Power generation and pollutant emissions in the European Union: A mean-variance model

Fernando deLlano-Paz (a), Anxo Calvo-Silvosa (a), Susana Iglesias Antelo(a), Isabel Soares (b)

a Universidade da Coruña, Faculty of Economics and Business, Department of Financial Economics and Accounting, Elviña Campus, Postal Code: 15071 A Coruña, Spain

b University of Porto, Faculty of Economics and CEF.UP. Rua Dr. Roberto Frias, 4200-464 Porto, Portugal

Abstract

In this work, portfolio theory is applied to efficient electricity generation from both an economic and environmental point of view. The proposed model includes all the generation costs for different technologies, including externalities; the risk derived from them, and a set of constraints on the emission of pollutant gases, such as carbon dioxide, sulphur dioxide, nitrogen oxides and particulate matter. Our results show that the EU technology portfolio, as proposed by the International Energy Agency for the 2030 horizon, is far from efficient. The joint cost-risk-environmental perspective confirms the need to increase the share of renewable energy technologies in the European energy mix, including photovoltaic energy, and to promote wind power as much as possible, to reduce the environmental impact. It is also necessary to continue to rely on hydro, CCS and nuclear technologies, in order to optimize the cost-risk tradeoff and the security of supply. In addition, it is concluded that restrictions on other pollutant gases should be also imposed, because they would contribute to reducing the environmental impact, with a relatively small increase in terms of cost-risk.

Keywords: Portfolio theory Energy planning, Environmental impact Power generation Pollutant emissions

ABBREVIATIONS: CCS, Carbon dioxide Capture and Storage; CO2, Carbon dioxide; EU, European Union; EU-ETS, European Emission Trading System; GHEH, Gases Harmful to the Environment and Human Health; MWh, Megawatts per hour; IEA, International Energy Agency; NP, New Policies Scenario; CP, Current Policies Scenario; 450, 450 Scenario; IPTS, Institute for Prospective Technological Studies; NOx, Nitric oxide and nitrogen dioxide; O&M, Operation and Maintenance; RES-E, Renewable Energy Sources for Electricity; PV, Photovoltaic; SO2, Sulphur dioxide.

1. Introduction: energy planning, portfolio theory and the importance of carbon emission reduction

The power generation challenge in each territory must be characterized by safety, cost efficiency, environmental protection and system reliability. Altogether, this will allow for the maintenance of competitiveness and ensure the sustainability of a key process in the economic and social development of the territory in question. In this line, the future portfolio design of power generation technologies would determine a country's role in terms of dependence on outside resources, the energy security level of the territory, and the social and environmental impact derived from the use of the different technologies in the power portfolio. The definition of the power generation technologies portfolio is therefore one of the most relevant decisions within strategic future energy and environmental planning.

A great many authors have used the initial proposal suggested by Bar-Lev and Katz (1976) and have developed and been inspired by other authors, such as Awerbuch (Awerbuch and Berger, 2003; Awerbuch and Yang, 2007) and Delarue (Delarue et al., 2011) to study the energy problem posed by power generation. This approach considers energy planning as a problem of long-term investment selection. Within this approach, the opportunity arises to use quadratic optimization methodology from Markowitz's portfolio theory (1952), which is based on the performance-risk tradeoff. In the energy context, it is usually based on the cost-risk tradeoff, thus making it possible to estimate the power production cost of the available technologies, as well as their risk, understood in terms of cost variability.

One relevant factor when determining the generation technologies lies in the consideration of externalities. This work follows the lines initiated by several previous studies on portfolio theory and energy planning (Humphreys and McClain, 1998; Krey and Zweifel, 2006; Arnesano et al., 2012; De-Llano et al., 2014; DeLlano-Paz et al., 2015) with regard to the inclusion of the externality costs derived from power production in the cost structure of the technologies. It is a matter of adding in those costs not taken into account by the integrated power companies (except for those related to CO2 emissions), including potential damages to ecosystems and society, which have a negative effect on well-being and public health (Liu et al., 2016; Garg et al., 2016). The intent of this is to partially correct the possible market error derived from not considering these costs, which are borne by society and the environment (Eyre, 1997; Schultman et al., 2001). As a result, the costs of pollutant technologies increase, and the difference between them and renewable energies decreases, thus improving their competitiveness. In addition, observation is made of the interest on the part of authors who use portfolio theory models to include CO2 emissions market cost (Peerapat Vithayasrichareon and MacGill, 2012; Lynch et al., 2013; Cuixia et al., 2014; Marrero et al., 2015; Jano-Ito and Crawford-Brown, 2017; Guerrero-Lemus et al., 2012; Lucheroni and Mari, 2017) and to study the impact of CO2 cost variability in the composition of efficient portfolios (Peerapat Vithayasrichareon and MacGill, 2012; Lynch et al., 2013; Kumar et al., 2015; Lucheroni and Mari, 2017).

The emission and concentration of pollutant gases have a negative and harmful impact on human life and the environment (DeLlano-Paz et al., 2015; Ghaith and Epplin, 2017; Cucchiella et al., 2017). The deforestation (Shen et al., 2016) and the use of fossil fuels in association with industry, transport and the generation of electricity represents the main cause of pollutant gas emissions (Wang et al., 2016; Chen et al., 2017; Kopidou and Diakoulaki, 2017). Recently, in 2015, the global carbon emission atmosphere concentration rose to 401 ppm, up from 312 ppm in 1950 (Ghaith and Epplin, 2017). This has resulted in a 1.02 o C increase in the average global temperature between 1900 and 2015 (Zeng et al., 2017b). There are numerous negative effects of this concentration: the global warming of the earth's surface, the rising sea level, air pollution, acid precipitation, pollution of the oceans and ozone depletion (Omer, 2008; Panwar et al., 2011; Hernandez-Escobedo et al., 2010; DeLlano-Paz et al., 2015; Marron et al., 2015; Zeng et al., 2017b).

In order to reduce these negative processes, territories can establish efficient measures that mitigate the negative externalities of climate change (Cretí and Joe€ts, 2017): national/regional emission reduction targets (Marcantonini and Valero, 2017), carbon trading mechanisms (Zeng et al., 2017a; Marcantonini and Valero, 2017) or a specific carbon tax per consumed kWh on household electricity (Ghaith and Epplin, 2017), among other energy policy measures. As a matter of fact, since 1990 greater environmental sensitivity has been observed by different countries. This takes shape based on the development of environmental policies and the creation of institutions that oversee environmental protection (Botta and Kozluk, 2014; Andersson, 2018). It constitutes the greatest challenge faced by the current generation (Zeng et al., 2017a; Damsø et al., 2017). From an economic perspective, there is talk of a low carbon economy (Cao et al., 2017), which takes advantage of the business opportunity presented by the current environmental trend (Piecyk and McKinnon, 2010; Wu et al., 2017; Yang et al., 2017).

There are, however, negative effects derived from the imposition of climate change policies. Among them is the so-called carbon leakage effect (Antimiani et al., 2013; 2016), which occurs as the result of possible distorting effects in the economy caused by the delocalization of companies to countries with more relaxed or non- existing environmental regulations in terms of emissions (Antimiani et al., 2013, 2016; Andersson, 2018). However, authors like Wu et al. (2017) present their doubts about the evidence of this relationship.

Considering the environmental objective sought by the low carbon economy, there are two key elements to consider in the analysis: the carbon intensity of the economy and energy savings (Wu et al., 2013; Renner, 2014; Zeng et al., 2017a). For this reason, analysis based on energy utilization and energy efficiency indexes has become more relevant (Meng et al., 2016). Along these lines, we see the work by Zeng et al. (2017b), who analyze the development of renewable energies in the BRICS countries through the study of the financing models used and the perspective of the theory of technological innovation systems. These authors indicate that the net increase of 1 percentage point in the level of electricity production using renewable energies (excluding hydroelectric technology) reduces carbon emission intensity by 0.16 points. Likewise, it should be noted the study of Wang et al. (2016), who review the GHG emissions derived from industrial sectors in China, particularly for the pulp and paper sector, which is highly intensive in terms of pollutant emissions.

Other authors such as Zeng et al. (2017a) enrich the analysis by using a structural vector autor regresive model (SVAR) to study the influence of the different factors conditioning carbon emissions trading and prices: policy factors, internal and international energy prices, macroeconomic variables, etc. Examples of these factors would be on a macro level (economic activities, economic recession, and energy, renewables and environmental policies) or on a micro level (different energy sources and power prices in particular emission trading markets). These authors also conduct an exhaustive and interesting review of the different methods used to study the effects and factors related to carbon emissions. Another methodology that is widely used in this field is Data Envelopment Analysis (DEA). In Meng et al. (2016), we find an exhaustive revision of employing Data Envelopment Analysis (DEA) in order to measure regional energy and environmental efficiency in China. The authors propose a series of recommendations from a methodological and empirical perspective related to the use of the DEA methodology.

From the perspective of portfolio theory applied to real electricity generation assets, a greater diversification level of the energy portfolio of a territory ein terms of sources and suppliers- and the introduction of a higher RES share in energy mix would permit the achievement of emission reduction targets, due to the absence of using fossil fuels in RES (Awerbuch and Berger, 2003; Jansen et al., 2006; Awerbuch and Yang, 2007; Zhu and Fan, 2010; DeLlano-Paz et al., 2015, 2017; Zeng et al., 2017a, 2017b). In addition, RES allows regions to reduce the energy dependence thanks to their autochthonous character (Panwar et al., 2011; Escribano et al., 2013; Cansino et al., 2015) and increase their power supply security level in terms of reducing a supply breakdown produced by geopolitical reasons (Chuang and Ma, 2013; Escribano et al., 2013). For all these reasons, the establishment of emission reduction objectives facilitates the achievement of a solution for challenge presented by the energy and environmental problem. As a result, energy security, economic development, technological innovation and environmental protection, as parts of the energy challenge, are benefited by the consideration of emissions reduction target (Chuang and Ma, 2013).

Some recent studies employing portfolio theory (Kumar et al., 2015; DeLlano-Paz et al., 2015; Jano-Ito and Crawford-Brown, 2017; Cucchiella et al., 2017) indicate the need to include data related to pollutant gas emissions and to establish pollutant gas emissions limits in the analysis. For example, the works by Kumar et al. (2015) and Jano-Ito and Crawford-Brown, 2017 consider CO2 emissions, and the study by DeLlano-Paz et al. (2015) also includes other pollutant gases and particles, such as SO2, NOx, and PM, and proposes emissions reduction limits according to European regu lations. Lucheroni and Mari (2017), in turn, compare the portfolio's CO2 emission levels based on an emission factor similar to that described in DeLlano-Paz et al. (2015).

The present work delves more deeply into the study proposed by DeLlano-Paz et al. (2015). It intends to apply a portfolio theory approach to real power generation assets to determine the composition of an efficient power generation technology portfolio containing both renewable and non-renewable energies. This work focuses on the study of efficient energy planning in the European Union for 2030, thus examining one of the leading regions in the implementation of renewable energy sources (hereinafter, RES) for power generation and in climate policies. It studies the impact that a more restrictive emissions reduction policy would have on the power generation technology portfolio at a European level, also including reduction objectives for CO2, SO2, NOx and PM. The se lection of these gases stems from the negative effects they have for both the environment and humans (Mayer et al., 2017). Some effects, such as global warming on the Earth's surface, the rising sea level, air pollution and ozone depletion are produced by the concentration of these gases in the atmosphere (DeLlano-Paz et al., 2015; Liu et al., 2016). The proposed work is based on a portfolio risk minimization approach, through the inclusion of constraints on the degree of compliance with targets for the emissions reduction of Gases Harmful to the Environment and Human Health (hereafter, GHEH) emissions proposed in the European Union (hereinafter, EU): CO2, SO2, NOx, PM.

The contribution of this work centers on the analysis of the inclusion of environmental criteria (pollutant gas reduction goals) when addressing the problem of energy planning while applying portfolio theory. More specifically, the impact on the technology portfolio composition is analyzed based on the comparison of the portfolios designed by the International Energy Agency (hereinafter, IEA) for the European Union in 2030 and the efficient portfolios provided by the proposed optimization model, while at the same time providing a measurement of proximity/distance in terms of efficiency of the IEA portfolios. Relevant conclusions are also reached about the emissions levels of efficient portfolios as compared to non-efficient ones, and a “portfolio normalized emission factor” is proposed as a measure identifying the overall degree of compliance of the portfolio's environmental emissions reduction objective.

In sum, our goal would be to find a portfolio that maximizes social well-being by presenting the lowest possible social cost, and one that presents a socially acceptable risk level and abides by environmental constraints (Jansen et al., 2006).

To that end, this study reviews the most relevant recent contributions found in the scientific literature, presents the model and the methodology, reports the results obtained and, finally, draws conclusions and proposes lines for further research.

2. Material and methods

2.1. The mean-variance portfolio theory

The application of Portfolio theory (Markowitz, 1952; Byers et al., 2015; Cucchiella et al., 2017; Cucchiella et al., 2016) application to the problem of selecting real asset and electricity production portfolios has been proven to be a valid option (Awerbuch and Berger, 2003; Awerbuch and Yang, 2007; Awerbuch et al., 2008; Roques et al., 2008, 2010; or Arnesano et al., 2012). This optimization approach seeks to minimize the portfolio cost or risk values subject to different constraints relevant to the definition of energy planning problem.

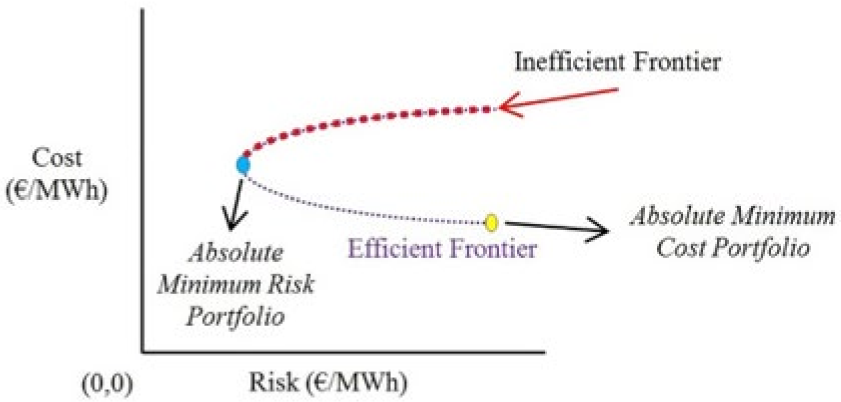

Fig. 1. Frontier Portfolios Curve: Efficient and Inefficient Frontiers. Source: authors' own calculations.

The solutions provided by the model (portfolios composed of different technology shares adding up to 100%) may be represented on a cost-risk coordinate system. The set of portfolios that either keep the cost to a minimum for a certain level of risk or minimize the risk for a given cost form what is called an Efficient Frontier (Fig. 1). This frontier line is shaped like a concave curve, as opposed to the traditional convex curve of the Markowitz approach, which is based on the yield of financial assets. It would be bound on the left by the efficient portfolio with the absolute minimum risk (the one that has the lowest possible risk) and on the right by the efficient portfolio with the absolute minimum cost (the one that has the lowest possible cost). Therefore, portfolios that have an equal risk but a higher cost, or an equal cost and a greater risk, than those that are efficient would lie on the Inefficient Frontier: the convex part of the Frontier Portfolios Curve.

The most recent works published present optimization models with objective functions that seek to minimize risk (Cuixia et al., 2014; DeLlano-Paz et al., 2015; Marrero et al., 2015; Lucheroni and Mari, 2017) maximize the Sharpe index (Cucchiella et al., 2017), and maximize the utility function (Go€kgo€z and Atmaca, 2017) or that of profitability based on the Net Present Value (Lynch et al., 2013). Other authors such as Kumar et al. (2015) propose using a multiple-objective model that includes the cost, risk and CO2 emissions functions. Jano-Ito and Crawford-Brown, 2017 employ an integrated model based on Multi-Attribute Utility Theory (MAUT) and portfolio theory that seeks to maximize performance as the antithesis to LCOE.

In the literature, a large variety of restrictions complement the definition of each model/study: the already mentioned financial constraint, technical constraints (such as the non-negativity of the variables, the necessity of the sum of the technology shares to be equal to one), restrictions on the installed capacity of some technologies (Huang and Wu, 2008), constraints regarding the inclusion of ramp rates in the production of some technologies (Delarue et al., 2011; De Jonghe et al., 2011), limits to production and transmission capacities (Rombauts et al., 2011) and to the participation of some technologies (Bhattacharya and Kojima, 2012; Doherty et al., 2008; Allan et al., 2010; Awerbuch and Yang, 2007; Jansen et al., 2006), the capacity of investment in the spot market (Gökgöz and Atmaca, 2012), and portfolio emissions (DeLlano-Paz et al., 2015; Kumar et al., 2015).

In sum, when applied to energy planning, portfolio theory confers a greater capacity and conceptual richness than the straightforward perspective of the lowest individual technology cost. The analysis is performed from the double perspective of cost and risk, and this undoubtedly represents a powerful strength of the portfolio theory. Furthermore, portfolio theory makes it possible to include some characteristic features from the energy analysis: the risk that arises from the changeability of power generation technologies costs, the virtues of risk mitigation due to the so-called portfolio effect, and the RES-E generation intermittence.

The proposed environmental model follows the De-Llano et al. (2014) approach. The portfolio is composed of the different shares of the available power generation technologies. Each of

them is characterized according to its generation costs (levelized costs of electricity) -including externality costs-, and its risk, measured as the standard deviation of its cost, since portfolio theory uses past volatility as a guide for the future. The objective function aims to minimize the risk of the portfolio being studied, subject to compliance with restrictions[1].

Twelve technologies are considered in this study: coal, coal with carbon dioxide emissions -CO2- capture and storage (hereinafter, CCS), natural gas combined cycle, natural gas combined cycle with CCS, oil, nuclear energy, large hydro, small hydro, on-shore wind, off-shore wind, solar photovoltaic -PV- and biomass energy. The sources consulted for the calculation of the technological costs come from various internationally recognised publications (IEA, 2010, International Energy Agency (IEA), 2010; IRENA, 2012; Eurelectric-VGB, 2011; De Jager et al., 2011; IPCC, 2005).

[1] Following the approach by Awerbuch and Berger (2003), total flexibility is assumed for the investment in and divestment of the different generation assets in the portfolio.

The cost of power generation technology Ct, in €/MWh; is obtained by adding up of the cost components including externalities (CCt): Investment, O&M, fuel, complementary[2] gas emissions, radioactivity, land use and potential plant accidents. It can be expressed as (Eq. (1)):

$$\begin{aligned} C_t &= \sum CC_t \\ &= \sum \left(Inv_t + O\&M_t + Fuel_t + Compl_t + CO_2 + SO_2 + NO_{X_t} \right. \\ &\quad \left. + PM_t + Rad_t + Land_t + Acc_t \right) \end{aligned} \tag{1}$$

The estimation of the risk of technology t ðst Þ is calculated as the standard deviation of its generation cost, which implies the square root of the sum of the variances of the different technology cost components and the covariances among them[3] (Eq. (2)).

$$\begin{aligned} \sigma_t = & \left(\sigma^2_{Inv_t} + \sigma^2_{O\&M_t} + \sigma^2_{Fuel_t} + \sigma^2_{Compl_t} + \sigma^2_{CO_2} + \sigma^2_{SO_2} + \sigma^2_{NOx_t} \right. \\ & \left. + \sigma^2_{PM_t} + \sigma^2_{Rad_t} + \sigma^2_{Land_t} + \sigma^2_{Acc_t} + 2\sigma_{Fuel_t}\sigma_{CO_2}\rho_{Fuel_t,CO_2} \right)^{\frac{1}{2}} \end{aligned} \tag{2}$$

The expected portfolio cost ½EðCpÞ is obtained the sum of the expecting generation costs of the twelve technologies considered, weighted by their shares in the portfolio xt (Eq. (3)):

$$\begin{aligned} E(C_p) &= \sum_T x_t C_t \\ &= \sum_T x_t \left[Inv_t + O\&M_t + Fuel_t + Compl_t + CO_2 + SO_2 \right. \\ &\quad \left. + NO_x + PM_t + Rad_t + Land_t + Acc_t \right] \end{aligned} \tag{3}$$

The expected portfolio risk ½sp is measured as the standard deviation of the expected portfolio cost (Eq. (4)). It includes the interactions "- measured as linear correlations ðrÞ- among the cost components of different technologies. However, in this study only the correlations among the O&M costs and among the fuel costs of each pair of technologies are assumed to be non-zero (Awerbuch and Yang, 2007). The Cost and risk data for each technology and the portfolio are shown in Appendix A (Table A. 1; Table A. 2; Table A. 3).

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[2] It includes costs associated with decommissioning and the management of waste from nuclear energy, intermittency costs for wind and solar PV power related to its non-manageability and carbon transport and storage costs for CCS technologies

[3] Statistical independence among the different components of cost for each technology is assumed, except for fuel and CO2 prices (based on Jansen et al., 2006).

$$\sigma_p = \left\{ \sum_{t=1}^{T} x_t^2 \sigma_t^2 + \sum_{t_1=1}^{T} \sum_{t_2=1, t_1 \neq t_2}^{T} \left(\sum_{\forall C_1} \sum_{\forall C_2} \sigma_{C_1 t_1} \sigma_{C_2 t_2} \rho_{C_1 t_1, C_2 t_2} \right) x_{t_1} x_{t_2} \right\}^{1/2} \tag{4}$$

The model seeks to minimize the Power Mix Portfolio risk and this is reflected in the following objective function and it is repre-sented by the objective function:

$$\begin{aligned} Min\sigma_p = & \left\{ \sum_{t=1}^{12} x_t^2 \left(\sigma_{Inv_t}^2 + \sigma_{O\&M_t}^2 + \sigma_{Fuel_t}^2 + \sigma_{Compl_t}^2 + \sigma_{CO_{2_t}}^2 + \sigma_{SO_{2_t}}^2 \right. \right. \\ & + \sigma_{NO_{x_t}}^2 + \sigma_{PM_t}^2 + \sigma_{Rad_t}^2 + \sigma_{Land_t}^2 + \sigma_{Acc_t}^2 + 2\sigma_{Fuel_t} \sigma_{CO_{2_t}} \rho_{Fuel_t, CO_{2_t}} \Big) \\ & + \sum_{t_1=1}^{12} \sum_{,t_2=1, t_1 \neq t_2}^{12} \Big(\sigma_{O\&M_{t_1}} \sigma_{O\&M_{t_2}} \rho_{O\&M_{t_1}, O\&M_{t_2}} x_{t_1} x_{t_2} \\ & \left. + \sigma_{Fuel_{t_1}} \sigma_{Fuel_{t_2}} \rho_{Fuel_{t_1}, Fuel_{t_2}} x_{t_1} x_{t_2} \Big) \right\}^{1/2} \end{aligned}$$

This objective function is subject to different constraints: the sum of the weights of the technologies in the portfolio would be 1 ($\sum_T x_t = 1;\ \forall t \in T : x_t \geq 0$) where xt is the proportion of technology t expressed on a per unit basis). The cost of the portfolio would be equal to an established value [EðCpÞ¼ CPortfolio⍰, the weights of the different technologies in the portfolio must be lower or equal to certain limits [xt ⍰ maximum weight of technology "t"] (see Figure B. 1 in Appendix B) and the portfolio's emission factor must be lower than or equal to the proposed limit [PEFGHEH <= GHEH emissions limit ; with PEFGHEH = Portfolio Emissions Factor and HEHx =(CO2; SO2; NOx; PM)]. The portfolio emission factor calculation is explained in the next subsection. Its analytic expression would be:

$$\begin{aligned} Min\{\sigma_p\} = & Min \left\{ \sum_{t=1}^{12} x_t^2 \sigma_t^2 + \sum_{t_1=1}^{12} \sum_{t_2=1, t_1 \neq t_2}^{12} \sum_{\forall C_1} \sum_{\forall C_2} \sigma_{C_1 t_1} \sigma_{C_2 t_2} \rho_{C_1 t_1, C_2 t_2} \Big) x_{t_1} x_{t_2} \right\}^{\frac{1}{2}} \\ = & \left\{ \sum_{t=1}^{12} x_t^2 \left(\sigma_{Inv_t}^2 + \sigma_{O\&M_t}^2 + \sigma_{Fuel_t}^2 + \sigma_{Compl_t}^2 + \sigma_{CO_{2_t}}^2 + \sigma_{SO_{2_t}}^2 + \sigma_{NO_{x_t}}^2 + \sigma_{PM_t}^2 + \sigma_{Rad_t}^2 + \sigma_{Land_t}^2 + \sigma_{Acc_t}^2 + 2\sigma_{Fuel_t} \sigma_{CO_{2_t}} \rho_{Fuel_t, CO_{2_t}} \right) \right. \\ & \left. + \sum_{t_1=1}^{12} \sum_{t_2=1, t_1 \neq t_2}^{12} \left(\sigma_{O\&M_{t_1}} \sigma_{O\&M_{t_2}} \rho_{O\&M_{t_1}, O\&M_{t_2}} x_{t_1} x_{t_2} + \sigma_{Fuel_{t_1}} \sigma_{Fuel_{t_2}} \rho_{Fuel_{t_1}, Fuel_{t_2}} x_{t_1} x_{t_2} \right) \right\}^{\frac{1}{2}} \end{aligned}$$

2.2.1. The portfolio emission factor

The portfolio emission factor ðPEFGHEHÞ for each GHEH follows the proposal by DeLlano-Paz et al. (2015). It is calculated by the sum of the emission factors for each GHEH and technology

(Eft), weighted by the proportion of each GHEH-emitting technology (coal, coal with CCS, natural gas, natural gas with CCS, oil and biomass) in the portfolio (Eq. (5)):

$$PEF_{GHEH_x} = \sum_{t=1}^{6} EF_t x_t \qquad (5)$$

Table 1 below shows the emission factors ðEFt Þ for each GHEH and technology, within the interval of those proposed by the International Energy Agency (IEA) (2010).

Table 1
Technology emission factors by GHEH: CO_2 (kg/MWh), SO_2, NOx and PM (gr/MWh).

GHEH	Coal	Coal with CCS	Natural Gas	Natural Gas with CCS	Oil	Biomass
CO_2	734.1	101.0	356.1	48.7	546.5	1.8
SO_2	73.5	21.8	8.8	9.8	54.7	151.0
NOx	182.5	173.7	254.7	284.2	135.9	397.8
PM	9.3	7.7	1.2	1.2	6.9	187.7

Source: Authors' own work, based on data collected from Bennink et al. (2010) and DeLlano-Paz et al. (2016).

In order to improve the analysis of the limits for 2030, GHEH emissions are established based on the definition of three emission reduction scenarios (minimum, mean and maximum reduction). The value of each GHEH limit for each scenario was calculated based on the value of the GHEH produced by the 2010 portfolio (IEA, 2012). The reduction targets calculated for the year 2010 are applied to the value obtained for each GHEH. To set the CO2 emission limits the European Commission proposals EC (2008; 2010; 2011; 2012a; 2012b) were followed. For the rest of the polluting gases (SO2,NOX and PM), the proposal made by Ammann et al. (2008) and used by Wesselink et al. (2010), based on the consolidated version of Directive 2001/81/EC (EC, 2001), was applied. Table 2 shows the reduction targets for each horizon, using 2010 as the base year.

Table 2
Pollutant gas reduction goals by horizon.

GHEH	Reduction scenario (Base Year, 2010)	2020	2030	2050
CO_2	Minimum Reduction	26.04%	45.30%	91.68%
	Mean Reduction	31.90%	53.63%	95.84%
	Maximum Reduction	35.26%	61.95%	98.81%
SO_2	Minimum Reduction	58.48%	58.48%	N.A.
	Mean Reduction	61.62%	61.62%	
	Maximum Reduction	64.76%	64.76%	
NO_X	Minimum Reduction	29.49%	29.49%	
	Mean Reduction	33.18%	33.18%	
	Maximum Reduction	36.87%	36.87%	
PM	Minimum Reduction	15.24%	15.24%	
	Mean Reduction	16.39%	16.39%	
	Maximum Reduction	17.53%	17.53%	

Source: Authors' own work, based on data collected from EC (2001; 2008; 2010; 2011; 2012a; 2012b), Ammann et al. (2008) and Wesselink et al. (2010).

The pollutant gas reduction goals by horizon were employed to calculate the portfolio emission limits for each reduction scenario and GHEH. The values for the emission factors in the IEA. EU portfolio (2010) (IEA, 2012) were multiplied by the percent reduction established as the objective for

2030 for the studied horizons (DeLlano-Paz et al., 2015)(Table 3).

Table 3
Maximum GHEH emission limits by power portfolio and horizon.

GHEH	2010	Emissions Limits 2030 Horizon (gr/MWh)		
	Base Emission Factor (gr/MWh)	Reduction Objective		
		Minimum	Mean	Maximum
CO_2	287.70	157.36	133.41	109.47
SO_2	29.15	12.10	11.19	10.27
NO_X	126.79	89.40	84.72	80.05
PM	10.97	9.30	9.18	9.05

Source: Authors' own work and DeLlano-Paz et al. (2015).

2.3. Efficiency evaluation of the portfolios

A study of the efficiency of the IEA. EU portfolios in terms of cost-risk for 2030 focuses on the analysis of the five most important efficient portfolios: the portfolio with the absolute minimum cost, that with the absolute minimum risk, the portfolio with the same cost as the IEA. EU portfolio, but with a lower risk, the one with the same risk as the IEA. EU portfolio, but with a lower cost and that which lies between each IEA. EU portfolio and the origin (0,0) of the radial line (Fig. 2).

A proposal is also made to apply a measurement that would make it possible to compare the distances between the IEA. EU portfolios and the portfolios that make up the efficient frontier. Therefore, the decision was made to use the mathematical expression calculating the difference between the two points (Eq. (6)):

$$\text{Distance between two portfolios} = \left[(C_a - C_b)^2 + (R_a - R_b)^2\right]^{1/2} \tag{6}$$

In which C represents the cost and R the risk of the two port-folios ða and bÞ. In addition, the radial measurement of the distance between the IEA. EU portfolio and the origin is also calculated. Depending on its location on the map, the imaginary straight line connecting them would intersect the efficient portfolio curve at one point, coinciding with that of an efficient portfolio; this would be referred to as the efficient-radial. This last measurement makes it possible to compare the distance of the portfolios proposed by the IEA from the efficient frontier. Thus, once the efficient-radial portfolio has been identified, the distance between it and the IEA. EU portfolio will indicate the relative proximity of the IEA. EU portfolio to efficiency (Fig. 2).

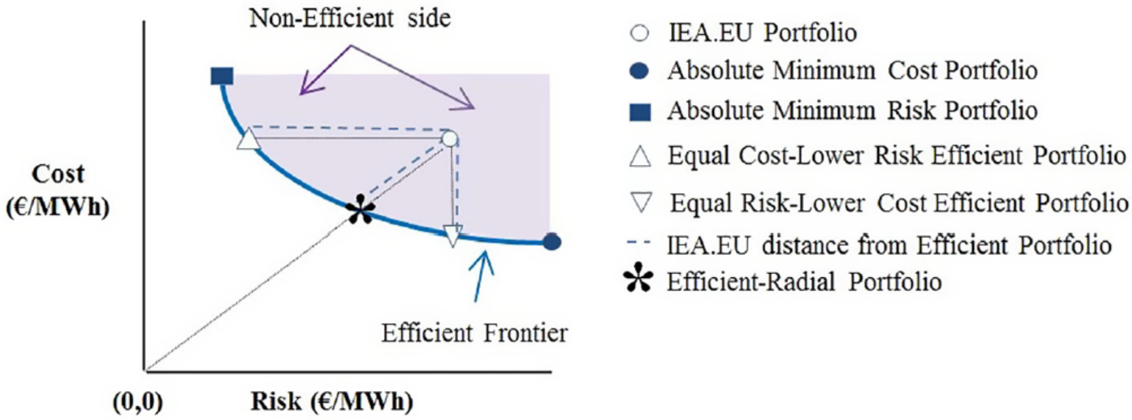

Fig. 2. Location of analyzed Efficient Portfolios. Source: Authors' own work.

2.4. Levels of compliance of the set of reduction objectives as a whole: a portfolio normalized emission factor

The analysis of the distances presented takes into account the portfolio cost-risk. With the aim of enriching the approach, it is suggested to include a measurement of the degree of compliance with the entire set of emission reduction objectives for each port-folio. This measurement would be defined by the following math-ematical expression (Eq. (7)):

This calculation of the overall degree of compliance of the portfolio's environmental emission reduction objective is based on a normalized expression. It permits establishing which analyzed portfolio emits the least GHEH (i.e., is the closest to the objective).

$$\begin{aligned} &\mathit{Portfolio\ distance\ from\ the\ emissions\ reduction\ objective}\\ &= \left\{ \begin{array}{l} [(CO_2EmissionFactor - CO_2EmissionLimit)/CO_2EmissionLimit] + [(SO_2EmissionFactor - SO_2EmissionLimit)/SO_2EmissionLimit] \\ + [(NOxEmissionFactor - NOxEmissionLimit)/NOxEmissionLimit] + [(PMEmissionFactor - PMEmissionLimit)/PMEmissionLimit] \end{array} \right\} \end{aligned} \tag{7}$$

This calculation of the overall degree of compliance of the portfolio's environmental emission reduction objective is based on a normalized expression. It permits establishing which analyzed portfolio emits the least GHEH (i.e., is the closest to the objective).

The minimum value for this measurement would be (⍰4), which would be equivalent to assuming zero emissions of each pollutant gas in the portfolio.

2.5. IEA.EU portfolios: 2030 horizon

The production portfolios analyzed are those proposed by the IEA (2012) for the EU in 2030. The IEA propose three scenarios: “Current Policies” assumes the continuity in terms of the govern-mental policies, “New Policies” considers the application of regu-latory obligations and measures to achieve increased energy safety and to fight climate change, and “450” prioritizes the fight against climate change, assuming the achievement (with a 50% probability) of the objective of limiting the average global temperature increase to 2 ⍰C above pre-industrial levels.

The differences between the EU 2010 and EU 2030 portfolios can be observed in Fig. 3. The share of RES-E should be increased in the portfolio from 20.6% in 2010 to a level around 33% and 48% in 2030. The increase in On-shore and Off-shore Wind and Solar PV tech-nologies stands out noticeably. This is most likely due to the fact that at the present time Wind technology can be considered competitive in terms of cost, as compared to fossil-conventional energy sources. Apart from the expected reduction in costs asso-ciated with this technology in 2030, its implementation would also be influenced by the evolution of its learning curve (IEA, 2012). Dzikuc and Tomaszewski (2016) confirm the necessity for a policy framework on pollutant emission reduction standards in order to achieve the promotion of RES-E. Labandeira (2012) and Fouquet (2010) point out the need to maintain Emission prices, which are potentially unique, high and global within the European Emission Trading System (hereafter, EU-ETS), in order to achieve the tech-nological change that would promote investment in low-carbon emission technologies. In addition, Rogge et al. (2011) point out the need to complement the EU-ETS with other incentives in order to promote technological change and innovation, which would permit achieving both long-term political power and environ-mental targets.

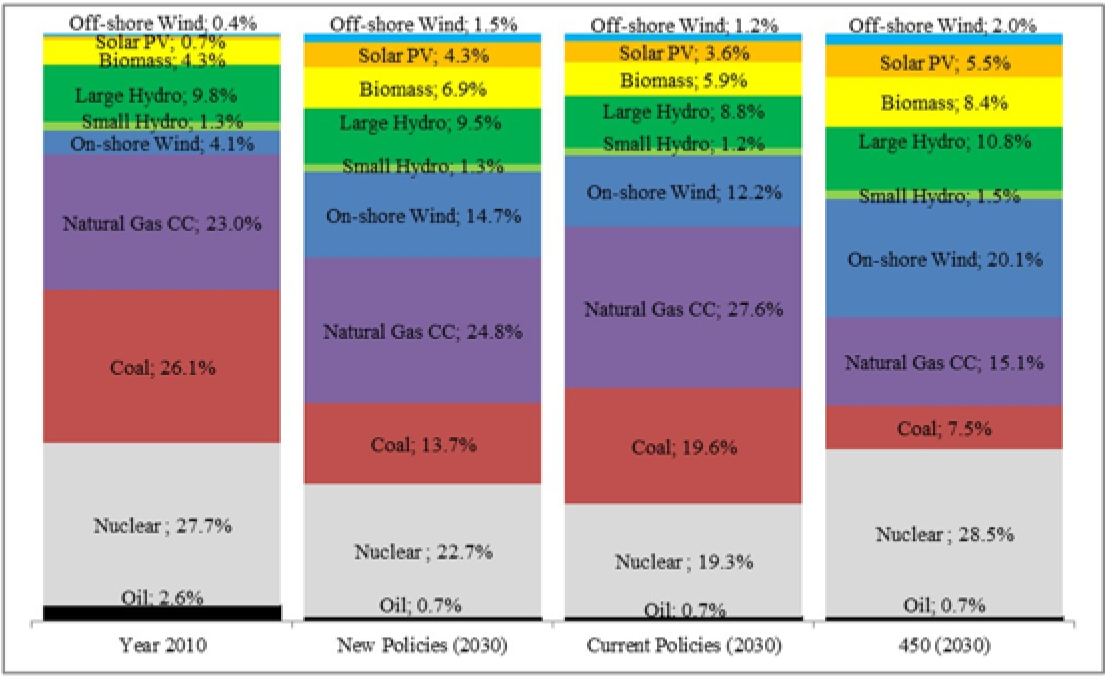

Fig. 3. Composition of IEA. EU (2010) and IEA. EU (2030) New Policies, Current Policies and 450 scenario portfolios in the Environmental model. Source: Authors' own work.

On the other hand, fossil fuel technologies would change from 51.6% to 23% (in IEA 450 scenario) or 48% (in IEA Current Policies scenario). Among them, Coal technology would present the highest reduction. Following what has been suggested by the IEA (2011) and IPTS (Russ et al., 2009), the reduction of the share of fossil fuel technologies must be within the framework of the EU climate policy, which has the EU-ETS as a key reference. This EU-ETS would, however, negatively influence the pollutant technologies costs.

The nuclear energy share would continue to play an important role, with a value between 19.3% and 28.5%. IEA Current Policies and New Policies portfolios include its negative impact, which is translated into the lowest share as the result of the negative social acceptance of this type of technology following the Fukushima disaster. The IEA 450, however, is based on this technology in order to achieve its particular emissions reduction goals (Fig. 3).

3. Results

3.1. Efficiency and distances

The model produces three efficient frontiers, one for each pro-posed emission reduction scenario (Fig. 4). Each of the three frontiers, in turn, would contain the five efficient portfolios being studied. The shift of the efficient frontier upwards and to the right can be observed in Fig. 4. The cost and risk of efficient portfolios is increased. This movement could be provoked by the intensity of the GHEH reduction goal. The penalty associated with power generation using pollutant technologies drives RES-E shares higher, which conditions the portfolio diversification behavior. It can also be observed in Fig. 4 that the IEA. EU 450 sits above the efficient frontier line, which means that it would never be the option selected.

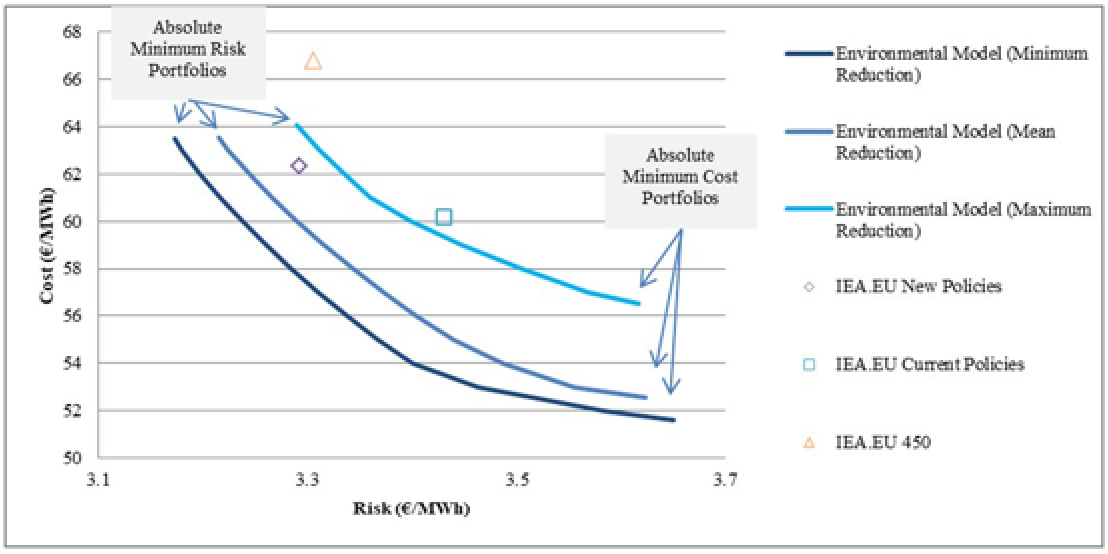

Fig. 4. Efficient frontiers and IEA. EU (2030) Portfolios according to the Environmental model. Source: Authors' own work.

The following Table 4 shows for the three proposed scenarios, the estimations of the distances between the IEA. EU portfolios and their corresponding efficient-radials, absolute minimum cost portfolios, absolute minimum risk portfolios, and the coordinate origin[4].None of the IEA portfolios is efficient from a cost-risk and environmental perspective. The approximation to the efficiency should be carried out by changing the technology shares in the portfolio.

[4] It must be noted that in this model it is not possible to find for the IEA.EU-27 450 portfolio the Radial Efficient (mean and maximum reduction scenario) and the Equal Cost-lower Risk portfolios for the IEA.EU-27 450 portfolio. The cost is too high and does not fit the curve of efficient portfolios for this model.

Table 4
IEA.EU (2030) and Efficient Portfolios according to the Environmental model. Distances from Radial-Efficient, Absolute Minimum Cost and Absolute Minimum Risk portfolios.

"Environmental Limitation" 2030 Portfolio	Distance from the coordinate origin			Distance from IEA.EU Portfolio			Distance from Absolute Minimum Cost Portfolio			Distance from Absolute Minimum Risk Portfolio		
Reduction Scenario:	Mini-mum	Mean	Maxi-mum	Mini-mum	Mean	Maxi-mum	Mini-mum	Mean	Maxi-mum	Mini-mum	Mean	Maxi-mum
IEA.EU NP	62.43			NA			10.7	9.8	5.8	1.2	1.2	1.7
IEA.EU CP	60.25						8.5	7.6	3.6	3.4	3.4	3.9
IEA.EU 450	66.90						15.2	14.2	10.3	3.3	3.3	2.7
Radial-Efficient IEA.EU NP	61.1	61.7	62.9	1.3	0.8	0.4	NA					
Radial-Efficient IEA.EU CP	57.8	58.5	60.1	2.4	1.7	0.1						
Radial-Efficient IEA.EU 450	61.8	NA	NA	5.1	NA	NA						
Absolute Minimum Cost	51.6	52.7	56.5	NA								
Equal Cost-Lower Risk NP	62.4	62.4	62.4	0.1	0.1	0.0						
Equal Cost-Lower Risk CP	60.2	60.2	60.3	0.2	0.1	0.0						
Equal Cost-Lower Risk 450 Equal	NA			NA								
Risk-Lower Cost NP	57.8	60.0	63.9	4.6	2.4	1.5						
Equal Risk-Lower Cost CP	53.6	55.3	59.4	6.7	4.9	0.8						
Equal Risk-Lower Cost 450	57.3	59.5	63.3	9.6	7.4	3.6						
Absolute Minimum Risk	63.6	63.6	64.2	NA								

Source: Authors' own work.

The IEA. EU Current Policies is the portfolio closest to the ab-solute minimum cost portfolio for the three reduction scenarios (Table 4). It could be brought even closer by reducing the weight of technologies with the highest cost and emission factors, namely, coal by more than half, and eliminating the share of biomass (as well as oil and solar PV energy), as seen in Fig. 5. The technologies that are increased are those that balance the cost and emissions associated with the portfolio: nuclear (þ10%) and RES: on-shore wind (þ8%), off-shore wind (þ0.8%), large hydro (þ2%) and small hydro (þ0.2%), each of which would reach maximum share limits.

Alternately, the portfolio closest to the absolute minimum risk is the IEA. EU New Policies portfolio for the three emissions goal scenarios. The approximation to the absolute minimum risk would be possible through: a slight increase in the share of nuclear energy sources (from 22% to 24e27%), the inclusion of RES-E up to their maximum limit (except in the case of biomass, the weight of which is decreased), a reduction in the weight of polluting technologies (coal from 13% to 4e10%, natural gas from 25% to 19e22% and biomass by one-third) and the introduction of CCS technologies (with 2e3% each) (Fig. 5).

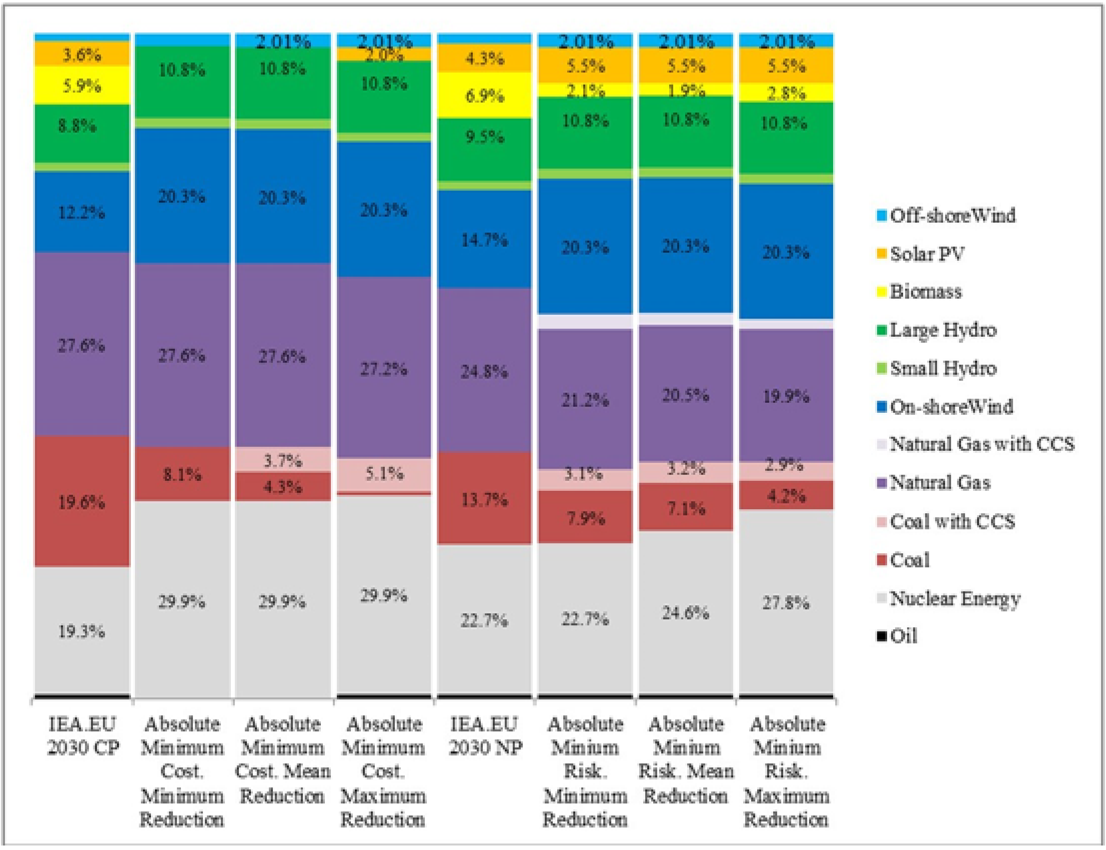

Fig. 5. Composition of IEA. EU (2030) Portfolios and Absolute Minimum Cost and Risk efficient mixes according to the Environmental model. Source: Authors' own work.

The analysis with the efficient-radials reveals that the portfolio closest to efficiency for the minimum reduction and mean reduc-tion scenario is that of New Policies, while for the maximum reduction scenario it is Current Policies (Table 4). However, this approximation to efficiency is not complete, due to the fact that while the IEA. EU Current Portfolio has a cost-risk value that is similar to the efficient-radial portfolio, its emission factors (deter-mined by its composition) are too high and distant from environ-mental efficiency. Proximity to the efficient-radial portfolios could be achieved through an increase in the weight of non-pollutant technologies, such as nuclear energy (from 22 to 23e29%), the reduction and transfer of part of the share of pollutant coal and natural gas to the same technologies with CCS, the sharp reduction of biomass (a source of emissions) and an increase to the maximum allowable limit of RES, with the exception of solar photovoltaic and biomass (as previously mentioned), both of which have high costs (Table A. 1 in Appendix A).

3.2. The effects of radial efficiency approximation on cost and risk

From an environmental perspective, greater efficiency results in cost and risk values that are below those associated with the portfolios proposed by the IEA. EU (except in the case of New Policies, in terms of maximum reduction) (Table 5). These therefore constitute attractive radial-efficient portfolios from the point of view of cost-risk (lower values) and the environment (lower GHEH emission). It can be concluded, after analyzing efficient portfolios, that the toughening of the reduction objective would lead to both a higher cost and a higher risk for efficient portfolios, but still below those of the IEA. EU portfolios. It can therefore be achievable by improving environmental aspects (compliance with emission reduction goals) and economic efficiency (with better cost-risk results than those proposed by IEA. EU, 2030) through a different composition of the power technologies portfolio.

Table 5
Risk and cost values of the IEA.EU (2030) and Radial-Efficient portfolios, according to the Environmental model, considering the Minimum, Mean and Maximum Emission Reduction Scenarios.

IEA.EU 2030 Portfolio	Risk (V/MWh)				Cost (V/MWh)			
	IEA	Efficient Portfolio:			IEA	Efficient Portfolio:		
Reduction:		Minimum	Mean	Maximum		Minimum	Mean	Maximum
NP	3.29	3.22	3.25	3.32	62.34	60.4	60.8	62.8
CP	3.43	3.29	3.33	3.40	60.16	57.9	58.1	60.0
450	3.31	3.17	e	e	66.82	62.1	e	e

Source: Authors' own work.

4. Discussion

4.1. From an analysis of economic to environmental efficiency

The proximity to efficiency of the IEA portfolios analyzed must be considered with a certain degree of caution. Since they would be near to efficiency in terms of cost-risk values (similar to the Mar-kowitz risk-return approach), they will not be able to be efficient in environmental terms: IEA portfolios fail to comply with GHEH emissions model reduction goals.

In order to be assessed in this study, the relevant portfolios are the ones that come the closest to complete efficiency, from both a cost-risk and environmental perspective. Therefore, these relevant portfolios would need to bridge the shortest distance to reach ef-ficiency for each scenario from a cost-risk perspective, and also meet GHEH emissions reduction goals. In order to improve effi-ciency, the future EU portfolio should include larger shares of zero emission technologies, such as on-shore wind (from 15% to 20%participation) and solar PV, and should reduce the coal pollutant technology by half, partially replacing it by coal with CCS. An interesting finding of this process is that these changes in the portfolio composition imply final cost-risk data lower than those from the proposed 2030 IEA. EU portfolios. Or in other terms, improved efficiency does not mean higher cost-risk values than those proposed by IEA.

A more in-depth analysis of the environmentally-friendly portfolio can be performed according to the results of the level of compliance with global emission reduction objectives (Eq. (7)). The data in Table 6 confirm that three 2030 IEA. EU portfolios present the highest values for the portfolio normalized emission factor. On the other hand, efficient portfolios show lower (negative) results of this measurement that are closer to its minimum value (-4), which would be indicative of low joint GHEH emissions and total compliance with the emission reduction goal for each GHEH.

Table 6
Normalized emission factor values for portfolios by reduction goal. 2030

IEA.EU Portfolio	Emissions Reduction Scenario		
	Minimum	Mean	Maximum
New Policies	1.98	2.45	3.05
Current Policies	2.60	3.16	3.88
450	1.11	1.45	1.87
Absolute Minimum Cost	1.24	1.32	1.50
Absolute Minimum Risk	0.54	0.48	0.32
Radial-Efficient NP	0.60	0.48	0.32
Radial-Efficient CP	0.62	0.48	0.48
Radial-Efficient 450	1.88	NA	NA

Source: Authors' own work.

The addition of the study of the Portfolio normalized emission factor to the set of analysis criteria would mean that the IEA. EU portfolio, which was previously the most efficient in terms of its position on the cost-risk graph (NP or CP), would not comply with reduction objectives; this rules it out as an inefficient portfolio in environmental terms. The model reveals efficient combinations that meet its requirements and would lead to the modification of the weights of the IEA. EU portfolios in order to become efficient from a triple perspective (cost-risk-emissions). It can be seen that the portfolios with the minimum absolute cost are the ones that attain the lowest emission factors (Table 6). This is why by opting for a minimum economic cost portfolio also means that the EU is choosing a low-emissions portfolio, which complies with the emissions reduction goals for each scenario.

4.2. GHEH portfolio emission factors

Fig. 6 shows that the GHEH emission factors considered for the IEA. EU portfolios are far above those obtained by its efficient portfolios (those with equal cost that present a lower risk) in the case of “Environmental Limits”. In a recent study, AlRafea et al.(2016) confirm that the health impact cost of PM presents the highest value, followed by NO2,SO2 and CO2.

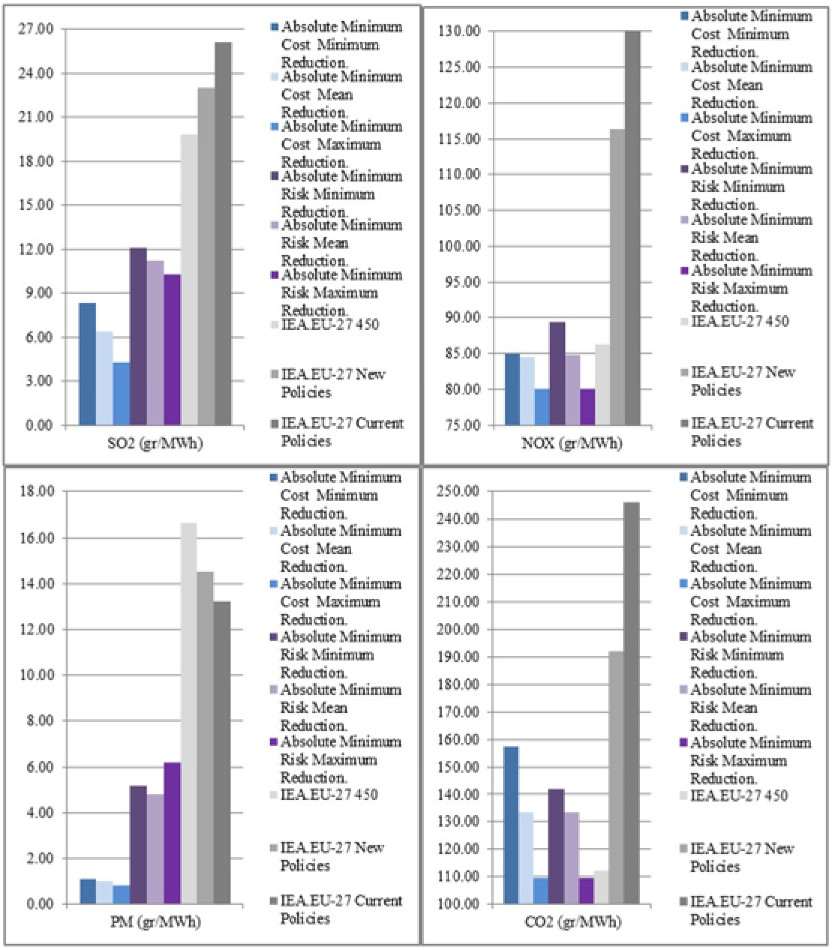

Fig. 6. Emission Portfolio Factor by GHEH (in gr/MWh) of the Efficient and IEA. EU Portfolios.
Source: Author's own work.

It is interesting to note what happens to the emission factor for particulate matter (PM). The tougher reduction objectives for GHEH causes an increase in the emission factor values for PM in certain efficiency cases (although they remain within the maximum established limits), and for the absolute minimum risk portfolios (Fig. 6). The model proceeds to internally reassign the weight of the polluting technologies, using the margin available for PM. The upward variations in the PM emission factor, while within the maximum limits, have a clearly negative effect on both the envi-ronment and society (Hall et al., 2010; Du et al., 2014). According to Annesi-Maesano et al. (2007) exposure to even low levels of PM increases mortality over the long term in humans through, by increasing the risk of death by natural causes or as the result of cardiopulmonary problems or long-term cancer; in the short-term, effects are observed in both adults and children (affecting the cardiovascular system). In fact, heart condition plays a vitally important role in the risk of death associated with air pollution in patients with chronic obstructive pulmonary disease (COPD). It is for this reason that the authors have concluded that it would be interesting for future research to study the negative health and environmental effects derived from the interaction among each pair or trio of GHEH analyzed.

4.3. Absolute minimum cost and absolute minimum risk portfolios: assessing the consideration of reduction objectives

The search for the minimum risk leads to the design of portfolios in which all available technologies play a part. This ensures the reduction of the portfolio risk, thanks to the diversification effect attributable to the zero correlation coefficients for RES-E for fuel and CO2 emission costs, and the different correlation coefficients for the O&M costs for all technologies, several of which are nega-tive. The portfolio also includes compliance with limits in terms of its GHEH emission factors, which implies lower emission values for the set of portfolios.

In the minimum risk portfolios, stricter reduction targets lead to an increase primarily in nuclear energy[5], requiring lower contri-butions from the polluting sources and with RES-E remaining much the same (with a gradual increase in biomass) (Fig. 7; Table 7).

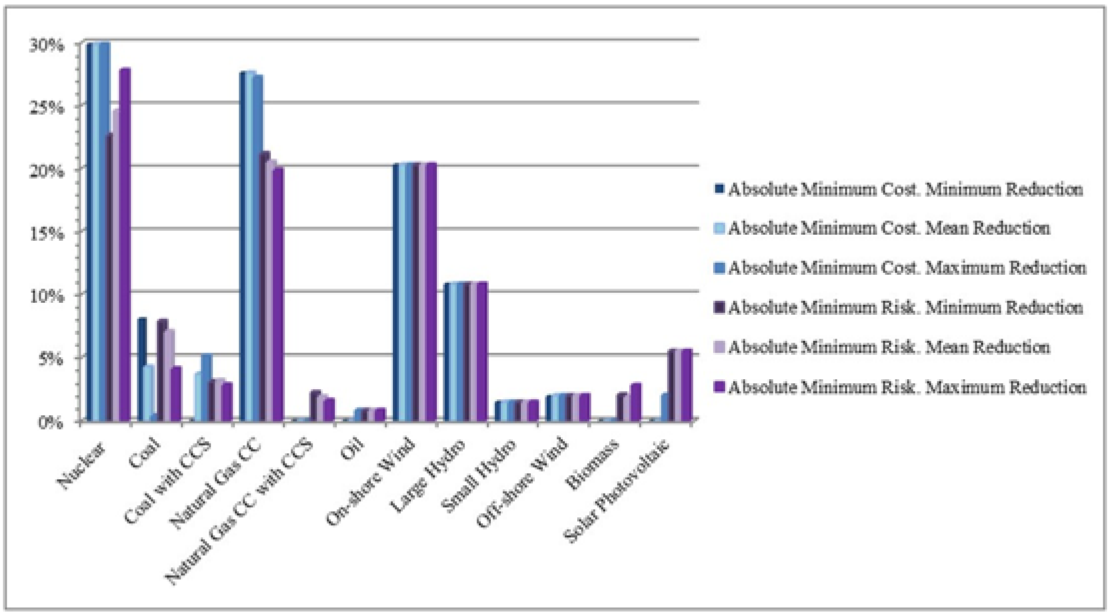

Fig. 7. Absolute Minimum Risk and Absolute Minimum Cost portfolios composition. Source: Author's own work.

[5] The higher share of nuclear energy as a result of the compliance of stricter reduction targets implies the increase of the portfolio risk ewhich are the lowest achievable values-.

Table 7
Risk and Cost evolution. Absolute Minimum Cost and Absolute Minimum Risk portfolios.

Reduction Scenario	Risk	Risk Evolution	Cost	Cost Evolution
Absolute Minimum Risk Portfolio				
Minimum	3.174	e	63.5	e
Mean	3.216	1.3%	63.5	0.0%
Maximum	3.290	3.7%	64.1	0.9%
Absolute Minimum Cost Portfolio				
Minimum	3.650	e	51.6	e
Mean	3.623	0.7%	52.6	1.9%
Maximum	3.616	0.9%	56.5	9.5%

Source: Author's own work.

In the case of absolute minimum cost, the share of nuclear technology, natural gas, wind and hydro energy are all raised to the highest permitted levels. Solar PV energy, oil and coal with CCS (associated with high costs) only come into play when there are more restrictive emission limits. The share of coal is replaced by coal with CCS as the emission restriction increases. Likewise, costly and polluting technologies are also replaced, as in the case of biomass and natural gas with CCS. The gradual incorporation of these technologies increases the cost of the analyzed portfolios in relation to the toughening of the reduction objective (Table 7). The reduction of risk would coincide with the introduction of the new coal with CCS technology, along with a greater share of RES-E (solar PV and off-shore wind). This is the result of both the increase in the number of technologies (with low GHEH emissions) and the set of O&M cost correlations, which are mainly negative, between RES-E and the rest of technologies.

In terms of the composition of both portfolios, it can be observed that the shares of RES, such as on-shore wind, off-shore wind, large hydro and small hydro, reach their maximum limits. Furthermore, the toughening of the reduction objective leads to the inclusion of solar PV energy in the portfolio, the decrease of coal and the in-crease of coal with CCS and nuclear technology (Fig. 7).

5. Conclusions and policy implications

IEA.EU 2030 Power mixes are not efficient in terms of portfolio theory. The model proposes different efficient energy compositions in order to jointly reduce pollutant emission factors, costs and the risk of the mix.

RES technologies are pre-emptive and necessary: they contribute to reducing the portfolio risk thanks to the absence of fuel costs, pollutant emissions costs and the negative correlation between their O&M costs and those of the other technologies; they have competitive costs as compared to conventional technologies if externalities are considered and they are free emissions technologies.

Our results show that wind energies are essential for the future EU power mix: they hold the maximum permitted shares in the model, reaching 20% for on-shore wind and 2% for off-shore wind. Therefore, EU policymakers should continue to promote these preferential technologies for the 2030 horizon, in order to facilitate the technological developments that make it possible to reach these shares and achieve a balanced system.

Solar photovoltaic energy would be included in 2030 power portfolio only if EU seeks to reduce the economic risk of its elec-tricity generation, which in turn compels it to reduce pollutant emissions. For this reason, in our opinion, EU policymakers should increase efforts to promote this technology in order to reduce the commercial cost of production. Through this policy action cost, risk and emissions would be reduced.

Hydro energies are preferential technologies in an EU efficient mix: both achieve the upper limits of participation in the event of minimum portfolio cost or risk. Therefore, we propose that EU authorities should ensure the maintenance of their relative weight in the mix for hydro technologies, especially in the case of large hydro (with a participation of 11%).

Nuclear energy stands out as a relevant technology, mainly in terms of achieving minimum cost and emissions reduction goals for the 2030 horizon. As a consequence, we confirm the required presence of nuclear energy in 2030 EU energy mix, with a partici-pation similar to its current share of 27%e29%.

CCS technologies would be needed in EU 2030 efficient portfo-lios. For this reason, we believe that the EU should continue to promote the development of this technology in order to favor its commercial availability in 2030 and to complement the RES-E emission reduction role.

The joint RES-E share should account for levels of between 30 and 45% of the total efficient portfolio, in response to an ambitious EU policy to reduce pollutant gases. Therefore, in our opinion, Eu-ropean policymakers should include reduction goals for other pollutant gases in the 2030 horizon besides those for carbon di-oxide (CO2), such as sulphur dioxide (SO2), nitrogen oxides (NOx) and particulate matter (PM) in order to boost RES-E participation and environmental protection. In addition, it has been confirmed that the toughening of the reduction objective brings about a lower increase in the cost and risk of efficient portfolios.

The future lines of research that open up as a result of this work focus on attempting to measure the degree of correlation between the emissions of the four GHEH studied, in order to add them to the model's risk data and to study in depth the impact of considering externality costs for each technology definition.

Appendix A

Table A 1
Total Technologies Costs and Risks (in V/MWh).

Types of Cost	Nuclear Energy	Coal	Coal with CCS	Natural Gas	Natural Gas with CCS	Oil	On-shore Wind	Large Hydro	Small Hydro	Off-shore Wind	Biomass	Solar PV
Investment þ O&M þ Fuel þ Decommission or Intermittency	30.04	33.88	75.91	29.89	62.38	79.50	60.69	38.62	42.95	73.81	96.58	212.03
CO_2 Emission Cost	0.00	18.35	2.52	8.90	1.22	13.66	0.00	0.00	0.00	0.00	0.05	0.00
Emission Costs (SO_2, NOx, PM) þ Potential Accidents þ Land use þ Radioactivity	27.16	2.43	1.89	2.30	2.55	1.76	0.98	0.22	0.34	1.06	13.38	0.52
Total Cost	57.20	54.65	80.33	41.09	66.15	94.93	61.68	38.84	43.28	74.87	110.01	212.55
Risk	7.608	7.679	8.587	6.307	8.479	13.539	6.457	10.285	3.595	7.214	13.836	10.501

Source: De-Llano et al. (2014).

Table A 2
Correlation Coefficients for O&M Costs.

Correlation Coefficients (O&M costs)	Nuclear Energy	Coal	Natural Gas	Oil	On-shore Wind	Large Hydro	Small Hydro	Off-shore Wind	Biomass	Solar PV	Nuclear Energy 1
	0	0.24	0.17	0.07	0.41	0.41	0.07	0.65	0.35		
Coal	0	1	0.25		0.18	0.22	0.03	0.03	0.22	0.18	0.39
Natural Gas	0.24	0.25	1		0.09	0	0.04	0.04	0	0.32	0.05
Oil	0.17	0.18	0.09		1	0.58	0.27	0.27	0.58	0.01	0.04
On-shore Wind	0.07	0.22	0		0.58	1 0.29	0.29	1	0.18	0.05	
Large Hydro	0.41	0.03	0.04		0.27	0.29	1	1	0.29	0.18	0.3
Small Hydro	0.41	0.03	0.04		0.27	0.29	1	1	0.29	0.18	0.3
Off-shore Wind	0.07	0.22	0		0.58	1	0.29	0.29	1	0.18	0.05
Biomass	0.65	0.18	0.32		0.01	0.18	0.18	0.18	0.18	1	0.25
Solar PV	0.35	0.39	0.05		0.04	0.05	0.3	0.3	0.05	0.25	1

Source: Awerbuch and Yang, 2007.

Table A 3

Correlation coefficients for Fuel and C=2 Costs

Correlation Coefficients (Fuel & CO2 Costs)	Nuclear Energy	Coal	0	Oil	Biomass	CO2
Nuclear Energy	1	0,97	0,99	0,88	-0,31	0,89
Coal	0,97	1	0,92	0,97	-0,53	0,99
Natural Gas	0,99	0,92	1	0,79	-0,15	0,97
Oil	0,88	0,97	0,79	1	-0,72	0,92
Biomass	-0,31	0,53	-0,15	-0,72	1	-0,4
CO2	0,89	0,99	0,97	0,92	-0,4	1

Source: De Llano et al. (214)

Appendix B

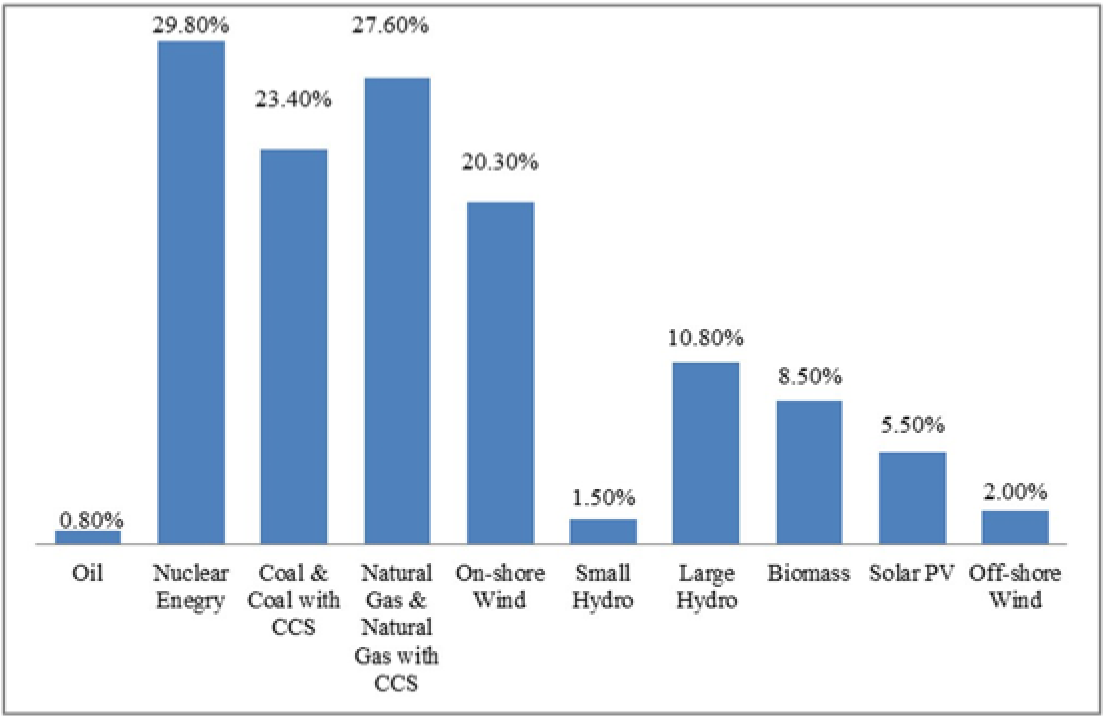

Fig. B 1. Maximum technology weighting limits in 2030 EU Power Portfolio. Source: Authors' own work considering data from IEA (2011; 2012), Russ et al. (2009) and DeLlano-Paz et al. (2015).

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