Multiple Criteria Decision Making and Risk Analysis as Risk Management Tools for Power Systems Planning

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Abstract—Uncertainties in power systems planning are getting more important nowadays due to the liberalisation of the electricity industry and the increasing concern for the environmental impact of electricity generation. This paper presents an electricity planning model which deals with uncertainty and its associated risk at two levels: at the first level, by minimising environmental risk through a multiple-criteria model; at the second level, by performing a risk analysis consistent with the multiple criteria model used before, and which applies classical decision rules for selecting the best planning strategy under uncertainty. Results show that the incorporation of additional criteria produce much more flexible and efficient strategies, which greatly reduce environmental risk at a little cost increment, while the risk analysis process selects flexible and robust strategies for the scenarios analysed.

Index Terms—Power system planning, Decision making, Risk analysis, Uncertainty.

I. INTRODUCTION

Electricity planning is subject to a large degree of uncertainty, due, among others, to the following aspects [1]:

- demand growth,
- price and elasticity of electricity,
- behaviour of other energy and financial markets,
- cost and availability of fuels and technologies,
- reliability of generating groups,
- inflation rates,
- interest rates,
- economic growth,
- environmental regulation,
- public opinion,
- etc.

Uncertainty is usually greater given the long term period generally considered for electricity planning purposes. Obviously, uncertainty is something inherent to the planning exercise, so it cannot be eliminated. However, we can minimise risk, that is, the danger to which the planner is exposed because of uncertainty.

The risk to which utilities are exposed is also larger within liberalised frameworks, since risk has been transferred from consumers, which usually bore the costs of erroneous planning decisions, to producers.

The risks that planners face are also increasing due to the growing environmental concern of modern societies. Future environmental regulations may render uneconomic their planning decisions, because of the large costs usually associated with the compliance of these regulations.

Up to now, these environmental risks have been incorporated into the planning exercise by establishing environmental constraints which attempt to anticipate future regulations. However, it is quite difficult to achieve efficient planning solutions when these constraints have to be specified ex-ante. Although there may be techniques for obtaining robust solutions, there are better ways of managing risk in an efficient manner.

Multiple-criteria decision making is one of these better ways. This is a paradigm under which decisions are not optimised according to a single criteria (usually, economic costs), but rather different and conflicting criteria are optimised simultaneously.

In order to handle environmental risk, these conflicting criteria would be economic costs and environmental impacts. By minimising them simultaneously, efficient solutions would be obtained, in the sense that these solutions would be the best adapted to any future environmental constraint, both from an economic and environmental point of view. The introduction of the decision-makers' preferences in this process is fundamental, since it reflects their attitude towards the different risks considered.

Of course, there are other uncertainties related to the electricity planning process, such as the ones cited above. The way they are handled differs according to the modelsanalysed. Some planning models are deterministic, using fixed values for the model parameters, usually determined by more or less complex estimations. The problem with them is that these estimations have proved to be erroneous most of the times [2]. The deviations observed are usually large, and also skewed towards the optimistic side [3]. This causes that the usual way of incorporating uncertainty to these models, sensitivity analysis, is not valid, since it considers small variation ranges, and therefore does not incorporate the large variations detected in some cases [4].

The other usual way of introducing uncertainty has been by probabilistic analysis. These models present several problems:
they are more complex from a computational point of view, and, what is more important, it is really difficult to assign probabilities to any of the different events considered. Although probabilistic analysis may be considered suitable for high-frequency, short-term uncertainties, this is certainly not the case for most uncertainties implied in a long-term electricity planning exercise. For low-frequency, long-term uncertainties we cannot assign probabilities, but rather possibilities [5].

This is why instead of relying on predictions, it is more and more recommended the use of scenarios, especially in a rapidly changing environment such as the electricity industry [6, 7]. Scenarios also present as an additional advantage the fact that they help decision-makers understand the role of uncertainties, and therefore allows them for taking more informed decisions in this uncertain context, by revealing new opportunities and strategic threats.

There have been lately two major approaches for managing risk in scenarios: risk analysis and fuzzy logic [8, 9]. Fuzzy logic has not been applied significatively to electricity planning, so its practical validity has not been confirmed. Risk analysis, on the other hand, has been expressly recommended by several authors [10, 11]. Under this approach, the solution chosen is the one which minimises risk. That is, the emphasis is not on obtaining “correct” solutions, what is rather difficult as has been mentioned, but rather on designing strategies which may respond to possible changes in an efficient way. Probabilistic approaches, on the contrary, usually result in riskier solutions, given that their results, once uncertainties are materialised, may differ substantially from the objective looked for [10, 12].

Risk analysis also presents some advantages when combined with a multiple-criteria decision making approach: it allows for including the preferences of decision-makers towards risk, and it may also be made fully consistent with a compromise programming approach.

Therefore, this paper presents an electricity planning model under uncertainty in which risk is addressed at two levels:

- at the first level, by incorporating environmental criteria in addition to the economic cost criteria, the model obtains efficient solutions which minimise both costs and environmental risks,
- at the second level, by formulating a decision problem in which the solution which minimises risk is obtained by the application of well-known decision criteria, such as Wald or Savage criteria.

These decision criteria, especially the Savage one, have a very interesting interpretation within the multiple-criteria approach. The maximum regret resulting from choosing a certain strategy instead of the optimal, under each scenario, may be equated to the distance from the solution corresponding to that strategy to the ideal solution under the considered scenario [9]. This distance may be calculated according to different metrics, depending on the type of solution searched, be it a maximum efficiency or a maximum equilibrium solution. The choice of these metrics, and their implications for the attitudes toward risk of the decision makers, is something not addressed in this paper, although it is considered a very interesting field for further research.

The paper is organised as follows. Section 2 presents the methodology developed, with an emphasis on the treatment of uncertainty through the multiple-criteria and risk analysis techniques. Section 3 shows the results obtained from the application of the methodology for the Spanish electricity sector. And Section 4 outlines the major conclusions of the study.

II. METHODOLOGY

Although there are already methodologies proposed and applications of electricity planning which consider multiple criteria, the problem is still dealt with in a partial way. Thus, most of the multiple-criteria methods proposed only look at risk at the first level mentioned before, and do not incorporate techniques for dealing with uncertainties not included in the multiple-criteria problem (e.g., [13, 14]), while the ones which do, either deal with uncertainties in a probabilistic manner, (what has been criticised by many authors (e.g., [10]), or do not solve adequately the multiple-criteria decision making problem, since they do not incorporate decision-maker's preferences (such as for example the trade-off/risk method [15]). The methodology presented in this paper tries to solve this problem, by the integration of the following characteristics:

- based on optimisation techniques,
- considers multiple criteria,
- takes into account the preferences of the different social interest groups,
- allows for the explicit integration of demand-side management measures,
- and incorporates techniques for dealing with uncertainty by means of risk analysis.

The core of the methodology is a model for indicative planning of electricity resources (PIRE, in Spanish) through which: a) efficient strategies are generated under every scenario; b) their behaviour under other scenarios is assessed, and c) the optimal planning strategy is determined according to the attitude towards risk of the decision makers. The different phases of this model are explained below. More details may be found in [16].

The first phase of the proposed method is the selection and characterisation of technologies and fuels, both in the generation and demand sides, which may be available for the electricity system for the time horizon considered. Therefore, it is recommended to rely on databases firmly established and agreed upon, so that discrepancies may be avoided among decision makers when assessing the possibilities of any of them.

The second step requires the generation of scenarios that incorporate all the uncertainties to which the planning process is subject (technical parameters, macroeconomic data,
regulatory measures, etc.) in a coherent and reasonable way. Given the interrelation among many of these parameters, it should be possible to generate only a small number of scenarios which cover the whole range of uncertainties, what is beneficial for the computing speed. These scenarios should be generated by means of a strong interaction between analysts and decision makers, using any of the multiple techniques proposed in the field (e.g., [5]).

Then, the preferences of the decision makers regarding the criteria considered have to be estimated. Here the method proposed is the Analytic Hierarchy Process (AHP) [17], since its use is easy and intuitive for decision makers, and reflects adequately their preferences, as has been demonstrated in past applications to the electricity system [13, 18]. It is based on a pairwise comparison of the criteria considered, and an assignment of values for this comparison from a lexicographic scale. In addition, this method may be extended for the estimation of group preferences, for example by the weighted arithmetic mean method [19] or by goal-programming.

It is well known that the preferences held by the decision-makers may vary depending on the range of attribute values, and therefore this information has to be presented to them before they elicit their preferences. The usual approach is to present them with pay-off matrices. Pay-off matrices are matrices where the values of the attributes of the problem are shown for the optimal solutions obtained for every one of the criteria considered. These matrices help understand the trade-offs among the conflicting criteria, and show the ideal (best) and anti-ideal (worst) values for each of the attributes or criteria. Pay-off matrices are built by running traditional single-criteria optimisation models for each of the criteria considered.

The problem with this approach is that, since the range of attribute values varies over scenarios, biased preference information may be obtained if the range presented comes only from one scenario. Therefore, the approach chosen here has been to present all pay-off matrices to the decision-makers, and thus the full range of attributes across scenarios, so that preferences may account for the uncertainty associated.

Once the criteria have been weighted, the generation of the efficient strategies for each scenario is undertaken by means of compromise programming theory [20]. Compromise programming is based on the assumption that the preferred solution will be the one whose distance to the ideal point (the one in which all criteria considered reach their optimum level) is minimal. The distances used have been the Manhattan distance and the Tchebycheff distance, since the two points obtained are the bounds of the compromise set of Pareto-efficient strategies [21]. The solution obtained for the Manhattan distance may be assimilated to the one corresponding to an additive utility function, while the one obtained for the Tchebycheff distance may be assimilated to the one corresponding to a Rawlsian utility function. The first one corresponds to a solution of maximum efficiency, while the latter corresponds to a solution of maximum balance between criteria.

However, the efficient strategies generated up to this moment may only be considered optimal in an economic and environmental sense. When other uncertainties are introduced, it is necessary to incorporate risk analysis into the decision making model. This is carried out by formulating and solving a decision problem. First the behaviour of the planning strategies is assessed under every scenario considered, by the simulation of an electricity dispatch in which the energy produced by the technologies and fuels installed is optimised according to the criteria considered. By doing this for all strategies and scenarios, a game matrix is obtained, in which the value of the attributes of each strategy under each scenario is reflected. From this matrix, the optimal strategy is chosen by using classical decision rules such as the Wald minimax or the Savage minimum regret, as has already been proposed by some authors for similar cases [22, 10].

III. RESULTS

The methodology described in the last section was applied to the Spanish electricity sector with a time horizon of year 2030, trying to optimise electricity planning and minimise environmental risk. The five criteria considered were: economic cost, CO2 emissions, SO2 emissions, NOx emissions, and radioactive wastes. The steps followed were those described before:

Step 1: Selection and characterisation of technologies and fuels
Step 2: Generation of scenarios
Step 3: Selection of decision-makers and elicitation of their preferences
Step 4: Generation of efficient strategies under each scenario
Step 5: Selection of robust strategies

A. Step 1: Selection and Characterisation of Technologies and Fuels

The first step consisted in the technical and economic characterisation of the technologies and fuels expected to be available for year 2030. These data were obtained from [23]. The incorporation of demand-side management measures was not possible due to the lack of information.

B. Step 2: Generation of Scenarios

The second step consisted on the generation of a small but consistent number of scenarios which might account for the uncertainty related to socio-economic aspects. For this exercise, four scenarios were considered, defined by the Spanish Ministry of Industry for their energy planning exercises [24]: a business-as-usual scenario (BASE), an economic recession scenario (DEBA), an environmentalist scenario (MIMA) and an economic liberalisation scenario (MERI).
C. Step 3: Selection of Decision Makers and Elicitation of their Preferences

Four types of decision-makers were considered necessary for this planning exercise, in order to account for all the possible views of society: regulators, academics, electric utilities’ representatives, and environmentalists. For each group, a variable number of representatives were selected, and their preferences elicited and then aggregated.

In order to obtain their preference weights, previous information was shown to them on the trade-offs between attributes for the different scenarios considered. This was done by means of the pay-off matrices, which were built with a single-criteria classical generation expansion model, by which the optimal combination of technologies and fuels according to each of the five criteria considered was determined. As an example, the pay-off matrix for the base case scenario is shown in Table 1.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Optimis. criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>cost (M$/yr)</td>
<td>9,172</td>
</tr>
<tr>
<td>CO₂ emissions (kt/yr)</td>
<td>73,817</td>
</tr>
<tr>
<td>SO₂ emissions (kt/yr)</td>
<td>67.05</td>
</tr>
<tr>
<td>NOₓ emissions (kt/yr)</td>
<td>56.76</td>
</tr>
<tr>
<td>Radioactive waste (TBq/yr)</td>
<td>3,685</td>
</tr>
</tbody>
</table>

As may be observed for this scenario, the maximum cost, and the largest emissions correspond to the strategy which minimises radioactive wastes. It may also be seen that the “traditional” minimum cost solution results in very large environmental impacts, which in turn imply very large regulatory risk if environmental regulation is tightened. The attributes corresponding to the ideal solution (the one in which all criteria reach their optimum values) are those placed along the main diagonal of the pay-off matrix.

Therefore, the four pay-off matrices obtained (one for each scenario considered) were shown to the different decision makers implied in the planning process, so that they might help them structure their preferences for every criterion. Every decision maker filled in a questionnaire, in which the different criteria were compared pairwise, according to the AHP method already proposed, and thus the individual preferences were obtained by goal programming.

This individual preferences were aggregated into the different groups, and also a “consensus” set of preferences was obtained. This was undertaken by means of the comparisons carried out by the decision makers among groups, using the weighted arithmetic mean method. Thus, the following aggregated preferences were obtained. These preferences reflect the attitude of these groups towards economic and environmental risk, and are shown in Table 2.

<table>
<thead>
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<th>Attributes</th>
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</thead>
<tbody>
<tr>
<td>cost (M$/yr)</td>
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<td>0.667</td>
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<tr>
<td>SO₂ emissions (kt/yr)</td>
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</tr>
</tbody>
</table>

It is interesting to see how the preferences of each group of decision makers towards the criteria considered are to a certain extent the ones expected: electric utilities are more concerned about economic risk, and environmentalists are more concerned about environmental risk (especially CO₂ and radioactive wastes), while regulators and academics are placed in intermediate positions. This causes that the consensus solution is quite near to the preferences of these latter groups.

D. Step.: Generation of Efficient Strategies under each Scenario

When the preferences elicited before were introduced into the multiple-criteria optimisation model, the different efficient solutions under every scenario were obtained. The multiple-criteria optimisation model developed here (see [16]) was basically a classical generation expansion model in which the objective function was formed by adding all the objectives considered, previously normalised and weighted, according to the compromise programming theory. As an example, Table 3 shows the optimal solutions corresponding to the Manhattan distance for the base scenario, for all the decision-maker groups considered. As mentioned before, this distance corresponds to a maximum-efficiency solution, which in turn may be poorly balanced. If the objective was to obtain a perfectly balanced solution, the Tchebycheff distance should be used. Table 3 also includes, for comparison purposes, the results obtained for a “traditional” planning for the same scenario, i.e., optimised only for economic cost.

<table>
<thead>
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<td>3,685</td>
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</tbody>
</table>

TABLE 2
AGGREGATED PREFERENCES FOR THE GROUPS CONSIDERED

<table>
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</tr>
<tr>
<td>Radioactive waste (TBq/yr)</td>
<td>0.131</td>
</tr>
</tbody>
</table>

TABLE 3
PLANNING RESULTS FOR THE BASE CASE SCENARIO

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Optimis. criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>cost (M$/yr)</td>
<td>11,152</td>
</tr>
<tr>
<td>CO₂ emissions (kt/yr)</td>
<td>27,584</td>
</tr>
<tr>
<td>SO₂ emissions (kt/yr)</td>
<td>6.78</td>
</tr>
<tr>
<td>NOₓ emissions (kt/yr)</td>
<td>15.22</td>
</tr>
<tr>
<td>Radioactive waste (TBq/yr)</td>
<td>29.00</td>
</tr>
</tbody>
</table>
It is interesting to remark that the introduction of additional criteria (besides from economic cost) generates, as should be expected, a more expensive solution, although with a much lower associated environmental risk, depending on the preferences of the decision-maker groups toward the balance between these conflicting objectives.

It is also important to note that these solutions will be modified when other uncertainties are introduced into the analysis, in such a way that the efficient strategies will be different under different scenarios. The determination of which of these efficient strategies is the best one when risk is considered requires, first, to evaluate their behaviour under every scenario considered, and second, to use a decision rule which incorporates the attitude of the decision maker towards risk. This is undertaken in the next step.

**E. Step 5: Selection of Robust Strategies**

First, the optimal strategies for each scenarios were obtained, for each set of decision-maker preferences. As an example, the values of the attributes of the optimal planning strategies for the consensus set of preferences, under each of the scenarios, are presented in Table 4.

<table>
<thead>
<tr>
<th>Attributes for the Optimal Strategies Under Each Scenario</th>
<th>BASE</th>
<th>DEBA</th>
<th>MIMA</th>
<th>MERI</th>
</tr>
</thead>
<tbody>
<tr>
<td>cost (M$/yr)</td>
<td>11,167</td>
<td>15,046</td>
<td>11,079</td>
<td>10,391</td>
</tr>
<tr>
<td>CO₂ emissions (kt/yr)</td>
<td>40,792</td>
<td>35,625</td>
<td>7,008</td>
<td>89,668</td>
</tr>
<tr>
<td>SO₂ emissions (kt/yr)</td>
<td>8.91</td>
<td>9.86</td>
<td>4.68</td>
<td>17.51</td>
</tr>
<tr>
<td>NOₓ emissions (kt/yr)</td>
<td>18.80</td>
<td>18.24</td>
<td>24.04</td>
<td>20.02</td>
</tr>
<tr>
<td>radioactive waste (Tbq/yr)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

As may be seen, the values of the different attributes are different across the scenarios considered. This reflects not only the fact that economic data are different across different scenarios, but also that the optimal expansion route under one scenario may be a bad one under another. So now it is required to select only one expansion route as the most robust. Given that, as mentioned before, assigning probabilities to scenarios poses many problems, the method chosen was not to assign probabilities or likelihoods of each of the scenarios occurring, but rather to use decision theory (the Savage criterion) to select the expansion route which minimises regret across all scenarios. In this case, regret was calculated as the Manhattan distance between the studied solution and the ideal solution for each scenario, as pointed out in [9]. As an example, these distances, or measures of regret, are shown in Table 5 for the consensus solution.

<table>
<thead>
<tr>
<th>Distances between Solutions and the Ideal for Each Scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strategies</td>
</tr>
<tr>
<td>BASE</td>
</tr>
</tbody>
</table>

Under the Savage criterion, and the consensus set of weights, the expansion strategy chosen is the one whose maximum distance across scenarios is minimal. As may be seen, the maximum distance or regret for MERI strategy is 0.0491, while for the rest of strategies the maximum regret is higher. Therefore, the MERI strategy was the one chosen as the most robust. The choice of this strategy results mostly from the high value given to non-supplied energy. It may be argued that this value should not be so large, given the long time horizon considered in the planning process. Anyway, it would be highly recommended to study a larger number of scenarios, so that the flexibility and robustness of the solution obtained would be ensured.

Of course, this result is only valid for the consensus set of weights. For other set of preferences (regulators, academics, etc.) the most robust strategy chosen may be different. It would also be interesting to analyse the robustness of the solution chosen to changes in the sets of preferences, although this has not been undertaken in this paper.

**IV. Conclusions**

This paper has presented a methodology for dealing with uncertainty and its associated risk at two levels. At the first level, a multiple-criteria decision making model has been formulated in order to obtain solutions which balance both economic and environmental risk in a Pareto-efficient way. This model incorporates the preferences of different groups of decision makers towards these risks and calculates an aggregated set of preferences, so that the results of the model may be interpreted in terms of the preferences of society towards these conflicting objectives.

At the second level, the results obtained from the multiple-criteria model are assessed under scenarios which cover a full range of uncertainties other than the ones considered before. By the application of classical decision rules, such as the Wald or Savage criteria, the most flexible and robust strategy is chosen for the planning of the power system.

Results show the interest of this methodology, since its application achieves large reductions in risk with small increments in cost, while allowing the society to express their preferences towards any of the risks considered.

Therefore, it is considered that the tool presented here may be applied successfully both at an institutional level and at the utility level.

At the institutional level, the methodology may be used for managing risk from the society point of view. This may be easier in those countries where power systems planning is still carried out in a centralised way, although exercises like this may still be undertaken in liberalised frameworks as indicative planning processes. In this context, the preferences of all possible interest groups affected by the planning process should be incorporated into the analysis, and the consensus set
of preferences towards the different risk considered should be determined.

At the utility level, a model like the one presented may help reduce the environmental risks to which the firm may be subject to in the medium term in an efficient way, and also help determine flexible and robust strategies when other uncertainties are considered. This efficient risk reduction is essential in liberalised frameworks, where the risk is totally transferred to producers, and therefore may be used for competitive advantage.

However, several aspects remain to be studied further:
- the elicitation of preferences from the decision makers and their aggregation into a consensus set,
- the incorporation of environmental criteria in a more precise way,
- the addition of other significant risks, or
- the analysis of the implications of the distance chosen between the solutions obtained and the ideal point with regard to the attitude of the decision makers towards risk.

are all aspects of the methodology which should be refined, in order to produce more efficient results for power systems planning in the presence of uncertainty.

V. ACKNOWLEDGEMENT

The author would like to acknowledge Prof. Carlos Romero for his guidance on multiple-criteria decision-making and on this work as a whole, as well as the decision makers who accepted to participate in the exercise.

VI. REFERENCES


into energy decision making, on renewable energy integration studies, and on energy planning models. His research interests include multi-criteria decision methods for environmental management, economic instruments for environmental policy, and the economics of the electricity sector.