Designing electricity generation portfolios using the mean-variance approach

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ABSTRACT

The mean-variance approach (MVA) is commonly used in the financial literature for the optimal design of financial asset portfolios. The electricity sector portfolios are also guided by similar objectives, namely maximising return and minimising risk. As such, this paper proposes two possible MVAs for the design of optimal renewable electricity production portfolios. The first approach is directed at portfolio output maximisation and the second one is directed at portfolio cost optimisation. The model was implemented on data compiled from the Portuguese electricity system collected for each quarter of an hour, for a period close to four years. Three renewable energy sources (RES) portfolios were used, namely hydropower, wind power and photovoltaic. This highlighted the resource seasonality demonstrating that hydropower output positively correlates with wind power and that photovoltaic correlates negatively with both hydro and wind power. The results show that for both models the least risky solutions are characterised by a mix of RES technologies, taking advantage of the diversification benefits. As for the highest return solutions, as expected, these are the ones associated with higher risk but the portfolio composition largely depends on the assumed costs of each technology.

1. Introduction

The need for investing in renewable energy sources (RES) is clear given the finite nature of many of earth's resources, 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 characterised 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 is highly dependent on the availability of natural resources such as wind, sunlight or rain, making 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 a risk mitigation strategy exploring the diverse and possible complementary behaviour of each renewable resource related to their annual seasonality and even to their intra-daily pattern.

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

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traditional least cost approach. However, it should be recognised that the characteristics of electricity generation technologies are not always comparable to the characteristics of financial assets. In the electricity planning context, authors have resorted to models either optimising the expected power output (e.g. [13]) or optimising portfolio cost (e.g. [14, 15]).

This paper contributes to the analysis of different electricity production portfolios recognising the importance of addressing both risk and return and proposes the use of the MVA approach as an electricity generation planning tool. The return of the portfolio is dependent on the power output of each technology included in the portfolio for a given period. As for risk, investments in renewable energy are affected by many sources of risk as described in [4]. The MVA approach addresses mainly the risk related to the variability of this power output, which in turn depends on the intra-daily and seasonal variability of renewable energy resources. The model is applied using the Portuguese case as an example and emphasising the particular role of the RES technologies, under a policy decision-making perspective. Optimal RES electricity generation mixes for the future are proposed, taking into account the past production pattern of each RES and optimising the trade-off between maximising output and minimising portfolio 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, it becomes crucial to introduce electricity planning methodologies that acknowledge the correlation between various electricity generation options, as well as the respective risk. Following the previously identified common approaches, in this paper two optimisation problems were formulated: one maximises the expected portfolio output for a given level of risk, and the other minimises portfolio cost for a given level of risk.

The results of the study show 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 mean-variance 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 [16]. The traditional approach to electricity generation planning has been the least-cost methodology [17], which is based on calculating the levelised costs of electricity generation, expressed in €/MWh, for different alternative production technologies and, after comparing those costs, choosing the lowest cost options. However, this approach has met with some criticism both when used to support policy-decision making and when used to support private investment decisions.

From the point of view of policy decision-making, a wide range of alternative technologies for electricity generation can be considered and can be operated in different institutional frameworks. This, coupled with a future that appears increasingly complex and uncertain [18], brings new challenges to electricity planners. 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.

As for the private investors' perspective, liberalisation of the energy markets has fostered interest in the quantification and management of market risks [19]. In fact, with the deregulation and liberalisation of electricity markets and the 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 [20]. 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 [20, 14].

Therefore, since different technologies are considered in electricity planning, which differ not only in terms of costs but 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 (MVA). In the particular case of RES production portfolios, this approach takes into account not only resource variability, but also the possible complementarity between resources, which can result on a better assessment of the storage needs and of the installed power.

The MVA approach was initially proposed by [21] for the efficient selection of financial asset portfolios and is based on the investors' goal of maximising future expected return for a given level of risk they are willing to accept (or minimising risk for a given level of return they wish to achieve). The main underlying assumption is that investors are risk averse, which means that when faced with a choice between two investments with the same risk level they always choose the one with higher expected return. Therefore, the MVA approach highlights the advantages of investment diversification among several financial securities [22]. In fact, the characteristics of a portfolio can be very different from the characteristics of the assets that comprise the portfolio [23]. Particularly, when the returns on different assets are independent, a portfolio comprising multiple assets can have lower risk than each individual asset.

This effect can be illustrated using the example of a two asset (A and B) portfolio, P. The portfolio expected return, $E(r_P)$, is given by the weighted average return of each asset, $E(r_A)$ and $E(r_B)$, included in the portfolio:

$$E(r_P) = \omega_A E(r_A) + \omega_B E(r_B) \qquad (1)$$

where ω_A and ω_B represent the proportion of each asset on the portfolio. For their turn, the risk of the portfolio, σ^2_P, is computed as:

$$\sigma^2_P = \omega_A^2 \sigma^2_A + \omega_B^2 \sigma^2_B + 2\omega_A\omega_B\rho_{AB}\sigma_A\sigma_B \qquad (2)$$

where σ^2_A is the variance (i.e. the risk) of the returns on asset A, σ^2_B is the variance (i.e. the risk) of the returns on asset B, ρ_{AB} is the correlation coefficient between the returns on the two assets, and σ_A and σ_B are the standard deviations of the returns on assets A and B, respectively. The last term in the expression of the variance is often written in terms of the covariance of returns between two assets: $\sigma_{AB} = \rho_{AB}\sigma_A\sigma_B$. One can see that the risk of the portfolio, σ^2_P, is not just the weighted average of each asset risk, but includes the correlation coefficient between assets' returns, which means that the benefits of diversification are a function of the correlation coefficient.

Generalising these results for the case of a portfolio comprised of N assets, its expected return, $E(r_P)$, and risk (variance), σ^2_P, are given by, respectively:

$$E(r_P) = \sum_{i=1}^{i=N} \omega_i E(r_i) \qquad (3)$$

and

$$\sigma^2_P = \sum_{i=1}^{i=N} \sum_{j=1}^{j=N} \omega_i\omega_j\rho_{ij}\sigma_i\sigma_j \qquad (4)$$

where ω_i and ω_j represent the proportion of asset i and j on the portfolio (with $i \neq j$), $E(r_i)$ is the return of asset i, ρ_{ij} is the correlation coefficient between the returns on assets i and j, and σ_i and σ_j are the standard deviations of the returns on assets i and j, respectively. It is clear that the variance of the portfolio (i.e. its risk) is partially determined by the variance of each individual asset (i.e. its risk) and partly by the way they move together – the covariance (σ_{ij}) 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 [24], portfolios of financial assets should be chosen not only based on their individual characteristics but also taking 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 by solving the following optimisation problem:

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

$$s.t.$$

$$\sigma_P^2 = \sum_{i=1}^{i=N} \sum_{j=1}^{j=N} \omega_i \omega_j \sigma_{ij} \le \hat{\sigma}^2$$

$$\sum_{i=1}^{N} \varpi_i = 1$$

$$\varpi_i \ge 0$$

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

Following this reasoning, there has been a growing application of the MVA approach to electricity generation planning in recent years. In fact, this approach can be used to determine the optimal portfolios of electricity generation both for a company and for a country. Since the main idea of the MVA approach is that the value of each asset can only be determined by taking into account portfolios of alternative assets [14], energy planning should be focused more on developing efficient production portfolios and less on finding the alternative with the lowest production cost [18, 14]. For example, in the context of combining conventional and renewable technologies for electricity production, Awerbuch [18] 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. This is due to the statistical independence of renewables costs, which tend to be not correlated 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, the MVA approach allows analysing the impact of the inclusion of renewable technologies in the mix of generating sources of electricity, providing a better risk assessment of alternative generation technologies, something that the traditional stand-alone least cost approach cannot do.

It should be noted that the advantage of applying the MVA approach to electricity generation planning is not the identification of a specific portfolio, but the establishment 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. In fact, it illustrates 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. 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].

Francés et al. [8] analysed the relationship between energy security and RES, since efficiency and diversification are important elements to improve energy security and to reduce energy vulnerability. Focusing on the European Union (EU) Mediterranean Solar Plan, they have concluded that "green electricity from RES, whether domestically produced or not, could improve energy security" [8]. A similar result was achieved by Bhattacharya & Kojima [9] which have demonstrated that a diversified electricity generating portfolio including low risk RES can in fact reduce the overall investment risk of the portfolio, contributing to "reduce the cost of risk hedging in terms of achieving a certain level of energy supply security" [9].

In another study Arnesano et al. [10] have recommended an increased investment in technologies based on RES, given that a reduction in total generation cost can be attained for the same level of risk. A similar empirical finding was obtained by Delarue et al. [11]: "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" [11]. Also, Zhu & Fan [17] have evaluated China's medium term (2020) planned generating-technology portfolio, 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. Their major conclusion 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" [17].

Finally, Awerbuch [18] 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 concluding 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" [18]. 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" [18].

The above mentioned papers have demonstrated the possibility of adapting a pure financial theory to electricity planning problems. In fact, the increase of RES in 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 as it takes into account both yearly seasonality and intra-daily variations of the production. Therefore, this paper proposes 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 optimise the trade-off between the variable production that characterises 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 recognises portfolio risk as a decision variable influenced by the risk of each technology output and,

most importantly, by the correlations between those outputs. For the MVA model, the risk of the portfolio is proxied by the variability of the expected power output which is measured by the standard deviation of each technology power output. 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 optimisation 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 [25]. 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 imports 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.

The share of RES is mainly due to large hydropower 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 demonstrates that in most recent years the impact of
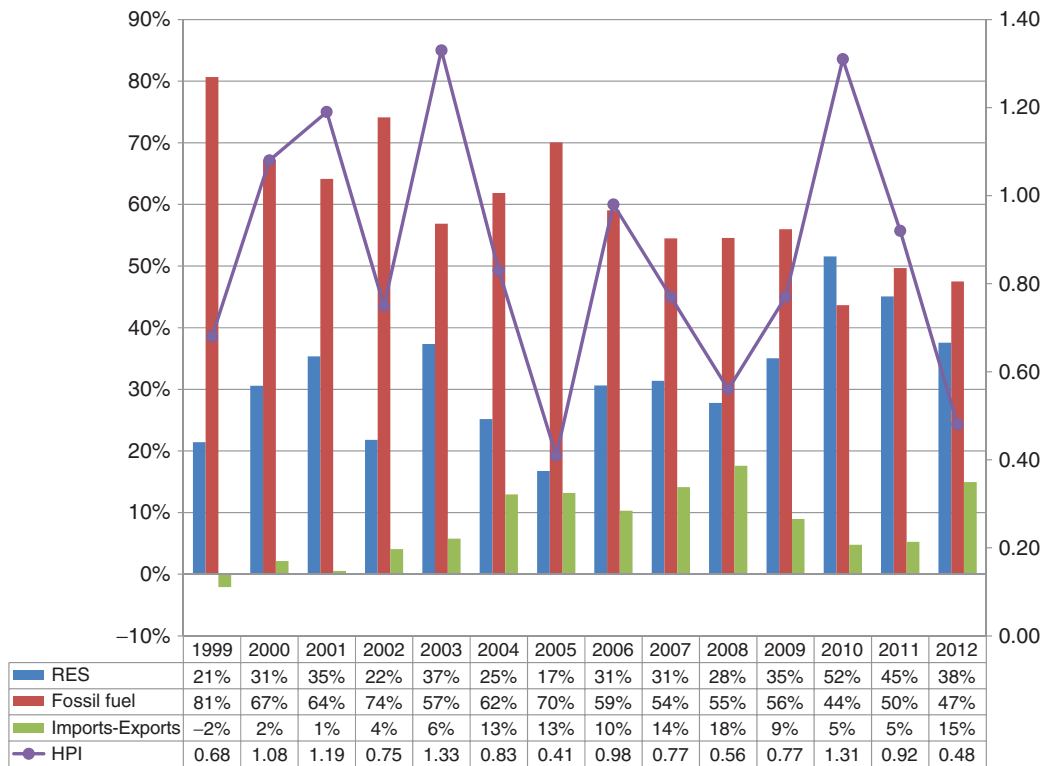
Figure 1: Evolution of the share of electricity consumption from RES, thermal sources and imports in Portugal, 1999-2012, and the hydroelectricity productivity index (HPI). Source: Own elaboration of [26, 25, and 27].

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 on this variability, Figures 2–4 show the average power output (MW) of wind, small-hydro, and photovoltaic computed for each month of the analysed period.

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 hydropower 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 respective installed power for each year 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
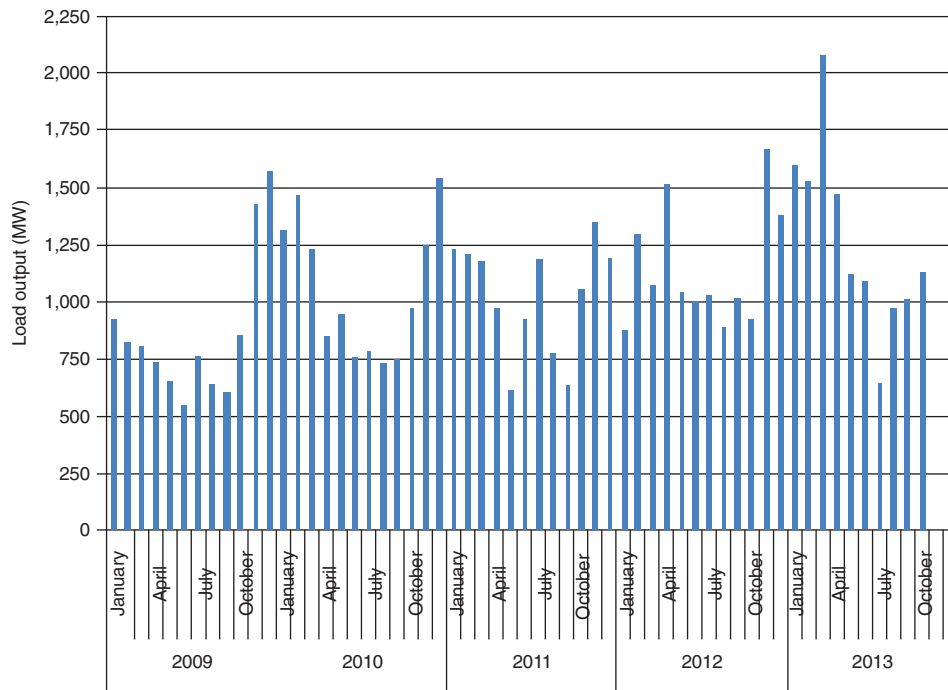
Figure 2: Average power output (MW) of wind computed for each month for the period January 2009-October 2013. (Source: Own elaboration from REN data).
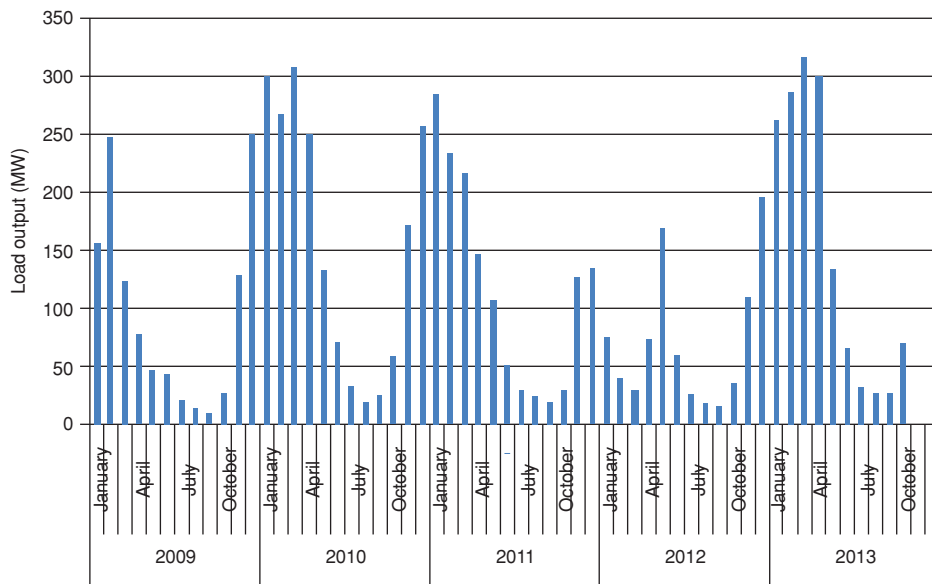

Figure 3: Average power output (MW) of small-hydro computed for each month for the period January 2009-October 2013. (Source: Own elaboration from REN data).

system; and the normalized photovoltaic output, representing the sun availability of the system.

From Table 1, one observes that the hydro technology is the one with the higher level of output production for
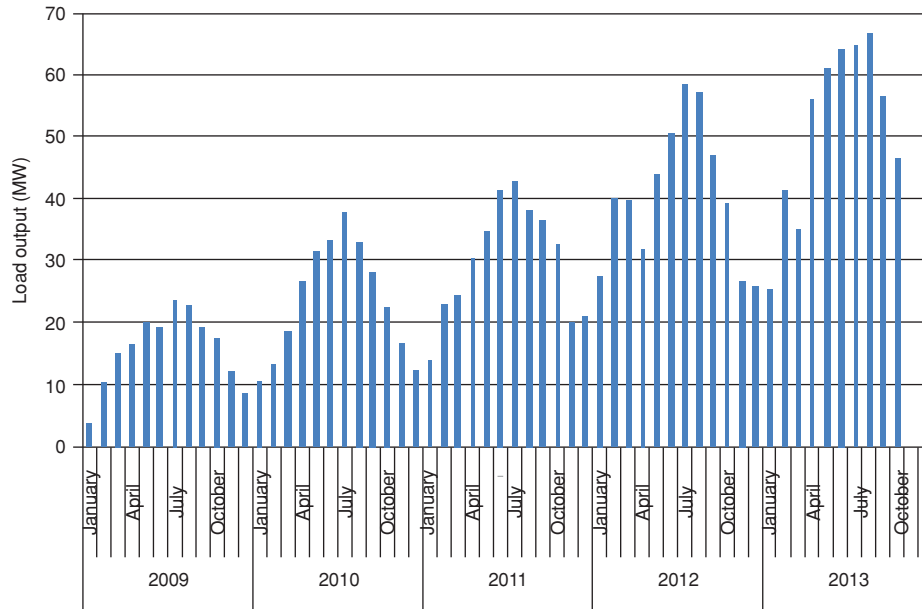
Figure 4: Average power output (MW) of photovoltaic computed for each month for the period January 2009-October 2013. (Source: Own elaboration from REN data).

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

	Hydro	**Wind**	**Photovoltaic**
Mean (MW/Installed MW)	0.3146	0.2509	0.1667
Standard deviation (MW/Installed MW)	0.2859	0.1874	0.2211
Correlation coefficient:			
Hydro	1	0.2633	−0.0688
Wind		1	−0.2255
Photovoltaic			1

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. The trade-off method was applied, consisting in the minimisation of one objective at a time, considering the other as a constraint bounded by allowable levels. The Pareto front was found by varying these levels. The return of the portfolio function was the primary objective and the risk was assumed as the constraint. Varying the risk allowable levels will make possible to obtain a set of solutions representing trade-offs between return and risk.

3.3.1. 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 (5) to (8).

Objective function:

$$\text{Max } E(L_P) = \sum_{i=1}^{3} W_i E(L_i) \tag{5}$$

Constraints:

$$\sigma(L_P) = \sqrt{\sum_{i=1}^{3} W_i^2 \sigma_i^2 + \sum_{i=1}^{3} \sum_{k=1(k \neq i)}^{3} W_i W_k \rho_{ik} \sigma_i \sigma_k} \tag{6}$$

$$\sum_{i=1}^{3} W_i = 1 \tag{7}$$

$$W_i \geq 0 \quad \forall_i \tag{8}$$

Where $E(L_p)$ represents the expected normalised output of the portfolio, 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 characterisation of a set of optimal portfolios (portfolios 1–7), and also the 2012 RES (wind, hydro and photovoltaic) portfolio computed according to the installed power of these technologies in 2012 [25] and the expected 2023 portfolio computed according to the National Plan for Renewable Energy [29]. Each of these portfolios is characterised by the expected normalised output (return), the standard deviation (risk), and the contribution of each RES technology for electricity generation.

From the analysis of Table 2 and Figure 5, the following results can be highlighted. Firstly, the 2012 mix and the 2023 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 hydropower which can be justified by its highest risk (standard deviation) but also by its highest return (output mean).

3.3.2. Minimising portfolio electricity generation costs

In this second case, the optimisation problem aims to achieve an efficient frontier with the objective of minimising the expected levelised cost of the RES system. The objective function is then computed as the normalised output of each technology multiplied by the corresponding levelised cost. The optimisation model is described by (9) to (12).

Objective function:

$$\text{Min } E(LC_P) = \sum_{i=1}^{3} W_i LC_i E(L_i) \tag{9}$$

Constraints:

$$\sigma(LC_p) = \sqrt{\sum_{i=1}^{3} W_i^2 LC_i^2 \sigma_i^2 + \sum_{i=1}^{3} \sum_{k=1(k \neq i)}^{3} W_i W_k \rho_{ik} \sigma_i LC_i \sigma_k LC_k} \tag{10}$$

$$\sum_{i=1}^{3} W_i = 1 \tag{11}$$

$$W_i \geq 0 \quad \forall_i \tag{12}$$

where $E(LC_p)$ represents the expected levelised cost (LC) of the portfolio per unit of installed capacity,

Table 2: Characterisation of the set of optimal portfolios.

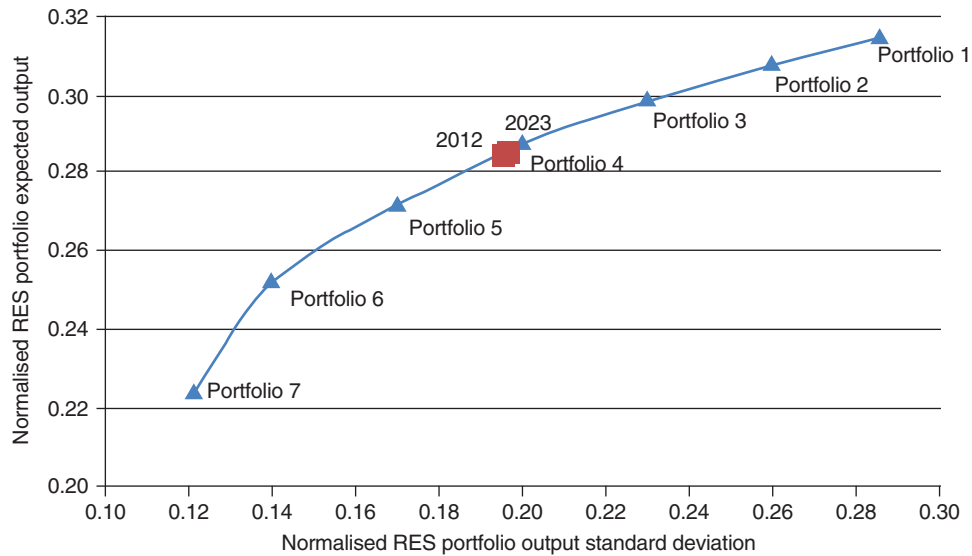|	σ (Lp)	E (Lp)	Hydro	Wind	Photovoltaic
Portfolio 1	0.29	0.31	100.0%	0.0%	0.0%
Portfolio 2	0.26	0.31	88.7%	11.3%	0.0%
Portfolio 3	0.23	0.30	74.4%	25.6%	0.0%
Portfolio 4	0.20	0.29	57.0%	43.0%	0.0%
Portfolio 5	0.17	0.27	43.0%	49.3%	7.7%
Portfolio 6	0.14	0.25	30.1%	48.7%	21.2%
Portfolio 7	0.12	0.22	11.9%	47.8%	40.3%
2012 Mix	0.20	0.28	56.2%	41.6%	2.2%
2023 Scenario	0.20	0.29	57.9%	38.9%	3.2%

Figure 5: Efficient frontier for maximising portfolio electricity generation.

$\sigma(LC_p)$ 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 characterisation of a set of optimal portfolios (portfolios 1–7), as well as the 2012 mix and the 2023 scenario.

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 characterised by a mix of wind, hydro and photovoltaic technology. Fifthly, although the 2012 mix is not on the efficient frontier (but is near) the 2023 scenario is on the efficient frontier and near Portfolio 7, reflecting the increasing share of technologies that

Table 3: Characterisation of the set of optimal portfolios.s

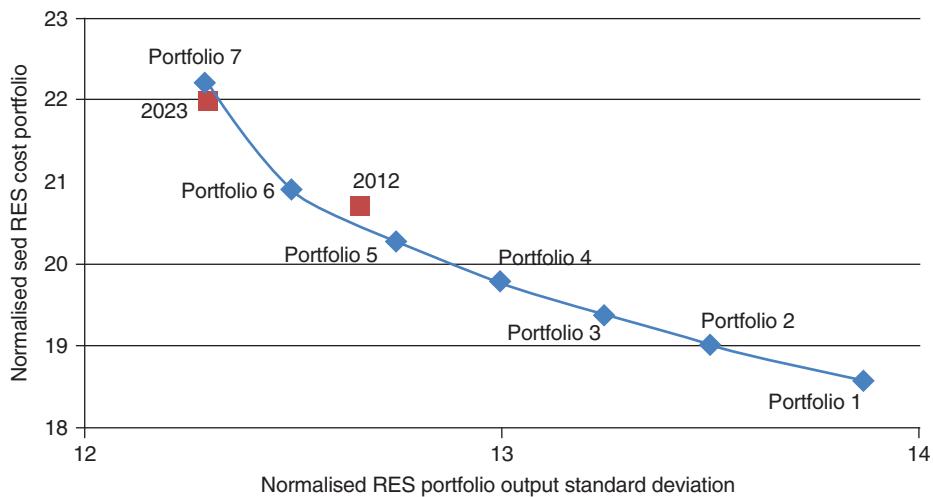|	σ (LC$_p$)	E (LC$_p$)	Hydro	Wind	Photovoltaic
Portfolio 1	13.87	18.56	0.0%	100.0%	0.0%
Portfolio 2	13.50	19.02	0.0%	98.6%	1.4%
Portfolio 3	13.25	19.38	0.8%	97.0%	2.2%
Portfolio 4	13.00	19.78	2.5%	94.6%	2.9%
Portfolio 5	12.75	20.26	4.4%	91.8%	3.8%
Portfolio 6	12.50	20.90	7.0%	88.1%	4.9%
Portfolio 7	12.29	22.19	12.3%	80.5%	7.2%
2012 Mix	12.66	20.71	11.1%	85.8%	3.1%
2023 Scenario	12.30	21.98	11.6%	81.6%	6.8%

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

allow to reduce portfolio electricity generation risk but that have higher costs. 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 2023 scenario [25, 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 hydropower, 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 characterised 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. As in the first optimisation model, both the 2012 mix and the 2023 scenario [25, 29] are close to the efficient frontier. The 2023 scenario demonstrates a risk reduction trend comparatively to the 2012 mix, however this is achieved at the expense of an increasing levelised cost of the portfolio.

Although the usefulness of the MVA approach for electricity generation planning scenarios has been demonstrated, the obtained results also highlight the need to supplement this approach with additional technical, legal and economic constraints when moving from the analysis of financial asset 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, Allan *et al*. [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, Awerbuch & Berger [14] pointed out that the characteristics of electricity generation technologies are not always comparable to the characteristics of financial assets for which the MVA approach was originally 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, Awerbuch & Berger [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, to some extent, on changing the electricity generation paradigm. In this regard, RES play an important role in the design of strategies for a 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 the uncertainty of production, which is 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 2023 forecasted scenario are on or close to the efficient frontier for both optimisation models. Both models allow the design of efficient frontiers, but it is still up to the decision makers to determine their preferred trade-off between risk and return. For example, in Figure 6 the cost can be reduced, but this will increase the risk. In fact, the obtained efficient portfolios represent Pareto optimal scenarios taking into account the risk and return variables, and no implication on the social interest of these scenarios can be inferred.

The first model represents a technical analysis of the system, where only the power output of each RES technology is considered. From this point of view, it can be considered that REN 2012 and 2023 represent scenarios reaching for a compromise between power output and variability of these outputs.

However, the second model shows a different perspective where scenario REN 2023 represents a solution of low cost risk but which is more expensive when taking into account the assumed costs for each technology. Evidently, the least cost solutions are the ones requiring only wind power as it presents the lowest costs. Less risky solutions rely on a mix of technologies including more expensive ones. However, it should be underlined that the results of both models are not directly compared: the first model proposes optimal RES portfolios comprised of wind, photovoltaic and

hydro (small and large) power and the second model proposes optimal cost RES portfolios also comprised of wind and photovoltaic but only small hydro is considered, according to the available feed-in-tariffs.

The results demonstrate the need to properly assess the cost of the technologies and for 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 2023 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 proposed portfolios do not attempt to represent 100% RES scenarios for an electricity system but rather to represent possible optimal combinations of RES technologies that can be included in electricity systems containing also other non-RES technologies. The results have demonstrated that the MVA can make an important contribution 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). In particular, future work addressing RES portfolios should also consider the demand variability and its relationship to RES power output aiming to minimise not only the variability of the portfolio output (standard deviation) but also to minimise the deviation between the demand and the RES production in each moment. Also, the inclusion of other technologies such as hydro with dam and biomass can make a significant contribution to the reduction of the portfolio risk as the power output of these plants can be controlled to some degree.

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