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An Optimization Approach to Select Portfolios of Electricity Generation Projects with Renewable Energies

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Abstract: The traditional approach to electricity planning has been the least cost methodology, which focus on finding the stand-alone cost of each technology in order to minimize power system cost. However, the increasing liberalization path of electricity markets as well as the growing inclusion of renewable energy sources in the power generation mix increased the complexity of the power system planning. To overcome these difficulties an alternative methodology has been proposed in the literature: the mean-variance approach, which has the advantage of explicitly taking into account risk measures as well as the potential correlation between technologies and fuels in power system planning. In this work seven technologies for electricity generation are considered to study the Portuguese case in 2009-2011. Five from these seven technologies are renewable ones. A multiobjective optimization approach is used to identify the optimal solutions, considering two conflicting objectives - risk and return. The computational results are obtained using the routine `fgoalattain` from the MATLAB optimization toolbox.

Keywords: Electricity planning, Renewable energy, Risk-Return, Optimization

1 Introduction

The least cost methodology has been the traditional approach to electricity planning in the last decades. This approach consists on identifying the technology with the lower electricity generation cost in order to minimize power system cost. However, given the main objectives of current energy policy at the European Union level [6] (namely, energy efficiency, reduction of energy dependence, security of supply, minimization of environmental impacts, promotion of renewable energy sources (RES), and liberalization of electricity markets), power system planning has becoming an increasing complex task. In fact, electricity planning has to stop being seen in a perspective of analyzing the cost of each technology in a stand-alone basis and become to be seen as a decision-making process of deciding what the best combination of technologies is in order to be included in a portfolio of electricity generation. In particular, the least cost methodology is unable to explicitly take into account the positive impact of the inclusion of RES technologies on a portfolio of electricity generation by reducing its risk, because RES technologies are usually uncorrelated with fossil fuel technologies [3]. In this context, two variables emerge as critical decision variables: the cost of each technology and the risk associated with the use of each technology for the production of electricity. In order to take into account these two dimensions of the power system planning, several authors (e.g. [3],[15]) have proposed the use of the mean-variance approach (MVA), initially developed for the selection of portfolios of financial assets by Markowitz in 1952 [12]. In fact, several studies (e.g. [1], [10]) have revealed the potential of this framework when applied to electricity planning, especially with regard to the inclusion of RES technologies. In this paper, the intuition underlying the MVA approach is applied to the selection of portfolios of electricity generation technologies including renewable energy sources. By explicitly including as a decision variable the risk of portfolio, this approach allows policy

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makers or private investors to integrate in a quantifiable manner the three main objectives of energy policy [14]: energy at competitive prices; security of energy supply; and mitigation of environmental impacts.

In this problem, there exist two conflicting objectives - minimizing the risk and maximizing the return. The main goal of this work is to solve the optimization problem of selecting portfolios of electricity generation projects for the Portuguese case (2019-2011) using a multiobjective approach.

The article is organized as follows. Next section presents the MVA approach and Section 3 describes its application to the Portuguese case. The optimization technique based on a multiobjective approach is reported in Section 4. The computational experiments as well as the conclusions are carried out in Section 5.

2 The Mean-Variance Approach (MVA) for Electricity Planning

The MVA approach has its roots on the seminal paper of Markowitz [12]. The main objective of this approach is the selection of investment portfolios based on maximizing the value of future expected return for a certain level of risk the investor is willing to take. According to [12], the portfolio selection process can be divided into two stages. The first starts with observation and experience and ends with a perspective on the future performance of available securities. The second stage begins with the perspective on the future and ends with the selection of a portfolio of assets. Any investor in securities should maximize the return on its investment within acceptable risk levels. Risk and return, typically, have a positive correlation with each other. When the former increases the latter also increases. However, Markowitz emphasized that diversification can reduce portfolio risk to lower levels, and this will depend on the correlation between assets within a given portfolio. Therefore, when deciding on their investments, investors should consider not only the expected return but also the dispersion of returns around the mean - the variance. This variance is then considered as a proxy variable for measuring the risk of the investment. Thus, the characteristics of an investment can be measured using these two variables [7] since it is assumed that expected returns follows a normal distribution. Therefore, assuming that investors are risk averse, instead of investing in a single financial asset, they should choose to invest in a portfolio comprised of various assets. Intuitively, there are two main reasons why diversification reduces investment risk [5]. On the one hand, as each asset included in a given portfolio represents only a small part of the funds invested, any event that affects one or some of these assets has a much more limited impact on the total value of the portfolio. On the other hand, the effect of specific events on the value of each asset within the portfolio can be positive or negative. In large and diversified portfolios, these effects tend to offset each other without affecting the overall value of the portfolio.

As mentioned before, in recent years an increasing application of the MVA reasoning to power system planning can be found in the literature (e.g. [1], [4], [10], [14]). As emphasized by [3], energy planning is no different than investing in financial securities, where efficient portfolios are widely used by investors to manage risk and improve performance. Thus, energy planning should be focused more on developing portfolios with efficient production than on finding alternatives with lower cost of production, because, at any given time, certain alternatives may have higher costs and others may have lower costs. However, over time, a favorable combination of alternatives may facilitate minimizing the overall cost of production compared to the risk [3] measured as the dispersion of the electricity output of the portfolio. Besides the fact that the MVA approach allows finding the optimal electricity generation portfolio, it also allows a better assessment of the risk associated with different technologies, illustrating the trade-off between production costs and risk, which means that it is not possible to achieve a lower cost of production of electricity, without assuming higher levels of risk [8]. In this context, is of particular interest the analysis of the inclusion of RES technologies on the portfolio of electricity generation technologies. In fact, [2] demonstrated that the introduction of RES technologies (e.g. wind, solar and hydro) in the energy portfolio, significantly reduces the total cost of energy and the production risk, since solar and photovoltaic technologies are risk-free, as their operation is not correlated with the change in the price of fuel [1].

3 MVA applied to the Portuguese case

Electricity production investments in Portugal have been focused, mainly, in renewable energy sources. This focus, beyond the issue of economic and energy self-sufficiency, follows the guidelines of the EU towards reducing CO2 emissions into the atmosphere, which justifies the decline of production of electricity through coal, despite the stability of its price in recent years. The cost production of electricity depends on the technology and primary energy source used. In the case of renewable sources, the critical component for calculating the associated cost is the capacity factor (CF) - the ratio of actual power produced and the power the generation plant could produce. The reason is that the initial investment is high and the marginal cost is very low. For each technology the respective levelized cost of eletricity (LCOE) was estimated for each t corresponding to the time period under study (quarter of an hour). The $LCOE_t$ represents then the total cost per MWh produced throughout the life of a plant calculated under the operating conditions of each time period.

$$LCOE_t = \frac{I + [M + (F_t + X_t)\,h]\,\frac{(1+r)^n - 1}{r(1+r)^n}}{E_t\,h\,\frac{(1+r)^n - 1}{r(1+r)^n}} \quad (1)$$

where I is the investment cost for each technology, M are the annual operation and maintenance costs, F_t are the fuel costs, X_t are the environmental costs, n is the lifetime of the plant, E_t is the power output measured in each time period, t is the time period under study, corresponding to an hour, h is the number of hours of an year and r is the discount rate.

The investment cost (related to the construction of various electricity generation plants) and the operation and maintenance costs (all expenses inherent in the process of producing electricity and maintenance of equipment such as labor or material costs) were obtained from the publication of the IEA [9]. The cost of fuel, naturally, only applies to thermal production technologies (coal and gas). The price of natural gas was obtained through the database ”Datastream, Thomson Reuters” and is expressed in €/MWh. In the case of coal, the price of this raw material was obtained through the source ”EUROPEAN COAL: CIF ARA”. The environmental costs refer to the amount paid by the operator of the power plant relative to the amount of CO2 released into the atmosphere and was obtained from ”Datastream, Thomson Reuters”. For the fuel and CO2 allowances prices, daily values were used and were assumed to remain constant during each day. The lifetime of the plant corresponds to the average life time (in years) estimated for all power plants corresponding to each technology, and values published by [9] and [11] were used. For E_t, data supplied by the Portuguese electricity system manager was used, representing the power output for each technology measured for each quarter of an hour for the period 2009-2011. This level of data detail was particularly important as is it allowed capturing de variability and seasonality of RES.

4 Optimization

Although, the MVA approach has been extensively applied in a financial context, in order to estimate the portfolio risk and expected return, it is also possible to use it for the selection of portfolios of electricity generation technologies [4]. In this context, costs are quantified as generation costs and the return is measured by the inverse of those costs [2].

The expected return of the portfolio p is expressed by the weight of each techonology’s return in the portfolio:

$$E(R_p) = \sum_{i=1}^{N} \omega_i E(R_i) \quad (2)$$

where N is the number of different technologies, $E(R_i)$ represents the value of the expected return of the i^{th} technology (R_i) and ω_i is the share of the i^{th} technology in the portfolio.

The inverse of the LCOE for each technology measures the return of a physical output per monetary unit as input [2]. In other words, lower cost means higher outcomes associated to the production of electricity using the same technology [1],

$$R_t = \frac{1}{LCOE_t} \quad (3)$$

where R_t is the return in period t, and $LCOE_t$ is the cost in period t for a given technology.

The risk associated with the portfolio p is calculated by (4) and is represented by the standard deviation of the portfolio (σ_p) by variations on the LCOE:

$$E(\sigma_p) = \sqrt{\sum_{i=1}^{N} \omega_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} \omega_i \,\omega_j \,cov_{ij}} \quad (4)$$

$i \neq j$, ω_i and ω_j are the variables corresponding to the weight of technologies i and j respectively, in the portfolio; σ_i represents the standard deviation of the rate of change of cost and the covariance of two technologies is given by (5):

$$cov_{ij} = \rho_{ij} \sigma_i \sigma_j \quad (5)$$

In this work seven technologies are considered ($N = 7$): gas, coal, large hydro, run of river, small hydro, onshore wind and solar PV.

The correlation between technologies i and j, ρ_{ij} characterizes the diversity within the portfolio. The lower the value of ρ_{ij} between portfolio’s technologies the higher the portfolio’s diversity and, consequently, contributes to a reduction in portfolio’s risk, $E(\sigma_p)$. In other words, increasing the diversity of the portfolio, by adding technologies uncorrelated or correlated negatively, reduces the risk of the portfolio, which can be observed by the tendency of correlation to zero [4]. Table 1 reports the covariance between technologies.

Markowitz [12] showed that in order to maximize the expected return (2) on any investment, and at the same time minimizing the associated risk (4), the investment should be diversified into more financial assets. Therefore, all assets considered in portfolio analysis should be characterized not only by the expected return but also by their variability, measured as the variance (or standard deviation) of expected returns.

4.1 First approach

The initial optimization approach [13] to solve the problem includes two phases. The first one aims to find

Table 1: Covariance between technologies

	Coal	Gas	Large hydro	Run of river	Small hydro	Onshore wind	Solar PV
Coal	-	0.00006386	0.00011628	0.00012446	0.00003649	-0.00005026	0.00002753
Gas		-	0.00021531	0.00012693	0.00002118	-0.00010592	-0,00001070
Large hydro			-	0.00148041	0.00024333	-0.00021508	0.00010374
Run of river				-	0.00022383	-0.00010571	0.00007913
Small hydro					-	-0.00001703	0.00009761
Onshore wind						-	-0.00012881
Solar PV							-

the lowest investment risk and the corresponding nonlinear constrained optimization problem is:

$$\begin{array}{ll} \min\limits_{\omega_i, i=1,\ldots,N} & E(\sigma_p) = \sqrt{\sum_{i=1}^N \omega_i^2 \sigma_i^2 + \sum_{i=1}^N \sum_{j=1}^N \omega_i \omega_j cov_{ij}} \\ \text{s.t.} & \sum_{i=1}^N \omega_i = 1 \\ & \omega_i \geq 0,\, i = 1,\ldots,N \end{array} \tag{6}$$

The solution of this optimization problem is the minimal risk denoted by σ_p^*.

After identifying this lower bound for the risk, a second optimization phase is performed in order to maximize the return taking into account σ_p^* as the upper bound of the nonlinear constraint concerning to the risk:

$$\begin{array}{ll} \max\limits_{\omega_i, i=1,\ldots,N} & E(R_p) = \sum_{i=1}^N \omega_i E(R_i) \\ \text{s.t.} & \sum_{i=1}^N \omega_i^2 \sigma_i^2 + \sum_{i=1}^N \sum_{j=1}^N \omega_i \omega_j cov_{ij} \leq (\sigma_p^*)^2 \\ & \sum_{i=1}^N \omega_i = 1 \\ & \omega_i \geq 0,\, i = 1,\ldots,N \end{array} \tag{7}$$

Few simulations were done relaxing the nonlinear constraint. Increasing its upper bound, the problem (7) was solved several times for a set of different upper bounds greater than $(\sigma_p^*)^2$ as can be seen in Figure 1.

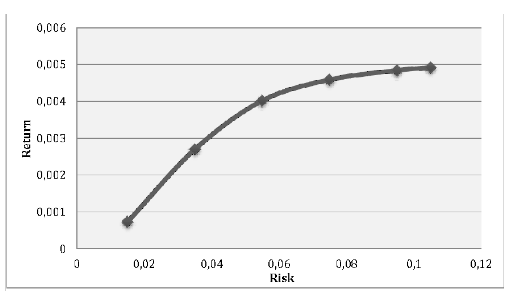

Fig. 1: Efficient boundary

To solve the problems (6) and (7) the Solver of Excel was used.

4.2 *Multiobjective* versus *uniobjective optimization*

The previous approach uses two uniobjective optimization problems being the second one solved several times. A multiobjective optimization formulation is proposed improving the efficiency and the final results.

A constrained multiobjective optimization problem (8) is formulated with two goals: minimize the risk and maximize the associated expected return. The two objetive functions are (4) and (2) with variables $\omega_i, i = 1,\ldots,7$, the contribution of each technology for the electricity production of the portfolio:

$$\begin{array}{ll} \min\limits_{\omega_i, i=1,\ldots,N} & \Big(\sqrt{\sum_{i=1}^N \omega_i^2 \sigma_i^2 + \sum_{i=1}^N \sum_{j=1}^N \omega_i \omega_j cov_{ij}}, \\ & -\sum_{i=1}^N \omega_i E(R_i)\Big) \\ \text{s.t.} & \sum_{i=1}^N \omega_i = 1 \\ & \omega_i \geq 0,\, i = 1,\ldots,N \end{array} \tag{8}$$

This problem (8) with two objective functions is reformulated into a uniobjective problem:

$$\begin{array}{ll} \min\limits_{\omega_i} & \alpha_1 \sqrt{\sum_{i=1}^N \omega_i^2 \sigma_i^2 + \sum_{i=1}^N \sum_{j=1}^N \omega_i \omega_j cov_{ij}} + \\ & + \alpha_2 (-\sum_{i=1}^N \omega_i E(R_i)) \\ \text{s.t.} & \sum_{i=1}^N \omega_i = 1 \\ & \omega_i \geq 0,\, i = 1,\ldots,N \end{array}$$

The different combinations of the associated weights (α_1, α_2) to each objective allow to find different solutions. An algorithm for uniobjective optimization is then applied.

5 Computational experiments and Conclusions

The multiobjective optimization problem was codified in MATLAB [16] and solved with the `fgoalattain` routine from the optimization toolbox. This routine solves the goal attainment problem, which is one formulation for minimizing a multiobjective optimization problem.

```
>>[x,fval] = fgoalattain(fun,x0,goal,weight,...)
```

For a general problem, the output is the vector of the problem variables `x` and the corresponding values of the objective functions `fval`. The input is composed by `fun` which returns a vector of objective function values, `x0` is the initial approximation to the solution, `goal` is a vector in $\Re^n$, the reference point, where n is the number of objective functions. The ideal point is the minimum values of each uniobjective formulation when executed individually and it was used as reference point. `weight` is a vector in $\Re^n$ and contains several normalized weights combinations to obtain different points of the Pareto front.

The routine `fgoalattain` is based on an algorithm ”after search” (*a posteriori*), ie, the search procedure is made without any preference information given by the decision maker. The decision maker chooses from search result which corresponds to a set of trade-off solutions. `fgoalattain` implements a scalarizing method, which means that the multiobjective problem is reformulated into an uniobjective problem. Then an algorithm to uniobjective optimization is applied to the new reformulation. The different combinations of the associated weights to each objective will allow to find different solutions.

The computational experiments were made on a *2.0 GHz Intel Core i7* with 8GB of RAM, Windows 7 64-bit operating system. The MATLAB version used was 7.13.0.564 (R2011b).

Table 2 presents the numerical results, with four decimal places, considering $N = 7$ different technologies. The first and second columns show the total risk and the total return for different weight simulations in the third and fourth columns.

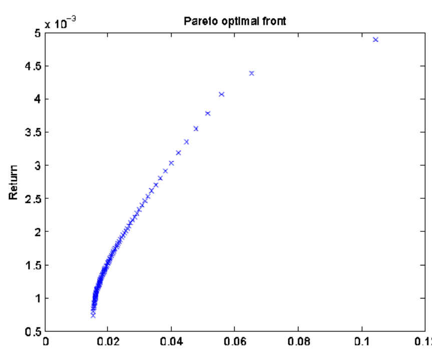

Fig. 2: Optimal solutions

Figure 2 presents the Pareto front with all optimal solutions taking into account the trade-offs risk and return. It is for the decision maker, depending on specific situations, choose the suitable solution. On the one hand, it is possible to realize in the lower left corner that a small risk variation leads to a large variation in the return. On the other hand, in the upper right corner, it appears that a significant increased risk only yields a small increase in return.

Some conclusions can be taken:

– portfolios with high risk and high return are based on the exclusive reliance on hydro: higher risk as the system would only rely on a technology with high output variability; higher return as the system would only rely on a technology with low operational costs and long life time[1];
– portfolios with low return and low risk are based on a mix of technologies: lower risk as the system would rely on a mix of technologies and as such ensuring higher diversification; lower return as the system would include more costly technologies.

This approach works like a decision support system to select portfolios of electricity generation projects. It allows the decision maker to choose the appropriate portfolio based on risk-return trade-off and environmental impact.

Furthermore, the proposed tool allows to assess whether the current electricity production mix of a country (and even the production mix foreseen for a given target year) would be efficient or not according to its position on Figure 2 when compared to the Pareto optimal front. The application example of the MVA approach shown in this paper is particularly interesting since it is related to a power generation system characterized by increasing share of RES based technologies, which are highly dependent on the seasonality and variability of the renewable resources. Moreover, this approach allowed to explicitly dealing with the cost aspects (by using the LCOE for the expected return computation), and with the variability of the system, by including the risk element in the analysis.

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[1] The results were highly influenced by the 2010 wet year that resulted in low LCOE for dams (large hydro)

Table 2: Numerical results

Total risk	Total return	Risk weight	Return weight	Coal (ω_1)	Gas (ω_2)	Large hydro (ω_3)	Run of river (ω_4)	Small hydro (ω_5)	Onshore Wind (ω_6)	Solar PV (ω_7)
0.0153	0.0007	0	1	0.2522	0.1955	0.0170	0.0243	0.2239	0.2585	0.0286
0.0158	0.0010	0.1	0.9	0.2278	0.1861	0.0380	0.0434	0.2067	0.2481	0.0498
0.0163	0.0011	0.2	0.8	0.2162	0.1816	0.0485	0.0520	0.1976	0.2426	0.0616
0.0169	0.0012	0.3	0.7	0.2055	0.1780	0.0581	0.0598	0.1893	0.2367	0.0726
0.0177	0.0013	0.4	0.6	0.1945	0.1735	0.0686	0.0687	0.1803	0.2313	0.0831
0.0188	0.0014	0.5	0.5	0.1823	0.1692	0.0790	0.0790	0.1712	0.2227	0.0966
0.0203	0.0016	0.6	0.4	0.1746	0.1715	0.0954	0.0922	0.1710	0.1877	0.1075
0.0226	0.0018	0.7	0.3	0.1441	0.1525	0.1141	0.1113	0.1384	0.2122	0.1275
0.0266	0.0021	0.8	0.2	0.1112	0.1404	0.1443	0.1377	0.1119	0.1972	0.1574
0.0351	0.0027	0.9	0.1	0.0450	0.1170	0.2011	0.1890	0.0584	0.1716	0.2181
0.1044	0.0049	1	0	-0.0000	-0.0000	0.9999	0	-0.0000	-0.0000	0.0001

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