ON QUANTIFYING UNCERTAINTY FOR PROJECT SELECTION: THE CASE OF A RENEWABLE ENERGY SOURCES' INVESTMENT

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The selection of a project among different alternatives, considering the limited resources of a company (organisation), is an added value process that determines the prosperity of an undertaken project (investment). This applies also to the "booming" Renewable Energy Sector, especially under the circumstances established by the recent activation of the Kyoto protocol and by the plethora of available choices for renewable energy sources (RES) projects. The need for a reliable project selection method among the various alternatives is, therefore, highlighted and, in this context, the paper proposes the NPV function as one of possible criteria for the selection of a RES project. Furthermore, it differentiates from the typical NPV calculation process by adding the concept of a probabilistic NPV approach through Monte Carlo simulation. Reality is non-deterministic, so any attempt of modelling it by using a deterministic approach is by definition erroneous. The paper ultimately proposes a process of substituting the point with a range estimation, capable of quantifying the various uncertainty factors and in this way elucidate the accomplishment possibilities of eligible scenarios. The paper is enhanced by a case study showing how the proposed method can be practically applied to support the investment decision, thus enabling the decision makers to judge its effectiveness and usefulness.

Keywords: *Renewable energy sources projects, Monte Carlo, Project selection, Uncertainty factors*

1/ INTRODUCTION

Although project selection lies on the boundaries of the project management processes (PMI, 2003), it is still a core decision that should be taken from the senior management. The selection of which project to develop, among possible alternatives (taking into account the limited resources), depends on the company's strategy, the people taking decisions and the criteria used. Typically, selection criteria are financial oriented (Kerzner, 2003), marketing oriented, and sometimes driven by qualitative factors such as public or political perception (Heldman, 2002). Although, most of the times, the decision is based on a combination of all these and even more factors, the economic criteria, such as the Net Present Value (NPV) are dominant.

The NPV criterion is usually calculated using point estimations for the input parameters, thus providing a single value outcome. However, this is just a possibility among many others, due to the range of values that the input parameters may take. A more complete approach, that is suggested hereafter, is to define the uncertainty factors. That is, the variables (specific costs or revenues) which take part in the NPV calculation and may receive more than one value. Having done that, the decision maker may feed the probabilistic NPV model with data according to the different available scenarios (alternatives) and come up with a probability curve for the NPV of each scenario. The tangible result is that the decision maker may now compare *n* curves (where *n* is the number of available scenarios) indicating the range of possible outcomes rather than comparing *n* deterministic values.

The aforementioned concept is even more important for a specific category of projects which deal with the development of “green” plants. Renewable energy sources (RES) projects present several characteristics that differentiate them from conventional projects, thus appear to be riskier. For instance, most of the RES technologies available up to now are very new and still, under development. Therefore, investment costs are not always easy to be determined with accuracy (usually they are dropping with the evolution of new technology), their actual performance usually deviates from the expected and there is a lack of expertise for managing this kind of projects. The paper focuses on this kind of projects and the method presented in the next section is used for the selection of the better, in terms of NPV (Benninga, 2000), solution among a set of different alternatives for a RES project.

Renewable energy sources include mainly the use of wind, solar, geothermal and biomass power for covering thermal, electricity, mechanical and other energy needs. Biomass has been serving humanity’s energy needs since ancient times, as prehistoric humans used wood as their first energy source. Up to now, biomass contributes the largest share of renewable energy, and it is still one of the main energy sources in many third world countries.

RES projects have been gaining significant support lately. Many governments worldwide are aiming at increasing the share of energy produced by renewable energy sources in their countries, while at the same time reducing their reliance on fossil fuels and conventional power sources. The recent ratification and activation of the Kyoto protocol has enhanced even further this trend towards increased use of RES. The target of EU for increasing the share of RES in its energy mix at 12% by the year 2010 is indicative of this trend (Commission of the European Communities, 2000).

Consequently, the collaboration of European countries and non-European ones in RES projects is quickly approaching and this papers aims to provide a method that will sort out the best, in terms of NPV, investments (projects) in this area.

2/ METHOD

The proposed method is based on the process depicted on Figure 1. After the project and the available scenarios (or alternatives) have been identified, the decision maker should define, for each scenario, the cost and revenue function. That is, the Net Present Value function of the investment including all the input parameters (costs and revenues) needed for the determination of the final outcome.

For each scenario, uncertainty factors should be identified. These uncertainty factors are parameters that cannot be handled with a deterministic approach. Such factors may include electricity selling price, thermal energy selling price or biomass cost.

After the determination of these factors, appropriate statistical distributions describing each one of them should be defined. The selection of the appropriate distribution is a quite difficult task which depends mainly on the experience and know-how of the decision maker. However, regardless the rate of accuracy of the statistical distribution that will be used, the outcome will be better (more indicative of the real world) than the one coming from a deterministic approach.

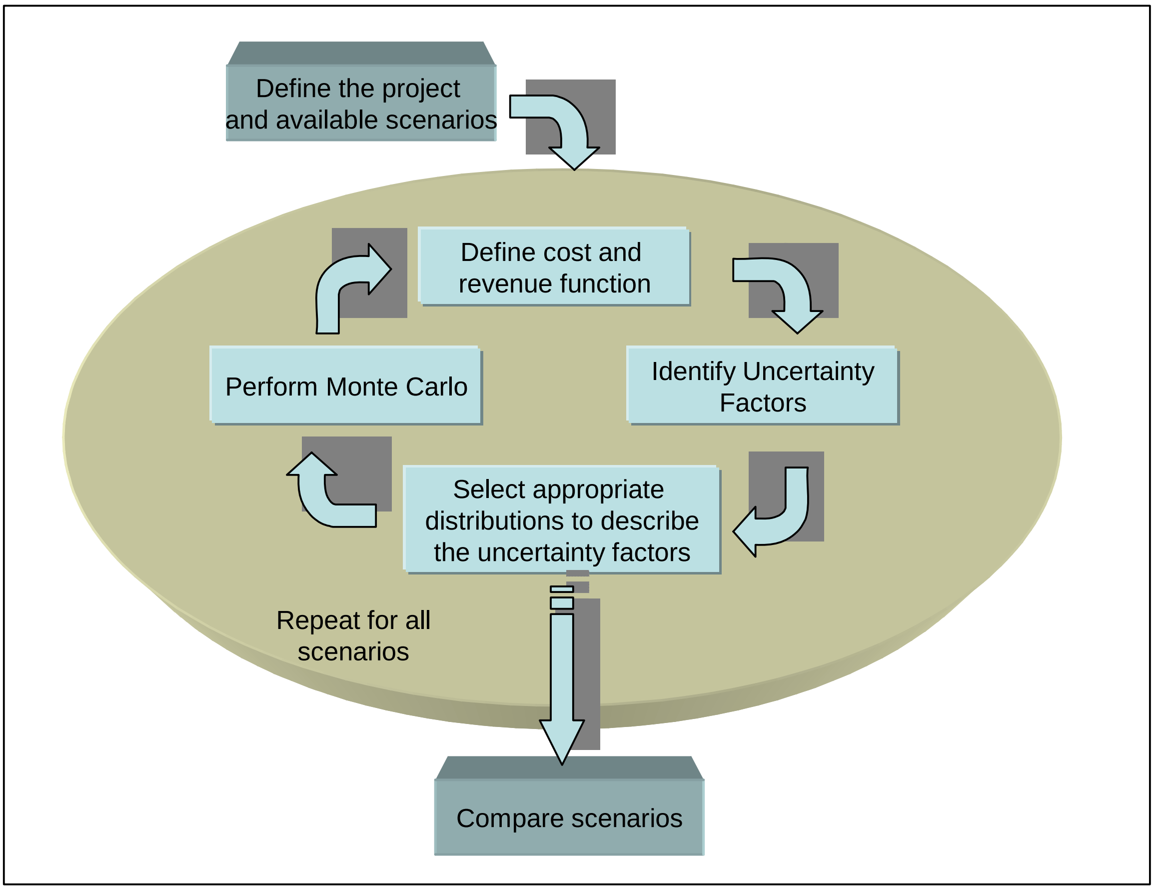

Figure 1: Description of the method

Having identified the uncertainty factors and selected the appropriate distributions, the decision maker is ready to perform the Monte Carlo Simulation (MCS). MCS consists a stochastic statistical methodology of quantitative solution and risk assessment for non-deterministic problems, using a pseudo-population of randomly produced alternative scenarios from prescribed statistical distributions. Concerning the general case of solving a problem with inconstant or not predictable, in an absolute way, input variables, the traditional approach of a point estimation suggests the adopting of one possible value for each variable. However, in the real world, the possible values of a parameter are almost uncountable, therefore the potential scenarios are infinite and the possibility of realisation of each one of them equals zero. On the other hand, the MCS suggests the modelling of the range of possible values for each input variable and the following reproduction of an efficient number of scenarios, so that the depiction of the respectively big number of results in a density function diagram could attribute in a reliable manner the needed distribution of the output variable, showing in parallel the possibility of occurrence for each value and marking out extreme or probable results (Vose, 2000). In a nutshell, by performing the MCS the estimation of the Net Present Value of a RES project is not a single figure but a distribution, which aids the decision maker to the selection of the right (most cost effective) scenario. This comparison of the NPV of the alternative scenarios is the last step of the process.

Although the method has been designed for a RES project, it can be used, as it stands, for any kind of project.

3/ CASE STUDY

3.1/ Problem description

The case study concerns the selection of the best case among three possible alternatives for providing 10 MW power through the development of Combined Heat and Power (CHP) plants, which utilise biomass as their energy source (one type of seasonal agricultural residues has been assumed as “raw material”). The three scenarios refer to the Greek energy market but they could be fairly fitted to any other country if the appropriate modifications in costs were made. The available scenarios include the development of (a) ten CHP plants having an electric power capacity of 1 MW (b), two CHP plants having an electric power capacity of 5 MW and (c) one CHP plant with an electric power capacity of 10 MW. Aim of the case study is to show that although a decision maker’s first thought would be to develop the large plant, due to the prospective economy of scale, a more detailed examination through the range NPV estimation process might lead to different decisions.

A brief technical description of the project under consideration is necessary in order for the reader to understand the basic factors involved. The calculations have been based on the analytical model of Tatsiopoulos et al. (2003) as well as a relative study made by Tolis (2001).

The operating time of the CHP power plant has been assumed to be fixed (7200 hours/year). The plant operates at an independent electricity producer mode, and therefore all its electricity production is sold directly to the grid. The thermal energy produced is also sold, but it is quite uncommon that all of it will be efficiently exploited, because of the high operating time. Therefore, it is assumed that a significant part of the thermal energy will not be exploited (expressed by factor Csalq). It is also assumed that the thermal energy will substitute current thermal energy needs met by the use of heating oil. The price of this thermal energy will be lower than the same amount of energy coming from oil, in order to provide an incentive for the consumers of thermal energy to change their energy source (expressed by factor cpq).

This paper assumes, due to the identical scope of the available scenarios, that the NPV function could be the basic criterion of the decision maker. The same methodology has been used for other investment criteria such as the IRR or ROI but is not presented here for reasons of brevity. The NPV function is described by equation (1):

$$NPV = Sel + Sth - OpCost - Biompr - II \quad (1)$$

Where Sel is the present value of electricity income plus income from power availability

$$Sel = (ckwh*Capel*TT+Capel*celp*Mel)*Dfc \quad (2)$$

Sth is the present value of thermal energy income

$$Sth = Capel*(n1/n2 -1)*TT*Csalq*Cpq*Op*Dfc /(\Theta 2*n1) \quad (3)$$

OpCost is the present value of operational costs

$$OpCost = Oper*Dfc \quad (4)$$

Biompr is the present value of all costs associated with procuring biomass (Bpr is expressed in present values already)

$$Biompr = Bpr*WB \quad (5)$$

II stands for the investment costs for the CHP unit.

For a more detailed description of each variable and its range of values please refer to Table 1. It should be mentioned at this point that the total amount of biomass required for each scenario is calculated using equation 6:

$$WB = N*Capel*TT/(n2*\Theta biom) \quad (6)$$

3.2/ Uncertainty factors

Table 1 presents the set of uncertainty factors that shape the final result. The risk that each factor will not take a predefined value (deterministic approach) is reduced by the use of a distribution which describes a set of possible values that this factor may take.

Description	Symbol	Unit	Distribution	Mean Value	Standard Deviation	Minimum Value	Maximum Value
RES Electricity selling price	*ckwh*	*euro/Kwh*	*normal*	*0,06611*	*0,04*	*0,03*	
Power reimbursement	*celp*	*Euro/kw/month*	*fixed value*	*1,697*			

Factor of power reimbursement – relevant to RES type	*Mel*	*-*	*fixed value*	*0,9*			
Electrical Power Capacity	*Capel*	*MW*	*fixed value*	*Scenario1:1 Scenario2: 5 Scenario3: 10*			
Operating time	*TT*	*h/year*	*fixed value*	*7200*			
Total efficiency factor	*n1*	*-*	*normal*	*0,8*	*0,05*	*0,5*	*0,9*
Electrical efficiency factor	*n2*	*-*	*normal*	*0,28*	*0,03*	*0,21*	*0,37*
Oil heating value	*Θ2*	*KJ/Kg*	*fixed value*	*40180*			
Purchasing price of oil	*Op*	*Euro/Kg*	*normal*	*0,42*	*0,3*	*0,2*	*0,7*
Price of thermal energy as a percentage of oil price	*cpq*	*-*	*uniform*			*0,7*	*0,95*
Percentage of thermal energy produced that is actually sold	*csalq*	*-*	*normal*	*0,8*	*Scenario1:0,10 / Scenario2: 0,15 / Scenario3: 0,20*	*0,4*	*0,9*
Operational costs	*OPER*	*Euro/year*	*normal*	*235262*	*50000*	*0*	
Inflation rate	*r*	*%*	*normal*	*0,025*	*0,003*	*0,001*	
Compound interest rate	*ir*	*%*	*normal*	*0,045*	*0,004*	*0,025*	
Investment life time	*N*	*years*	*fixed value*	*15*			
Biomass price	*Bpr*	*Euro/kg*	*normal*	*0,025*	*0,008*	*0,01*	*0,05*
Biomass heating value	*Θbiom*	*KJ/Kg*	*fixed value*	*8852*			
Number of units	*Un*	*-*	*fixed value*	*1*			
Investment for CHP plant	*II*	*euro*	*normal*	*Scenario1:1849396 Scenario2: 8785526 Scenario3: 17047606*	*Scenario1: 400000 Scenario2: 3000000 Scenario3: 6000000*		

Table 1: Characteristics of distributions for each variable

For each one of the variables that were described in the previous paragraph, Table 1 provides the characteristics of the adopted statistical distribution (normal, fixed value etc. and mean, standard deviation, minimum or maximum where appropriate). These characteristics are quite difficult to be determined and usually arise from the thorough research and extensive experience of the decision maker and his/ her team. Because of this the use of peculiar distributions (other than normal and uniform) is avoided. In our case, the statistical distributions and the relative attributes that describe the uncertainty factors were specified after a brainstorming session conducted among four senior engineers with specific expertise in RES projects and the decision maker. As it can be deducted from Table 1, all the parameters that are not described by a fixed value "carry" an embedded uncertainty (risk). However, some of these parameters are not only uncertain but, moreover, differentiate for each scenario (i.e. Percentage of thermal energy produced that is actually sold).

3.3/ Monte Carlo Simulation and Results

Having identified the uncertainty factors the implementation of the Monte Carlo Simulation took place (Kirytopoulos, 2001). Monte Carlo included a 10.000 iterations random sampling for each variable according to the above defined statistical specifications and a, respectively, extended number of results were calculated for each scenario.

The typical method of determining deterministically the NPV of each scenario ended up to the results given in Table 2. It should be noted that the mean values of the parameters, for each scenario, was used (mean values used) and the results for scenario 1 and 2 were multiplied by 10 and 2 respectively, in order to depict that the total power supplied for any of the three scenarios would sum up to 10 MW (refer to section 3.1).

Scenario #	NPV (€)
1	*24.999.196*
2	*49.602.140*
3	*53.085.590*

Table 2: Deterministic NPV results

If the decision maker had to select one of the three scenarios, holding only the information provided in Table 2, he/ she would probably proposed the third solution as significantly better. However, the deterministic approach does not provide any measure of the uncertainty or risk that the investor undertakes in each occasion. For example, it does not refer at all any indication of the possibility of negative NPV or the best profitability that one could expect.

The results of the proposed probabilistic estimation by the use of the Monte Carlo Simulation ended up to the results presented in Figure 1 and Table 3. Figure presents the probability density function of the 10.000 results that occurred for scenarios 1, 2 and 3 by the use of a common scale, supports the comparative view of the distributions. Table 3 apposes various descriptive measures for the occurred distributions.

The major advantage of the proposed method is the richer (comparing to the deterministic approach) information provided to the decision maker. The decision maker is now able to modulate his selection by taking into consideration more that one strategic objectives. For example, he could select the option that performs better in an algorithm such as the following:

$$M = \frac{\alpha \times (LeftX) + \beta \times (Median) + \gamma \times (RightX)}{\alpha + \beta + \gamma} \qquad (7)$$

where α,β & γ are numbers that quantify the strategic objectives (for example a big value for α shows a risk averse tendency, while a big value for γ gives preference to scenarios with possible very high profits).

Another possible measure would be, for example, the percentage of occurred iterations with a negative NPV. A risk averse decision maker (refer to Hillson, 2004 for risk perception) who adopts such a measure will face difficulties in selecting Scenario 2 or 3 (3,4% and 3,1% of negative NPV correspondingly).

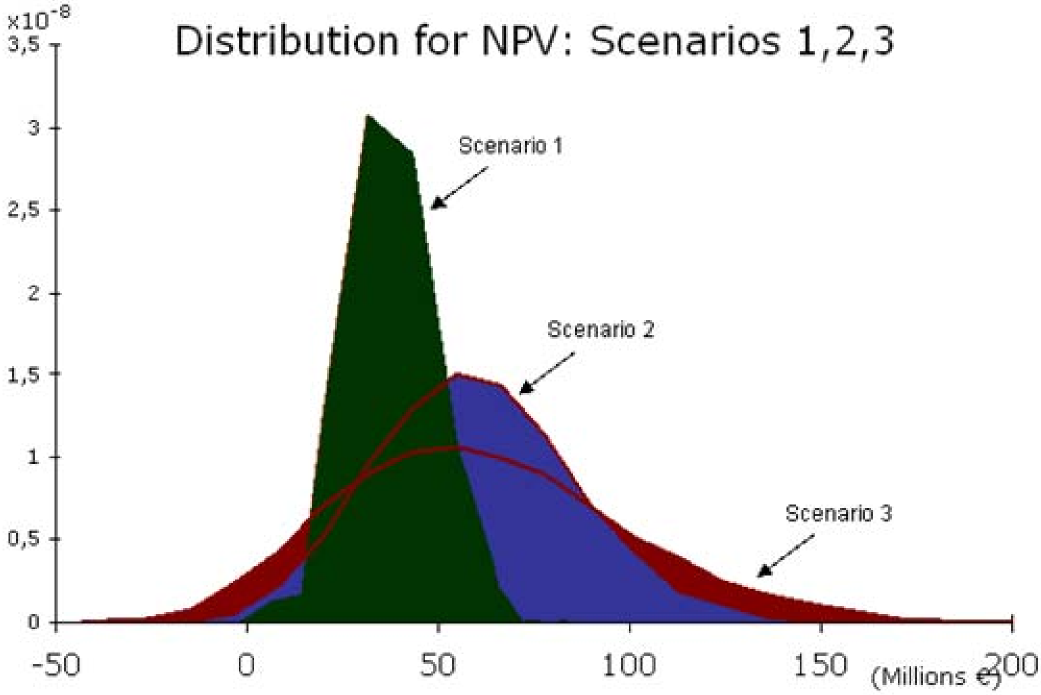

Figure 1: Scenarios 1, 2, 3

Statistic	Scenario 1	Scenario 2	Scenario 3
Minimum	*-1.767.598*	*-18.883.582*	*-43.866.604*
Maximum	*86.613.168*	*162.311.584*	*211.369.488*
Mean	*36.927.711*	*59.631.396*	*61.523.469*
Std Dev	*11.614.330*	*26.117.461*	*37.200.761*
Variance	*1,34893E+14*	*6,82122E+14*	*1,3839E+15*
Skewness	*0,164199672*	*0,237467241*	*0,407301949*
Kurtosis	*3,058967913*	*2,997313926*	*3,063140915*
Median	*36.621.784*	*58.665.808*	*58.947.900*
Mode	*42.206.820*	*62.152.064*	*36.329.393*
Left X	*18.191.792*	*18.392.896*	*5.485.886*
Left P	*5%*	*5%*	*5%*
Right X	*56.695.140*	*104.336.584*	*127.792.904*
Right P	*95%*	*95%*	*95%*
Diff X	*38.503.348*	*85.943.688*	*122.307.018*
Diff P	*90%*	*90%*	*90%*

Table 3: Simulation Results

In the case study under investigation, although the deterministic approach indicated that the better solution would be scenario 3, the probabilistic approach makes the decision maker to have second thoughts. If the one who takes the decision is not a risk seeker, he/ she would probably drop the third scenario in favour of the second. Although the third scenario may lead to very high profits it may also lead to quite important loses. Moreover, the comparison among the mean, median and mode values of the second and third scenarios does not indicate that one of two should clearly prevail. Thus, a risk neutral or a risk averse person would prefer the second scenario as this leads to loses with a substantially reduced probability.

4/ CONCLUSION

The project selection process takes place prior to the project initiation face and one may claim that it is out of the boundaries of the project and should be dealt with by the senior management only. But who would be better to take part in the selection process than the project manager who is going to be asked to execute the project, right afterwards? The authors of this paper believe that the project management professional should always aid the senior management team to take the decision about which is the better alternative, in case there are more than one options. An experienced project manager is the one who better knows the uncertainty factors and the one who may provide the most reliable data for the description of the associated statistical distributions.

The RES project selection case study revealed that a probabilistic approach may alter the verdict of a decision maker due to the provision of richer information. Even if one had no alternatives at all, the use of a probabilistic approach would be of significant value, as it would reveal the level of accuracy of the deterministic value approach, through the estimation of the standard deviation of the final curve (no matter what the criterion would be – NPV, IRR or ROI).

The paper attempted to make clear that, using the proposed probabilistic method through Monte Carlo Simulation, the quantification of uncertainty factors that co-shape the decision criteria (in the presented case study the NPV function) of a project is feasible and the risk that each decision bears is statistically defined in a compatible with the strategic objectives way, that may lead to results that are different from those proposed by the traditional deterministic methods.

The method provided would be of specific benefit to the selection of the RES projects that are going to be developed in the near future, as a result of the activation of the Kyoto protocol.

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Dr. Konstantinos KIRYTOPOULOS holds a Mechanical Engineering Diploma (Bachelor plus MSc equivalent) and a PhD on Project Risk Management. He is specialised in Industrial Management and is currently occupied as a Lecturer in the Aegean University (Greece), an external scientific associate of the National Technical University of Athens and as a freelance consultant. His main research interests are Risk Management in the Bidding Process, as well as Project Risk Management. He has participated in major risk management projects and has already published a significant amount of papers at International Conferences and Journals. He has also won a distinction from the Technical Hellenic Chamber for his outstanding performance during the last year of his graduate studies.

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