Designing electricity generation portfolios using the mean-variance approach

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ABSTRACT

The use of the mean-variance approach (MVA) is well demonstrated in the financial literature for the optimal design of financial assets portfolios. The electricity sector portfolios are also guided by similar objectives, namely maximizing return and minimizing risk. As such, this paper proposes two possible MVA for the design of optimal renewable electricity production portfolios. The first approach is directed to portfolio output maximization and the second one is directed to portfolio cost optimization. The models implementation was achieved from data obtained for each quarter of an hour for a time period close to four years for the Portuguese electricity system. A set of renewable energy sources (RES) portfolios was obtained, mixing three RES technologies, namely hydro power, wind power and photovoltaic. This allowed to recognize the seasonality of the resources demonstrating that hydro power output is positively correlated with wind and that photovoltaic is negatively correlated with both hydro and wind. The results showed that for both models the less risky solutions are characterised by a mix of RES technologies, taking advantage of the diversification benefits. As for the highest return solutions, as expected those were the ones with higher risk but the portfolio composition largely depends on the assumed costs of each technology.

KEYWORDS

Renewable energy sources, Electricity generation, portfolio selection, mean-variance approach, investment risk

1. INTRODUCTION

The need for investing in renewable energy sources (RES) is clear given the possibility of depletion of finite resources of earth, particularly fossil fuels [1]. The European Commission Directive 2009/28/EC reinforces the European RES strategy, underlying the contribution of the sector to reduce greenhouse gas emissions, to promote local and regional development and to contribute to security of energy supply. The electricity sector is particularly relevant and the contribution of RES to electricity production in the EU-27 has been increasing from 14.2% in 2004 to 21.7% in 2011 according to data drawn from [2]. However, these RES power projects are frequently characterized, by high investment costs, high uncertainty and risk in the long run and substantial impacts on society and the population’s well-being [3, 4, 5, 6]. The return of these projects highly depends on the availability of natural resources such wind, sun lightning or rain turning them extremely vulnerable to the climatic conditions and to the seasonality. As such, the possibility of using different RES technologies on each electricity generation portfolio can be seen as risk mitigation strategy exploring the diverse and possible complementary behaviour of each renewable resource related to their annual seasonally and even to their intra-daily pattern.

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For that purpose, several works (e.g. [7, 8, 9, 10, 11, 12, 13, 14]) have demonstrated how the mean-variance approach (MVA), formerly applied for the selection of portfolios of financial assets, can also be used for the selection of electricity generation portfolios, as an alternative to the traditional least cost approach. However, it should be recognized that the characteristics of electricity generation technologies are not always comparable to the characteristics of financial assets.

This paper aims at contribute to the analysis of different electricity production portfolios recognizing the importance of addressing both risk and return and proposes the use of the MVA approach as an electricity generation planning tool. The model is demonstrated taking the Portuguese case as an example and emphasising the particular role of the RES technologies. Optimal RES electricity generation mixes for the future are proposed, taking into account the past production pattern of each RES and optimizing the trade-off between maximizing RES output and minimizing RES variability. With the growth in the deployment of RES in Portugal, it becomes pertinent to study possible scenarios of exploiting RES (e.g. hydro, wind, photovoltaic, and biomass) in electricity generation projects to ensure the necessary power to customers and quality in supply, while conveying a sense of trust to consumers. Therefore, becomes crucial to introduce methodologies that allow including in electricity planning the correlation between various electricity generation technologies projects, as well as the respective risk

The results of the study have shown the usefulness of this approach for electricity power planning in a system with strong RES influence contributing to a sustainable future. Simultaneously, it was possible to compare the set of portfolios resulting from the application of this approach with the combination of technologies currently comprising the Portuguese electricity system. An advantage of the proposed approach is that it enables policy makers to consider the mix of electricity generation technologies from a broader perspective, explicitly including the expected return and the risk of the RES portfolio.

The remainder of the paper is organised as follows. Section 2 presents the theoretical foundations of the MVA approach in the context of electricity generation planning. Section 3 corresponds to the empirical study undertaken focusing on the Portuguese case and considering only three RES technologies for the portfolio proposal. In section 4 a discussion of the main results achieved is presented. Finally, Section 5 draws the main conclusions of the paper and presents avenues for further research.

2. ELECTRICITY GENERATION PLANNING AND THE MVA APPROACH

Electricity generation planning is related to energy and demand forecasting, supply- and demand-side management, evaluation of future power investment plans, assessment of the optimal expansion strategy and its feasibility [15]. The traditional approach to electricity generation planning has been the least-cost methodology [16], which is based on calculating the levelised costs of electricity generation, expressed in €/MWh, for different alternative production technologies and, after comparing those costs, choose the one with the lowest cost.

However, some criticisms to the use of this approach can be found in the literature. Firstly, the fact that electricity planning decision makers are faced both with a wider range of alternative technologies for electricity generation and different institutional framework in which they operate, coupled with a future that appears increasingly complex and uncertain [17]. Secondly, as energy markets have been liberalised, the interest in quantifying and manage market risks grew [18]. In fact, with the deregulation and liberalisation of electricity markets, with a corresponding increase in competition, electricity generation companies will no longer have a guaranteed return because the price of electricity varies depending on a number of factors. In this context, it is essential that those companies can manage electricity price risk [19]. Additionally, there is the issue of security of energy supply [14]. In fact, given the global shortage in terms of primary fuel sources [1], policy makers increasingly need to consider a diversification of electricity production. Simultaneously, the price volatility of fossil fuels raises the question of what are the best options in terms of energy needs of a country. Finally, an important feature of renewable technologies is that they correspond to capital intensive investments, which translates into a relatively fixed cost structure over time, with very low (or practically zero) marginal costs, and that are uncorrelated with important risk drivers, such as fossil fuel prices [19, 14].

Therefore, since different technologies are considered in electricity planning which differ not only in terms of costs but have also in terms of the associated level of risk, some authors (e.g. [7, 8, 9, 10, 11, 12, 13, 14]) argue that a better alternative methodology would be the use of the mean-variance approach.

For example, in the context of combining conventional and renewable technologies for electricity production, [17] emphasised that although renewables may present a higher levelised cost, it does not necessarily mean that the overall cost of the portfolio of generation technologies become more expensive due to the statistical independence of renewables costs, which tend not to correlate with fossil-fuel prices. In fact, the inclusion of renewable technologies in an electricity generation portfolio is a way to reduce the cost and risk of the portfolio, although in a stand-alone basis the cost of those renewable technologies might be higher [14]. Therefore, electricity generation planning should be focused more on developing efficient generation portfolios and less on finding the alternative technology with the lowest production cost [17, 14].

The MVA approach was initially proposed by [20] for the efficient selection of financial assets portfolios and is based on an investor's goal of maximising future expected return for a given level of risk he is willing to take (or minimising risk for a given level of return he wants to achieve). The main underlying assumption is that investors are risk averse which means that when faced with the choice between two investments with the same risk level they always choose the one with higher expected return. Therefore, the MVA approach allows explaining the advantage that an investor has to diversify their investments among several financial securities [21]. In fact, the characteristics of a portfolio can be very different from the characteristics that comprise the portfolio [22]. For example, when the returns on two different assets are independent, a portfolio comprising those assets can have lower risk than either asset. Since the expected return, $E(r_P)$, and the variance, σ^2_P, for a given investment portfolio, P, comprising N assets is, respectively:

$$\mathrm{E}(r_P) = \sum_{i=1}^{i=N} \omega_i \mathrm{E}(r_i) \tag{1}$$

and

$$\sigma_P^2 = \sum_{i=1}^{i=N} \sum_{j=1}^{j=N} \omega_i \omega_j \rho_{ij} \sigma_i \sigma_j \tag{2}$$

one concludes that the variance of a portfolio is partially determined by the variance of individual assets and partly by the way they move together – the covariance of the assets belonging to the portfolio (which can also be measured statistically by the coefficient of correlation). And is this term that explains why and in what amount portfolio diversification reduces the risk of investment. Therefore, as emphasised by [23], portfolios of financial assets should be chosen not only based on their individual characteristics but taking also into account how the correlation between assets affects the overall risk of a portfolio. This suggests that the proportion (or share) of each asset in the portfolio can be determined solving the following optimisation problem:

$$\begin{aligned}
&Max\mathrm{E}(r_P) = \sum_{i=1}^{i=N} \omega_i E(r_i) \\
&s.t. \\
&\sigma_P^2 = \sum_{i=1}^{i=N} \sum_{j=1}^{j=N} \omega_i \omega_j \sigma_{ij} \leq \hat{\sigma}^2 \\
&\sum_{i=1}^{N} \varpi_i = 1 \\
&\varpi_i \geq 0
\end{aligned}$$

where two additional constraints have been included: the fact that the sum of individual share of each asset is equal to one; and that the share of each asset is a non-negative number.

In recent years there has been a growing application of the MVA approach to electricity generation planning. In fact, this approach can be used to determine the optimal portfolios of electricity generation both for a company or a country. Since the main idea of the MVA approach is that the value of each asset can only be determined taken into account portfolios of alternative assets [18], energy planning should be focused more on developing efficient production portfolios and less on finding the alternative with the lowest production cost [17, 14]. Therefore, the MVA approach allows analysing the impact of the inclusion of renewable technologies in the mix of generating sources of electricity. In particular, it provides a better risk assessment of alternative generation technologies, something that the traditional stand-alone least cost approach cannot do, particularly in terms of the impact of renewable energy sources in reducing the risk of the portfolio of technologies to be adopted, since it allows illustrating the trade-off between production costs and risk: the lower the cost the higher the risk, meaning that it is not possible to achieve a lower electricity production cost without assuming higher levels of risk.

It should be noted that the result of applying the MVA approach to generation planning is not identifying a specific portfolio, but the identification of an efficient frontier where the optimal portfolios will be located. These are Pareto-optimal, that is, an increase in returns (or a decrease in costs) is only achieved by accepting an increased risk. On the other hand, an important aspect in the MVA approach is the assumption that past events are the best guide for predicting the future. Not to say that unexpected events will not occur, but that the effect of these events is already known from past experience [14].

A study that used the MVA approach to obtain evidence about the best mix of electricity generation in Scotland was undertaken by [12]. Based on the efficient frontier, the authors analysed the portfolios suggested in four scenarios for the electricity generation mix in 2020, seeking to clarify what role renewable technologies can play in setting up those portfolios. The main conclusion reached by those authors were that the portfolios of electricity production corresponding to the four scenarios analysed were not mean-variance efficient and that it is possible to have an improvement in the generation mix in the sense of Pareto. A similar study was conducted by [7] for the Brazilian case, comparing in particular the current situation and the energy policy objectives proposed in the 2020 Decennial Plan for Energy Expansion (DPEE), using the estimated efficiency electricity generation frontier for Brazil. They have concluded that since the average cost of the 2020 DPEE plan is only three per cent higher and the risk is ten per cent higher than the estimated average efficient portfolio, it would be preferable to reduce the risk than the cost of the 2020 DPEE plan, through a higher level of diversification.

[8] used the MVA framework to analyse the relationship between energy security and RES, since efficiency and diversification are important elements to improve energy security and reducing energy vulnerability. They have focused on the European Union (EU) Mediterranean Solar Plan, which is "a project projecting massive international RES electricity trade". The results achieved by those authors suggest that "green electricity from RES, whether domestically produced or not, could improve energy security. However, regarding international RES trade, such improvement could not occur unless some measures to balance the regulatory energy risks between exporting and importing countries had been taken".

[10] followed the reasoning of [14] but emphasising the financial characteristics of RES for their whole life cycle and taking into account the features connected to realization and utilization phases. They argue that in this way the assessment of costs and risks associated with the resources availability is more precise, allowing, also, to detail the application of the analysis of the energy portfolio on a national, provincial, municipal scale. They have concluded that the analysis suggested investing more in technologies based on RES, given that a reduction in total generation cost can be attained for the same level of risk. Also [9] highlighted the need to fully clarify financial risk as a part of the decision-making process in power sector investment, and have demonstrated that a diversified electricity generating portfolio including low risk RES can in fact reduce the overall investment risk of the portfolio. This would in turn "reduce the cost of risk hedging in terms of achieving a certain level of energy supply security".

[11] presented a somewhat different strategy for portfolio optimisation where they explicitly distinguish between "installed capacity (power), electricity generation (energy) and actual dispatch decisions", and focusing on the particular role of wind power, arguing that it allows to properly including wind power variability in the optimisation model. Their major empirical finding was that "lowering the overall risk can be a motivation for the implementation of wind power", which "confirms the renewables risk-lowering argument often found in the literature […], at least to a certain extent".

[16] applied the MVA approach to the Chinese context, emphasising the need to evaluate the risk and return characteristics of power generation investments, given the need to meet the increasing electricity demand. This is particularly important due to the impact that the "overreliance on coal-fired power has had on the security, stability, and sustainability of the whole power system". Therefore, those authors argue that it is crucial "to determine which generating technologies should be prioritized for development and how they should be developed". For that purpose, [16] have evaluated China's medium term (2020) planned generating-technology portfolio, as described in "the power industry's Eleventh Five-Year Plan", which aims to reduce the portfolio's generating risk through appropriate diversification of generating technologies, and where a strong focus on the deployment of renewable energy technologies is foreseen. The main conclusion reached by those authors was that "the future

adjustment of China’s planned 2020 generating portfolio can reduce the portfolio’s cost risk through appropriate diversification of generating technologies, but a price will be paid in the form of increased generating cost”.

Another study was conducted by [13], where they tried to optimise wind power investment portfolios across countries taking into account the correlation between wind farms output located in different geographical areas. These authors concluded that the current and projected portfolios for 2020 are far from the efficient frontier and, therefore, there is scope for wider benefits arising from greater coordination of European renewable development by providing "incentives for location of new wind farms so as to maximise the efficiency of the overall European wind portfolio" [13].

Although based on the mean-variance reasoning, [24] used instead the internal rate of return (IRR) concept for an electricity generation investment project as the return measure and the standard deviation of the IRR as the risk measure in order to obtain an optimal investment portfolio comprised of different renewable energies, allowing to analyse these technologies individually and collectively using investment risk simulations. They have concluded that “an increase in external financing increases the portfolio’s risk due to the increase in return”, and that the “technologies that have the lowest risk and the lowest return […], increase their market quota in more conservative scenarios”.

In turn, [18] applied the MVA approach in order to optimise generation electricity portfolios but focusing their attention "on private investors' investment incentives in liberalized electricity markets, where fuel-mix diversification is a possible strategy for reducing exposure to electricity, fuel, and carbon price risks". In fact, according to these authors, the electric utilities operating in deregulated markets cannot easily pass on to the sales price changes in their production costs. Thus, utilities have to take into account the risks that may affect their profits when they have to decide about its investment projects. In this context, the risks regarding electricity, fuel and carbon prices become relevant in determining the optimal production portfolios. The results obtained by [18] have demonstrated the importance of the degree of correlation between the prices of electricity, fuel and carbon in the definition of the optimal generation mix. Hence, they have concluded that "liberalized electricity markets characterized by strong correlation between electricity and gas prices […] are unlikely to reward fuel mix diversification sufficiently to make private investors' choices align with the socially optimal fuel-mix, unless investors can find counterparties with complementary risk profiles to sign long-term power purchase agreements".

Also [19] applied the MVA approach from the perspective of a private generation company operating in a liberalised electricity market. Those authors argued that in this type of markets, it is essential that utilities companies can properly manage the electricity price risk, given the strong competition among the different operators in those markets. To address this issue, [19] adopt the MVA approach in order to define the best strategy for electricity trading for a company that is considering selling in the spot market or establish bilateral contracts. The question that arises is "how to allocate energy among these potential transactions in order to maximize profits with relatively low risk" [19]. In fact, the combination of different trading strategies of electricity can be seen as constituting a portfolio which can be optimised using the MVA approach.

Finally, [17] presents a summary of the application of the MVA approach in the evaluation of different electricity generation planning scenarios for the case of U.S., EU and Mexico, where was perceived that the mix of electricity generation can be improved in terms of cost and/or risk, by expanding the use of renewable technologies. The author states that "compared to existing, fossil-dominated mixes, efficient portfolios reduce generating cost while including greater renewables shares in the mix thereby enhancing energy security. Though counterintuitive, the idea that adding more costly renewables can actually reduce portfolio-generating cost is consistent with basic finance theory". It follows an important conclusion: "in dynamic and uncertain environments, the relative value of generating technologies must be determined not by evaluating alternative resources, but by evaluating alternative resource portfolios" [17].

The above mentioned papers have demonstrated the possibility of adapting a pure financial theory to electricity planning problems. In fact, the increase of RES to electricity generation creates important challenges to grid managers due to the expected variability of the power output of most of these RES power plants. The adoption of a model based on portfolio theory can be particularly useful for electricity systems highly RES supported, allowing to take into account both yearly seasonality and intra-daily variations of the production. Therefore, this paper proposes to demonstrate the use of the MVA approach on these systems based on the particular case of the Portuguese electricity system to identify optimal RES portfolios. The aim is to optimize the trade-off between the variable production that characterize some of the RES and the return of these projects, measured according to a set of proxy variables.

In the following section an application of the MVA approach to the case of Portuguese electricity generation planning is shown, with a particular focus on the role of RES technologies.

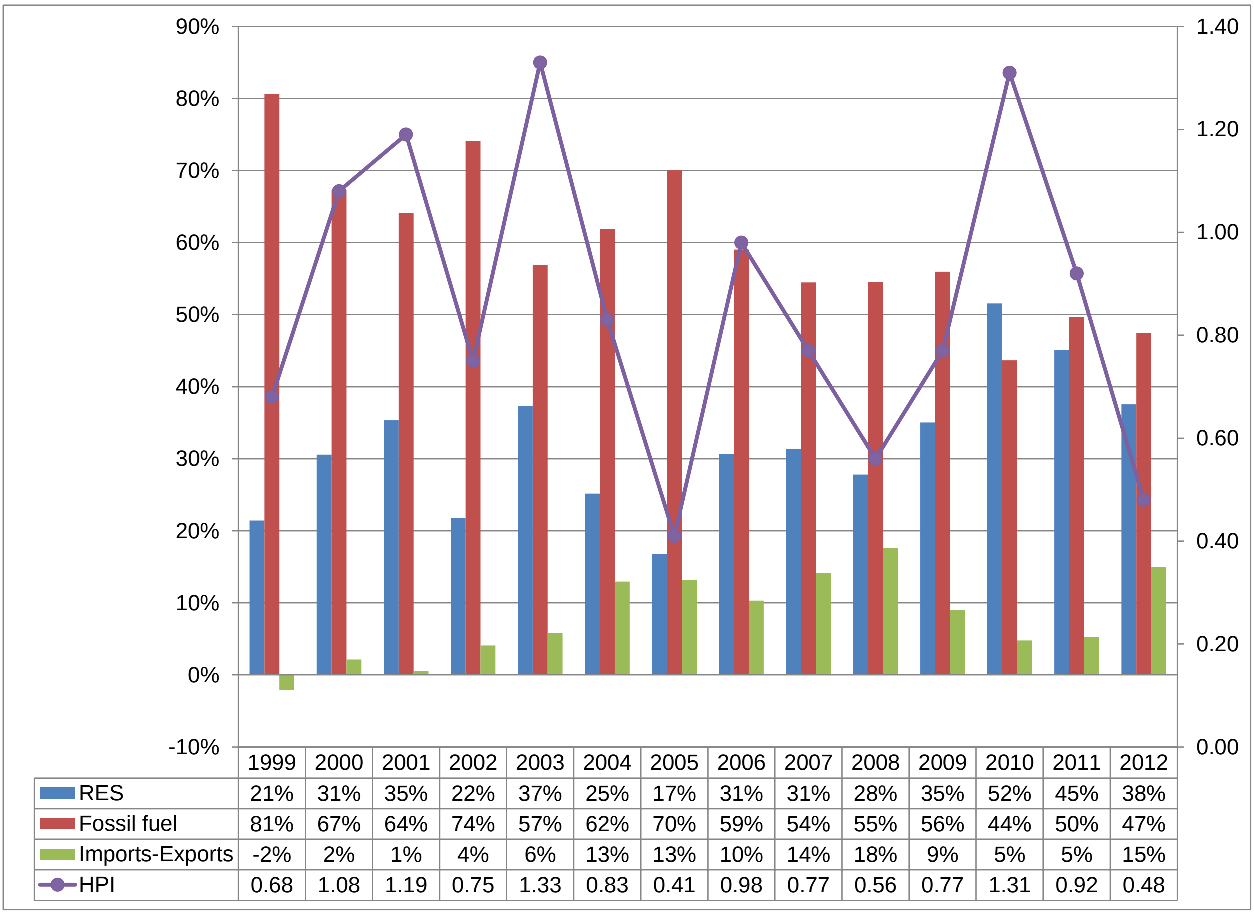
3. EMPIRICAL STUDY

One advantage of the MVA approach is the fact that it explicitly recognize portfolio risk as a decision variable influenced by the risk of each technology output and, most importantly, by the correlations between those risks. In the empirical study undertaken, the main goal was to present possible RES generation mixes that would ensure minimum cost for each given portfolio risk level, obtaining the correspondent efficient frontier. The use of the Portuguese case, as an electricity system strongly influenced by RES seasonality behaviour, is expected to contribute to demonstrate how MVA approach can provide a way to complement cost optimization models with a quantitative risk evaluation of the electricity generation portfolio.

3.1 RES in the Portuguese electricity sector

One feature that should be highlighted in the Portuguese electricity system is the significant share of RES in the current technological production mix [4]. In fact, the role of RES has been increasing over the years due to the government objectives of reducing energy imports and CO_2 emissions. Therefore, the electricity system is mainly based on a mix of thermal, hydro and wind power technologies. The wind sector grew rapidly in the last years and an increase on the hydropower investment is also foreseen for the next years, strongly justified by the need to compensate the variable output of wind power plants.

Figure 1 shows the evolution of the share of electricity consumption from RES, fossil fuel sources and importation balance for the period 1999-2012. One can observe the increasing share of RES on electricity consumption along those years, starting with a share of 21% in 1999 and reaching a value of 52% in 2010, although being reduced to 38% in 2012.



	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
RES	21%	31%	35%	22%	37%	25%	17%	31%	31%	28%	35%	52%	45%	38%
Fossil fuel	81%	67%	64%	74%	57%	62%	70%	59%	54%	55%	56%	44%	50%	47%
Imports-Exports	-2%	2%	1%	4%	6%	13%	13%	10%	14%	18%	9%	5%	5%	15%
HPI	0.68	1.08	1.19	0.75	1.33	0.83	0.41	0.98	0.77	0.56	0.77	1.31	0.92	0.48

Figure 1. Evolution of the share of electricity consumption from RES, thermal sources and imports in Portugal, 1999-2011, and the hydroelectricity productivity index (HPI). Source: Own elaboration of [25, 26, 27].

The share of RES is mainly due to large hydro-power and wind-power plants. It should also be noted that, regarding hydroelectricity production, total RES contribution is extremely vulnerable to the rainfall conditions, which explains why in rainy years, such as 2003 and 2010, the share of RES in total production was higher than in remaining years (37% and 52%, respectively) and in dry years, such as 2005 and 2012, its share is lower. This pattern is also shown by the evolution of the Hydroelectricity productivity index (HPI) which is much higher in rainy years than in dry years. The figure also demonstrate that in most recent years the impact of the HPI on the overall RES share is not as high as in the first years of the 2000 decade, which is largely explained by the increasing role of wind power able to smooth to a certain extent the impacts of a dry year.

3.2 Data set

The data used to solve the optimisation models were drawn from public information available on [28]. The data consisted, for each technology included in the study (i.e. wind, small-hydro, and photovoltaic), of the load output measured for each quarter of an hour for a time period between January 2009 and October 2013, comprising 168,572 measures for each technology, which allowed to capture the daily and yearly seasonality of RES technologies output. To get some insights about this variability, Figures 2-4 show the monthly average of the load output of wind, small-hydro, and photovoltaic.

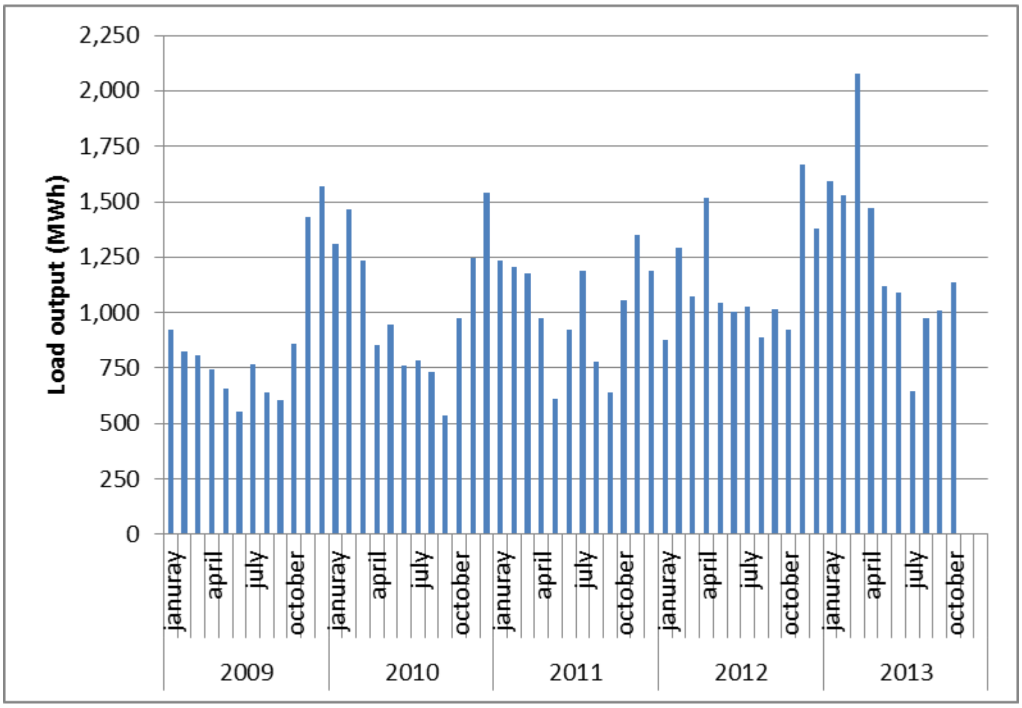


Figure 2. Monthly average of load output for wind for the period January 2009-October 2013. (Source: Own elaboration from REN data)

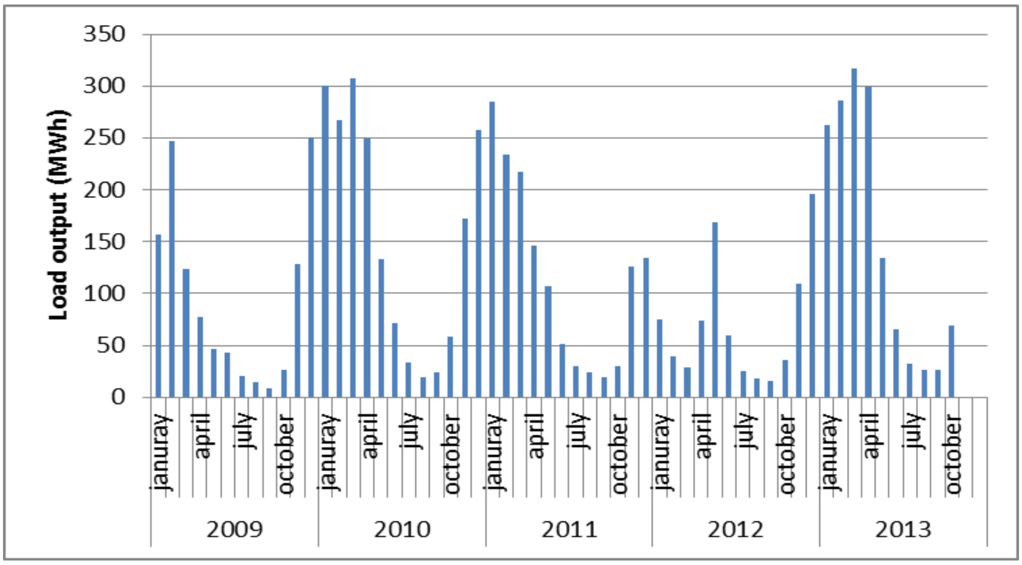


Figure 3. Monthly average of load output for small-hydro for the period January 2009-October 2013. (Source: Own elaboration from REN data)

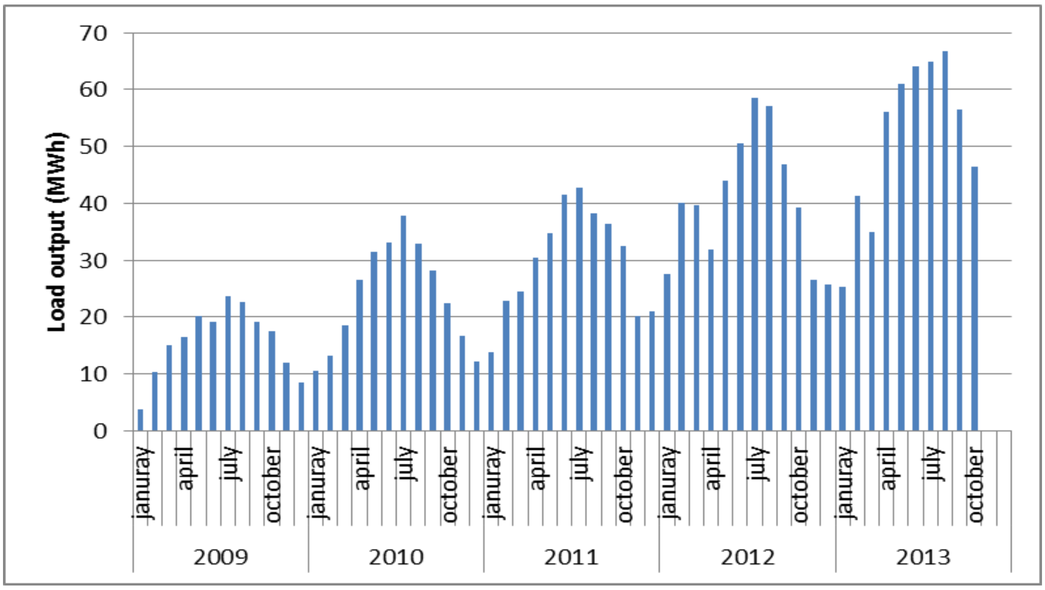


Figure 4. Monthly average of load output for photovoltaic, for the period January 2009-October 2013. (Source: Own elaboration from REN data)

From the three figures, one can see the high variability of the RES output, which is mainly due to the non-storage capacity of RES production. The wind and small-hydro output production is much higher on autumn and winter seasons than in summer whereas for photovoltaic the contrary happens. Although representing yet a small fraction of total production, it is also possible to witness the increasing share of photovoltaic for electricity production. As for the small hydro power plants most of them do not present storage capacity and as so it was assumed that their production could represent a proxy variable for the hydro availability. Both the wind power and photovoltaic loads were assumed as proxy variables for the underlying resource availability.

To allow for comparability among variables, the output of each technology (wind, small-hydro, and photovoltaic) was normalized by the average installed power for the period 2009-2013. The proxy variables included on the proposed MVA model are characterised in Table 1 and include the normalized small hydro output, representing the hydro inflows (hydro availability) to the system; the normalized wind power output, representing the wind availability of the system; and the normalized photovoltaic output, representing the sun availability of the system.

Table 1. Characteristics of the proxy variables for MVA models.

	Hydro	Wind	Photovoltaic
Mean (MW/Installed MW)	0,3279	0,2577	0,1921
Standard deviation (MW/Installed MW)	0,2980	0,1958	0,2798
Correlation coefficient:			
Hydro	1	0,2596	-0,0506
Wind		1	-0,1690
Photovoltaic			1

From Table 1, one observes that the hydro technology is the one with the higher level of output production for each unit of installed capacity, whereas photovoltaic shows the lower value. On the other hand, using the coefficient of variation, the normalised wind output shows the lower variability whereas photovoltaic shows the higher one. Regarding the correlation between the outputs of each technology, it is seen that hydro is positively correlated with wind and that photovoltaic is negatively correlated with hydro and wind.

3.2 Illustration of the MVA approach

To apply the MVA approach reasoning, two different optimisation models were performed: one consisted in maximising portfolio output electricity generation, and the other in minimising portfolio electricity generation costs. To find optimal solutions for each optimisation problem the Excel Solver was used.

3.2.1 Maximising portfolio electricity generation

In this first case, the aim was to obtain the efficient frontier that can maximise the expected RES production per unit of installed capacity for each risk level. The optimisation model is described by (3) to (6).

Objective function:

$$\text{Max } E(\mathrm{L_P}) = \sum_{i=1}^{3} \mathrm{W_i E(L_i)} \quad (3)$$

Restrictions:

$$\sigma(\mathrm{L_P}) = \sqrt{\sum_{i=1}^{3} W_i^2 \sigma_i^2 + \sum_{i=1}^{3} \quad \sum_{k=1(k\neq i)}^{3} W_i\, W_k \rho_{ik} \sigma_i \sigma_k} \quad (4)$$

$$\sum_{i=1}^{3} \mathrm{W_i} = 1 \quad (5)$$

$$\mathrm{W_i} \geq 0 \quad \forall_i \quad (6)$$

Where $E(L_p)$ represents the expected return of the portfolio (RES generation per installed MW), W_i represents the share of technology i, $E(L_i)$ represents the expected i technology output (i generation per installed MW), $\sigma(L_p)$ represents the standard deviation of the portfolio, σ_i represents the standard deviation of i technology output, and ρ_{ik} represents the correlation coefficient between i and k technologies outputs.

Table 2 and Figure 5 describe the results obtained, including the efficient frontier, the characterization of a set of optimal portfolios, and also the 2012 RES (wind, hydro and photovoltaic) portfolio computed according to the installed power of these technologies in 2012 [26] and the expected 2020 portfolio computed according to the National Plan for Renewable Energy [29].

Table 2. Characterization of the set of optimal portfolios

	σ(Lp)	**E(Lp)**	**Hydro**	**Wind**	**Photovoltaic**
Portfolio 1	0.30	0.33	100.0%	0.0%	0.0%
Portfolio 2	0.26	0.32	83.9%	16.1%	0.0%
Portfolio 3	0.23	0.31	69.5%	30.5%	0.0%
Portfolio 4	0.20	0.29	54.5%	42.6%	3.0%
Portfolio 5	0.18	0.28	46.0%	45.0%	8.9%
Portfolio 6	0.16	0.27	36.1%	47.7%	16.3%
Portfolio 7	0.14	0.25	14.6%	53.3%	32.2%
2012	0.20	0.30	56.2%	41.6%	2.2%
2020	0.21	0.30	60.0%	35.5%	4.5%

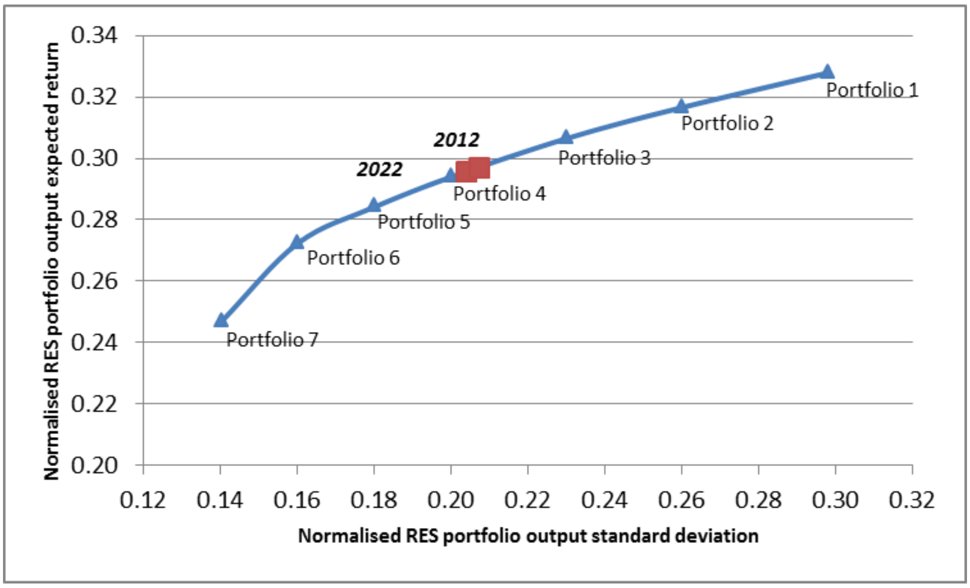


Figure 5. Efficient frontier for maximizing portfolio electricity generation

From the analysis of Table 2 and Figure 5, the following results can be highlighted. Firstly, the 2012 mix and the 2022 scenario are on the efficient frontier, reflecting the Portuguese energy policy goals of increasing RES share on the electricity system, diversifying the energy sources, and promoting a strategy based on hydro reinforcement to deal with the increasing wind share. Secondly, most of the less risky scenarios point to a mix of hydro-wind and even photovoltaic power demonstrating that these are the more efficient portfolios. Finally, more risky strategies rely, mainly, on hydro power which can be justified by its highest risk (standard deviation) but also by its highest return (output mean).

3.2.2 Minimising portfolio electricity generation costs

In this second case, the optimisation problem aims to achieve an efficient frontier with the objective of minimising the total expected cost of the RES system per unit of installed capacity for each risk level. The optimization model is described by (7) to (10).

Objective function:

$$\text{Min } E(\mathrm{LC_P}) = \textstyle\sum_{i=1}^{3} \mathrm{W_i LC_i E(L_i)} \qquad (7)$$

Constraints:

$$\sigma(\mathrm{LC_P}) = \sqrt{\textstyle\sum_{i=1}^{3} W_i^2 \sigma_i^2 + \sum_{i=1}^{3} \sum_{k=1(k\neq i)}^{3} W_i W_k \rho_{ik} \sigma_i \sigma_k} \qquad (8)$$

$$\textstyle\sum_{i=1}^{3} \mathrm{W_i} = 1 \qquad (9)$$

$$\mathrm{W_i} \geq 0 \quad \forall_i \qquad (10)$$

where $E(LC_p)$ represents the expected levelised cost (LC) of the portfolio per unit of installed capacity, $\sigma(LC_p)$ represents the standard deviation of levelised cost of the portfolio and LC_i represents the levelised cost of each i technology.

The values for the LC of each technology were based on the indicative values of the feed-in-tariffs for the three technologies under the Portuguese market conditions in 2013. These values are defined according to Decree-Law 225/2007 and were assumed to be a good proxy for the LC, corresponding to 74 €/MWh for wind, 91 €/MWh for small hydro and 310 €/MWh for photovoltaic (information obtained from [30].

Table 3 and Figure 6 describe the results obtained, including the efficient frontier and the characterization of a set of optimal portfolios, as well as the 2012 mix and the 2022 scenario.

Table 3. Characterization of the set of optimal portfolios

	$\sigma(LC_p)$	$E(LC_p)$	Hydro	Wind	Photovoltaic
Portfolio 1	0.20	19.07	0.0%	100.0%	0.0%
Portfolio 2	0.19	19.65	5.4%	94.6%	0.0%
Portfolio 3	0.18	21.19	12.0%	86.0%	2.1%
Portfolio 4	0.17	23.04	12.3%	81.1%	6.5%
Portfolio 5	0.16	25.14	12.8%	75.6%	11.6%
Portfolio 6	0.15	27.76	13.3%	68.7%	17.9%
Portfolio 7	0.14	33.67	14.6%	53.3%	32.2%
2012	0.20	24.80	56.2%	41.6%	2.2%
2022	0.21	27.35	60.0%	35.5%	4.5%

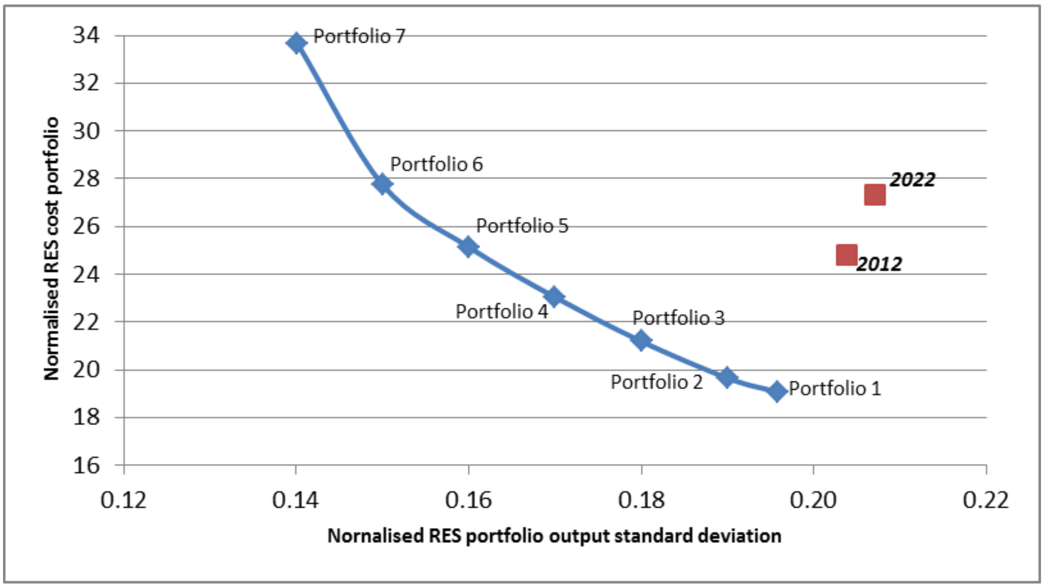


Figure 6. Efficient frontier for minimising the levelised cost of the portfolio

From Table 3 and Figure 6 the following findings emerge. Firstly, the results seem to be driven by the levelised cost of the technologies. Secondly, a strong reliance on wind power is evident along the efficient frontier. Thirdly, what seems to be the best solution (Portfolio 1) in terms of minimum cost achieved is, however, compromised by a 100% wind power share. From a technical point of view it would be an extremely improbable solution, due to the already existing hydro capacity and for motives of security of supply. Fourthly, the solutions with lower risk (e.g. Portfolio 7) are characterized by a mix of wind, hydro and photovoltaic technology. Fifthly, the 2012 mix and the 2022 forecasted scenario are far from the efficient frontier. This means that, for example, it would be possible to decrease the cost of the portfolio of electricity generation technologies for the same level of risk and, therefore, increase the efficiency of the production mix. Finally, it should be noted that the proposed MVA model only included data related to small hydropower plants, which show a much higher variability than large storage hydropower.

4. DISCUSSION OF RESULTS

The results indicate that both the 2012 mix and the 2022 scenario [26, 29] are close to the efficient frontier for the first optimisation model (maximising RES output). In fact, both these scenarios reflect the Portuguese energy policy goals of increasing RES share on the electricity system, diversifying the energy sources and promoting a strategy based on hydro reinforcement to deal with the increasing wind share. In the same way, most of the less risky scenarios described in Figure 5 point to mix hydro-wind power scenarios as the more efficient ones. More risky strategies rely mainly on hydro power, the option with higher expected return but also the one with higher standard deviation. Although a positive correlation exists between wind and hydro, it does not seem to be enough to jeopardize the mix of these technologies in most of the scenarios. On the other hand, photovoltaic presents a less interesting expected value and a risk level close to the hydro one. It presents, however, the advantage of being negatively correlated to both wind and hydro. As so, less risky scenarios tend to include also this option combined with hydro and wind.

The second optimisation model performed (minimising portfolio electricity generation costs) presents quite different results, clearly driven by the levelised cost of the technologies. A strong reliance on wind power is evident along the efficient frontier, as this is the option with lowest expected cost and with the lowest standard deviation when considering the levelised cost normalized by the installed power. Solutions with lower risk are characterized by a mix of wind, hydro and, to a lower extent, photovoltaic technology, leading to a higher expected cost but also taking advantage of the portfolio diversification.

Although the usefulness of the MVA approach for electricity generation planning scenarios has been demonstrated, the obtained results put also in evidence the need to enrich this approach with additional technical, legal and economic constraints when passing from the analysis of financial assets portfolios to the analysis of portfolios of real projects. In fact, there are some limitations of the MVA approach that should be dealt with. For example, [12] emphasised two issues. On the one hand, the failure to consider transaction costs associated with changes in generation mix. Second, the fact that, generally, the studies carried out do not take into account the feasibility of the efficient portfolios obtained with the MVA approach in the context of existing energy infrastructure. Moreover, [14] pointed out that the characteristics of electricity generation technologies are not always comparable to the characteristics of financial assets for which the MPT theory was developed. Firstly, markets for assets (e.g. turbines, coal plants) related to electricity generation are usually imperfect in contrast with capital markets, which also make them less liquid. Secondly, financial assets are almost infinitely divisible and fungible, which does not happen with electricity generating real assets. Finally, investments in electricity production technologies tend to be lumpy, especially renewable technologies. However, [14] argue that "for large service territories or for the analysis of national generating portfolios, the lumpiness of individual capacity additions becomes relatively less significant".

5. CONCLUSION

Sustainable development depends, in some extent, on changing the electricity generation paradigm. In this regard, RES have an important role for the design of strategies for sustainable future. These strategies have been fostered by several international environmental agreements, such as the Kyoto protocol and the RES Directive, which have the advantage, for countries like Portugal, of promoting the use of endogenous resources, reducing external energy dependency and diversifying energy supply.

However, the raising trend of RES brings considerable challenges to decision makers due to uncertainty of the production highly dependent on the availability of the underlying resources. Therefore, this paper was an attempt to apply an alternative tool for electricity planning – the MVA approach – in relation to the traditional least cost methodology. This allowed addressing both the expected return and the RES portfolio risk, taking into account both the standard deviation of each technology output and the correlation coefficient between technology outputs.

The major findings of the study were that: (a) less risky solutions are characterised by a mix of RES technologies for both optimisation models performed; and (b) both the 2012 production mix and the 2022 forecasted scenario are on the efficient frontier for the first optimisation model and far from the efficient frontier for the second optimisation model. This last result can however be explained by the assumed LC of electricity of each technology that drives the results of this cost model. This demonstrates the need to properly assess the cost of the technologies and of different projects to be included in the portfolio, as LC of RES can dramatically change from one location to another depending on the renewable resource conditions. In fact, the 2012 and 2022 scenarios are strongly constrained by other restrictions not included in these models, namely the RES and non-RES power plants already operating in the electricity system, the legal and technical requirements, the demand requirements and fluctuations and the existing interconnection with Spain. Notwithstanding, it is worth to underline that both MVA point to the same solution for the minimum risk portfolio, establishing that diversification is in fact an effective strategy to reduce risk not only for financial assets but also for the electricity production sector.

The results have demonstrated that the MVA can give an important contribute to decision making in the electricity sector, due to the recognition of the risk variable and correlation of technologies. Though recognising its usefulness, the results obtained also clearly indicate that this approach should be enriched with additional technical, legal and economic constraints given the different nature of financial assets (for which the MVA approach was initially proposed) and real assets (as is the case of power plants).

ACKNOWLEDGMENT

This work was financed by: the QREN – Operational Programme for Competitiveness Factors, the European Union – European Regional Development Fund and National Funds- Portuguese Foundation for Science and Technology, under Project FCOMP-01-0124-FEDER-011377 and Project Pest-OE/EME/UI0252/2011.

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