69] propose using the Shannon-Wiener and Herfindahl-Hirschman in- dexes to evaluation supply security. Stirling [65] and Chuang and Ma [22] provide good reviews of the concept and the different indexes of portfolio diversification.

It is possible to improve diversification by including RES technologies in a portfolio [11,19,21,25,30,35,38,39,42,47,69]. This would increase the level of potential diversification and would make it possible to distribute the risks among a larger number of alternatives [42]. One of the main causes determining portfolio risk comes from the strong correlation between fossil fuel prices and their variability [26,30,59]. In this context, Escribano et al. [4] stress that the flow of electricity produced by RES contributes to the increase in the diversification of the sources of the internal portfolio, to the geographical diversification of energy suppliers to the extent that a good interconnection system is achieved among the states, and to the increase in the means of electricity transport (alternating current and high voltage direct current lines). It would be a matter of taking advantage of the lack of correlation between the fuel costs for technologies that use fossil fuels and those that use renewable sources, the production of which depends on solar, hydro and wind energy sources [22]. This would reduce the risk of the portfolio [14,38,39]. In this manner, the introduction of RES in the portfolio makes it possible to reduce exposure to geopolitical risk and with it, possible supply disruptions.

Authors such as [4,11,29] stress the benefit of including RES in the portfolio, considering them to be risk-free technologies, since they have fixed costs with no standard deviation: their beta and specific risk would be zero. Thus, by including RES technologies in the portfolio, it

[15] The beta of portfolio p is defined as $\beta_p = \frac{\sigma_{p,M}}{\sigma_M^2} = \frac{\sigma_p \sigma_M \rho_{pM}}{\sigma_M^2} = \frac{\sigma_p}{\sigma_M}\rho_{pM}$. It is calculated based on the relationship between the covariance of portfolio and the market ($\sigma_{p,M}$), and the risk associated with the market itself, expresses in terms of variance: σ_M^2.

would be possible to reduce the risk through appropriate diversifica- tion. However, other authors propose the characterization of renewable technologies as assets that entail a risk derived from the market [54] or risks derived from the physical availability of the renewable flow used [39]. Another type of risk that these technologies would present is that related to the level of technological dependence on production factors [43].

However, the introduction of RES in the portfolio is not free of difficulties. The intermittent and non-manageable nature of RES technologies results in instabilities for the system and higher costs [32]. Rombauts et al. [34] propose in their study improving the cross- border transmission capacity among states to reduce the variability-intermittence of wind energy. Roques et al. [32] therefore opt to assign the locations of the wind farms in a more efficient and coordinated manner among the European states, in order to minimize the negative impact of the variability of wind production in Europe. Johansson [43] adds the improvement of the transmission grid, the installation of capacity reserves and increased storage (batteries or pumping). In any case, any of the options proposed would lead to higher portfolio costs in the form of maintenance costs to ensure the reliability of the system and its equilibrium [4,32]. At any rate, we are warned that as a type of technology that is different from the rest of the portfolio, the participation of RES technologies would be subject to diversification and optimization criteria. Accordingly, it has been shown that the participation of the different RES is preferable [55], but with limita- tions, if the aim is to minimize the risk [30,42].

In addition to the optimization technique on which the portfolio theory methodology is based, there is another technique very com- monly used in the electricity markets, related to risk control by private investors: the so-called hedging technique [36,49,77,78]. Price risk hedging in the spot market is carried out through the acquisition of derivatives (forward-contract purchases, futures, options, etc.) to compensate for possible losses that might occur. These contracts allow the investor to cover the risk related to the unavailability and/or high prices by establishing the price before the moment of availability. This allows the portfolio risk to be reduced. Safarzynska and Van den Bergh [79] reiterate the idea that the existence of a futures market makes it possible to maintain the benefits of the plant and reduce the volatility of spot prices. With it, it is possible to reduce the extent to which both production and the use of inputs are affected by fuel prices. Woo et al. [78] propose the hedging of the risk derived from the volatility of spot prices and the uncertain behavior of demand . They seek to determine the composition of the optimal portfolio of forward-contract purchases from local distribution companies. They attempt to answer three questions: how to obtain the best price, when to buy (contract) and how much to buy. Huisman [77] proposes a one-period framework to evaluate the optimal purchase locations for the both peak and off-peak forward contracts of a rational electricity purchaser who wishes to take a hedging position for price and risk.

As previously indicated, portfolio optimization attempts to find the assignment of energy assets that permits maximizing benefits and minimizing risks through diversification. In this alternative focus on optimization, two approaches are combined: those based on the physical delivery of the product (market contracts, operation of a spot market, etc.) and those that contemplate financial hedging (forwards, futures, options, etc).

4.3. Main methodological contributions

Different lines can be found in the literature in relation to the new methodological proposals that complement the application of MPT to the energy asset portfolios. In particular, methodological contributions have been made after the publication of the proposal by Awerbuch and Berger [11], although the literature generally considers the initial work to be that by Bar-Lev and Katz [27].

Awerbuch and Yang [30] point to a line of research that involves establishing a possible measurement of risk for individual technologies through the CAPM beta. This would attempt to index the risk of each technology in relation to the set of technological alternatives available. Marrero et al. [59] have done work along these lines, establishing how to obtain the betas by Rolling-OLS. They study the relationships between technologies and fuels and each market risk. These authors allege that oil prices condition the volatility of the electricity portfolios and transport, as they have found differences in volatility according to the systematic risk derived from commodity prices. Along these same lines, but beyond the scope of CAPM, Humphreys and McKlein [28] are concerned with measuring the impact of fossil fuel (oil, natural gas and coal) price shocks on the portfolio through a GARCH model. Dunlop [61] proposes another perspective on the variability of the Beta connections of the natural resource (wind), with its availability in specific locations (small and large wind farms).

Doherty et al. [51] try to evaluate the usefulness of MPT in producing diversified portfolios in light of the variability in fuel prices. To do this, they compare the results of the diversification concept study, using two approaches: portfolio theory and the Shannon-Wiener index. The consideration of this diversification index came about based on the critique by Stirling [66], who denied the capacity of MPT to evaluate diversification on the grounds that it is not appropriate when fluctuations occur and there is no well-defined explanatory pattern. Stirling [66] further indicated that diversification is a response to a lack of knowledge instead of a quantifiable risk. Doherty et al. [51] concluded that the solution provided by portfolio theory and the SW index can be considered to be similar. Chuang et al. [22] proposed using indexes that have evolved from the SW and Herfindahl- Hirschman indexes to measure the degree of diversification of the portfolios that make up the efficient frontier of an MPT model for Taiwan.

Some authors have attempted to incorporate improvements in their studies in terms of the estimates of the variables considered to generate the portfolios analyzed. Accordingly, Humphreys and McClain [28] proposed using time-varying variances and covariances estimated with generalized autoregressive conditional heteroscedastic models when developing their model. Krey and Zweifel [20] incorporate the correla- tions between unobserved changes, which improve the estimates of efficiency and influence the cost of the power-generating technologies. Krey and Zweifel [20] stress the importance of deriving estimates from the covariance matrix that are reasonably invariable over time. An attempt is made to ensure that the time series for the generation costs considered do not contain systematic changes when estimating the prediction values. They follow a Seemingly Unrelated Regression that consists of estimating the regression equations (one for each technol- ogy) and performing an OLS contrast, which is appropriate whenever there is a correlation among the errors of the different technologies. The method permits the simultaneous estimate of the expected returns of the generation technologies of a regression, taking into account the possible correlation of the leftovers of the equations (unobserved change components), and seeks to increase the efficiency of the estimate. Marrero et al. [59] estimate by rolling-OLS a CAPM model based on which they obtain efficient estimates and more robust constant betas. They also indicate how to proceed when analyzing the results, depending on whether it is energy technologies or commodities are considered, for which the time-varying estimation may result more or less appropriate.

A group of works use simulation in the absence of historical return or generation cost data [26,37,44,71] or as a measure to estimate the behavior of demand [26,33,34,40,70]. Bhattacharya and Kojima [37] highlight the potential provided by simulation, as it offers the option to generate multiple scenarios for analysis and makes it possible to work with variables, even if they are subject to uncertainty, given that it approximates their real values. From a methodological perspective, Roques et al. [26] use the Montecarlo simulation applied to a discount model of cash flows for investments in combined cycle plants using coal and nuclear energy to calculate the distribution of the profitabilities of the plants and their correlations. Previously, Rombauts et al. [34] based their work on the model proposed by Roques et al. [26] and added cross-border transmission capacity constraints to assess in greater depth the management of electricity derived from wind power. De Jonghe et al. [40] use simulation to obtain the Load Duration Curve within a Screening Curve methodology and to find the optimum mix of generation technologies in the context of perfect competition. Delarue et al. [33] demonstrate the application of the integrated investment model they propose through simulation. To do this, they use an algorithm that selects a number of weeks to generate the yearly load profile of the demand, and later use these data to apply the MPT optimization model. Bhattacharya and Kojima [37] include simulation within the process of optimizing the electricity supply portfolio in terms of expected risk and cost and when generating the share limits for the RES technologies in the model. Lynch et al. [44] propose a minimum cost approach for system maintenance, backed by simulation when obtaining the unit commitment and economic dispatch, instead of assuming the capacity factor. Lucheroni and Mari [71], in turn, use simulation to obtain the individual distributions of each LCOE per technology and for the portfolio within the proposed analysis. They base their decisions on fully stochastic LCOE theory in order to analyze the impact on the diversification of the price volatility for CO_2 emissions when deciding on the composition of the portfolio. They include the study of the impact of uncertainty on nuclear energy costs. This methodology represents an improvement when determining the LCOES, as it makes it possible to manage the risk derived from uncertainty in relation to the variables that determine the LCOES.

Likewise, a series of works can be found that propose a dynamic analysis of portfolio formation, as an alternative to the individual analysis of a static portfolio not subject to variations in production or demand. These works incorporate concepts related to the behavior of demand, the formation of the Load Duration Curve (LDC) within the power generation and management process [32–34,40,44,56,58,60,70] propose a model based on the demand side and use the Load Duration Curve to establish different demand blocks. Along these lines, De Jonghe et al. [40] establish a static linear programming investment model which includes operational constraints. Their proposal falls within Screening Curve Methodology. They propose an example of a portfolio that includes ramp rates, transmission interconnections and storage possi- bilities. They calculate the optimal number of hours of operation combined with the load duration curve. The generation input through wind energy is assumed as a negative load. These authors also evaluate the impact of the variability in the availability of this technology on the system. Delarue et al. [33] propose a dynamic multiple time-period approach from the perspective of power generation (dispatch power generation delivery). They base their work on an integrated investment model that includes actual load patterns based on both hour-by-hour loads and multiple time-period loads, as well as restrictions related to dispatch and ramp rates. The model optimizes the generation portfolio for a specified load period. In spite of it being a very complete approach, Lynch et al. [44] indicate that the approach used by Delarue et al. [33] does not allow for considering the commitment of generating units, and thus the model does not consider the variable costs derived from operations in the power generation plant, which is particularly relevant in the case of RES. In fact, Lynch et al. [44] offer an improvement in this sense, as they do not consider the production factors by default and they simulate unit commitment and economic dispatch based on a least-cost system approach. In this same vein, Peerapat and MacGill [58] establish an approach very similar to that of Delarue et al. [33] in order to incorporate into the proposed model the action electricity generated via renewable sources (wind, solar, run of river hydro) of a variable, non-storable and unmanageable-intermittent nature. Their aim is to deter- mine the existing capacity and the new capacity required for each of the portfolios generated. Finally, the works by Roques et al. [32] and Rombauts et al. [34] can be framed within another line of work related to the management of the electricity produced by wind energy and the evaluation of the system capacity to integrate it and minimize variability. In this manner, Roques et al. [32] propose a complementary approach to conventional system-planning models. They propose an improvement based on the work of Drake and Hubacek [62], contemplating the variability of hour by hour wind production instead of obtaining this from data time series directly. They focus on evaluating the impact of interconnection among the EU member states in terms of wind energy production. Rombauts et al. [34] use the model by Roques [32] as a basis, and include cross-border transmission capacity constraints to assess wind energy production.

When establishing what could be the current line of study, we could highlight the interest in including the decision-maker's perspective regarding the level of risk assumed. Accordingly, two of the latest works published in 2017 [35,50] attempt to incorporate the preferences of decision-makers through Multi-attribute Utility Theory Model [35] and Utility Function Maximization [50]. This is joined with previous studies [26,36,60] that work with different risk profiles of investors through the measurement of the risk aversion factor and its impact on the results of the utility function. In this function, the value of the return (or cost) of the investment is diminished (increased) by the risk, expressed in the form of variability (variance or standard deviation), weighted by the aversion factor to said risk. The intent is to maximize the utility function, thus obtaining results that contain information about the two main variables of the MPT model at the same time.

4.4. Main conclusions regarding the inclusion of RES in the portfolio

The literature review backs the hypothesis that RES participation contributes to reduced portfolio risk (to the lowest level) and improved portfolio diversification, without any increase [11,14], with an increase [37] or even a decrease in total portfolio cost [39]. Other studies add the improvement in energy density per unit of capacity and the conversion efficiency due to the inclusion of RES [56], derived from a high RES portfolio share. These authors confirm that the greater the aversion risk, the greater the positive effect is by introducing RES.

The reduction in the expected portfolio risk (and greater energy security) due to the inclusion of or increase in RES is related to a greater degree of diversification [2,4,30,38,42,43,67], as well as the non-existence of any relationship between the price change for fossil fuels and RES [11,30]. Studies relate the reduction of portfolio risk by means of an increased share of renewable energies to a reduction in foreign dependence of the analyzed region [23,42,48]. In fact, the combination of alternative technologies with negative correlation coefficients and/or those that are risk-free (non-correlated) [25] enables us to achieve lower portfolio risks associated with the volatility (fluctuations) of the price of imported fossil fuels and/or as the result of geopolitical events that might interrupt the supply [4,22].

There are a great many studies that confirm the possibility of achieving portfolio efficiency by means of a greater share of wind or other RES [11–13,20,30,33,35]. Indeed, incorporating wind energy reduces the expected risk [13,35] and even portfolio cost [12] in addition to increasing a portfolio's return [45]; it also permits the reduction of portfolio CO_2 emissions [30]. The incremental RES technology selected depends on the study:

- Wind energy in the U.S. and solar and hydro in the case of Switzerland (2003) [20];
- Wind and biomass energy in the Netherlands (2030, reducing the risk by up to 20%, and the cost by 4%) [19];
- Wind for EU-2020 [30];
- Wind for China in 2020 [25];
- Wind power and hydro power up to the limit for the EU-27 (2030) [42], with wind technology in a high wind availability simulated scenario [33];
- Marine technologies in the Scottish (2020) portfolios that have a

lower share limit for on-shore wind energy [14];

- Wind and mini-hydro energies (high prices scenario) or solar PV (reduced prices scenario) and thermoelectric technologies in a Spanish RES portfolio case (2010) [46];
- Solar PV with an 8–12% increase in the Chinese Portfolio (2020–2030) [16];
- Solar PV in Japan's portfolio [37];
- Geothermal and Wind in Mexican´s portfolio [35].

Additionally the maximum limit for RES in efficient portfolios also depends on the analyzed territory and the horizon:

- For Japan, the limit is between 1.37% and 9% [37];
- For the EU in 2030, this limit is between 34.5% and 43% [42];
- For Scotland in 2010, the share limits would reach 31% for on-shore wind energy and 5–10% for off-shore wind technology [12];
- For California in 2020, it would be possible to increase the share of RES from 20% to 45% without increasing the portfolio cost, with a maximum RES share of 64% [54].

Alternatively, in other studies, authors suggest the removal of some technologies from the portfolio, such as biomass and solar energies, the shares of which would not be guaranteed in terms of efficiency in the 2030 European portfolio [42].

In some cases, the increase in the RES share depends on additional aspects of energy policy, based on continued support in the form of governmental policy. In this way, different policy and regulatory actions have been proposed in order to achieve diversification [52,53], to promote off-shore wind energy in the Netherlands [19] and to promote solar energy in China, so that it reaches the expected level of development [16]. Among the measures to adopt to reduce the investors' risk [26], the following have been proposed: establishing rates or premiums, credit guarantees for investing and mechanisms to reduce the capital cost of investment. Bhattacharya and Kojima [37] suggest that the policies must seek to control the variability of fuel prices, rather than to reduce prices, as they condition the portfolio risk. For this reason, certain regulatory policies are needed in order to regulate government price support for fossil fuel procurement, fuel price protection and subsidies. Along these lines, other authors [47,55] indicate the need for support from the authorities in the form of legislation to achieve the effective incorporation of RES in the portfolio. Cuchiella et al. [47] advocate the continuity of the support for Solar PV in order to achieve its profitability. Guerrero-Lemus [57] observe complementarity among the energy policies for fossil technologies, biofuels and electricity in the transport sector. Their combination should permit some reduction in dependence and increase diversifica- tion, while reducing pollutant emissions. Kumar et al. [38] indicate the need to include a measure in MPT studies that takes into account the complementary costs or barriers to configuring technology portfolios. These costs would include the availability of space, resources and infrastructures and the impact of public policies.

In other cases, CO_2 emission prices are fundamental in the construction of efficient portfolios, the inclusion of non-pollutant technology shares and the achievement of emission reduction goals [58,70]. Some studies relate the increase in the wind energy share (limit of 22%) to the inclusion of emissions costs in the model [52,53], or claim that the position of RES and natural gas depends on a high CO_2 price, as well as security of supply [19]. In Scotland, a 5% share of off-shore wind energy would reduce the risk, without increasing the total cost in the case of the high gas prices scenario [12]. Arnesano et al. [39] indicate a €35 limit for CO_2 cost in order to achieve no variation in the portfolio shares. Likewise, some studies alert that failing to incorporate RES leads to greater risks (10%) [19], and that an excessive increase in the share of RES leads to an increase in the portfolio risk [54]. Bhattacharya and Kojima [37] claim just the opposite, confirming that the price of carbon has not influenced the decision to invest in RES.

Nuclear energy is an available alternative among the different technologies in the portfolio. Its non-pollutant emissions and its consistent cost structure (without considering externalities) make this controversial technology a preferred option [25,30,35,42]. Moreover, this technology presents the minimum economic risk, as in the case of China [25]. In the case of Taiwan [56], nuclear energy is the best alternative to reduce the portfolio risk related to the limitation on the development of RES, while in Italy, the inclusion of nuclear energy (with a limit of 36%) would result in a reduction of 66% in the installed capacity linked to fossil fuels [39]. Lucheroni and Mari [71] indicate that the volatility of CO_2 prices is what encourages investors to increase the share of nuclear energy in portfolios with coal and gas. For the EU- 27, nuclear energy is considered a preferential technology (even including externality costs), as its shares reach the maximum possible limits [42]. In order to minimize the risk, the share of nuclear energy must be increased in the Swiss and U.S. portfolios [20].

Many studies include comments about system requirements in order to take on increased RES production. In fact, the increase in the wind portfolio share necessitates a greater degree of flexibility and the appropriate development of technical requirements [32–34,40]. Delarue et al. [33] indicate that the introduction of wind energy must be accompanied by additional rampable technologies. Roques et al. [32] propose a combined production from among the different EU member states, as well as a coordinated European action in terms of policies and systems of incentives: wind farms must be installed in the best geographic locations identified on a European level. Following this idea, Rombauts et al. [34] confirm that the increase in inter-State transmission capacity shifts the efficient frontier to the left, which leads to a lower overall risk and increases the diversification effect on the portfolio. However, the optimal transmission capacity to be maintained will depend on the return-risk and cost-benefit balance that this capacity returns. In this case, De Jonghe et al. [40] point out that it is possible to adapt the total installed capacity to the optimal capacity needed, thanks to a greater capacity for interconnection and energy storage. The base-load plants should be gradually replaced with medium-load plants, which have a lower impact from the starting factor. In another case, Roques et al. [32] focus their study on the role of wind power. They propose minimizing the variability of wind power or maximizing the contribution of wind energy production in order to achieve greater system reliability during peak demand hours.

The assessment of the portfolio efficiency includes the combination of RES with conventional fossil fuel technologies. In fact, natural gas is presented as a preferred conventional technology [13,26,31,33,52,53] and it complements the share of RES in the portfolio. Doherty et al. [53] point out that the combined gas cycles are the least expensive alternative for both low and high emissions cost, while Roques et al. [26] associate a high share of natural gas (100%) with an intermediate degree of aversion and a correlation greater than 70% between the price of electricity and natural gas. Marrero and Ramos [23] confirm that the minimum risk portfolio for the Canary Islands should be formed mainly by natural gas as the main source, and a share of wind energy up to its limit. This combination permits a decrease in costs, risks, dependency and emissions. However, other authors identify this technology as one of the riskiest technologies, due to price volatility and higher related costs than nuclear energy [25].

5. Conclusions

The work presented here consists of an exhaustive review of the literature in relation to the application of MPT methodology to the field of energy planning and electricity production. In line with the objectives set out in the first section, a new classification has been proposed, from a financial perspective, based on the selection of long- term investments from the preceding studies. It delves deeper into the explanation of the limits to the methodology and into the key concept of risk, from both a financial and an energy perspective. The main methodological contributions found in the literature have been reviewed, indicating the conclusions of the works analyzed in terms of RES technologies and the policy implications derived from them. According to our findings, and as a corollary, the following conclusions can be drawn from our study:

- The MPT methodology stands out for being simple to apply and for the characterization of the variables based on a trade-off that includes risk. This constitutes an undesirable variable, and thus decision-makers, with differing degrees of aversion, try to reduce it or minimize it through the portfolio optimization process. As a risk-control methodology, MPT attempts to achieve the best diversification possible among the alternatives analyzed, and therefore, to find efficient portfolios.
- A review of the literature shows that there is no single focus in terms of defining the type of efficient frontier. Studies can be found that are based on economic criteria and on electricity production criteria.
- The studies that are based on the application of economic criteria produce both return-risk frontiers (return measured as the inverse of cost, NPV, IRR) and cost-risk frontiers. Risk is expressed through the variability of the returns/costs for the set of technologies. The models based on production criteria consider the expected value of average production and variability of electricity production
- The application of modern portfolio theory (MPT) to energy planning has been widely accepted, and confirmed by numerous studies. However, its limitations in terms of the different nature of the assets analyzed (financial vs. real) are accepted by the authors. The contributions of the studies have attempted to improve their adaptation to the field of energy through demand-side models and simulation techniques. Likewise, the inclusion of externality costs and portfolio emission factors favor the correct characterization of the technologies in the models and approaches with a social dimension.
- The studies generally consider that the inclusion of RES technolo- gies favor the reduction of the portfolio risk; to the extent that their geography and the system capacity to integrate the electricity generated by them so permit. The introduction of RES technologies in the portfolio is conducive to approaching efficiency. By incorpor- ating them, the economic risk of the portfolio is reduced, as are the risk of supply disruptions -as the result of greater diversification-, and the environmental risk -due to a reduction in pollutant gases-.
- There are two main points of view on how to handle the risk associated with RES technologies: as risk-free technologies, since they do not use fuel, or technologies with economic risk, expressed through intermittency costs or incomplete availability due to climate and weather behavior.
- The decision to incorporate RES technologies (essentially, wind energy) in the portfolio implies giving the system greater flexibility. Power plants must lean towards those with a lesser impact on the starting factor. A commitment is made to greater flexibility in interconnection capacity between states, and to storage in order to increase the share of RES technologies in the portfolio. However, it has been seen that an excessive share of this type of technology could increase the portfolio risk through instability or system imbalances.
- In scenarios characterized by high fossil fuel prices or CO_2 emission prices, the introduction or increase in the share of RES do not necessarily lead to an increase in the cost of the portfolio, in spite of high individual costs for RES technologies. In these scenarios, nuclear energy tends to be considered the technology with the lowest cost, and thus an alternative to RES to reduce emissions.
- The technologies with the greatest risks are those that are based on the use of fossil fuels: natural gas, petroleum and derivatives are usually subject to a high degree of price variability. Coal and natural gas have the lowest costs (as the most widely used technologies), as long as emissions costs are not included.
- The studies agree that the increase in the RES share depends on additional energy policy aspects (normally based on a continued governmental policy support); for example, giving premiums or credit guarantees for investment, controlling the variability of fuel prices and establishing a coordinated policy in order to position RES technologies in the best places.

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