Wind Farm Optimal Design Including Risk

Javier Serrano González, Manuel Burgos Payán and Jesús M. Riquelme Santos
Department of Electrical Engineering
University of Seville – Escuela Superior de Ingenieros
Sevilla, Spain
javierserrano@us.es, mburgos@us.es, jsantos@us.es

***Abstract*—An Evolutive Algorithm (EA) for wind farm optimal design, including the investment financial risk, is presented. The algorithm objective is to optimize the profits given an investment on a wind farm including the main risk management aspects. Net Present Value (NPV) will be used as a figure of the revenue in the proposed method. To estimate the NPV is necessary to calculate the initial capital investment and net cash flow throughout the wind farm life cycle. The maximization of the NPV means the minimization of the investment and the maximization of the net cash flows (to maximize the generation of energy and minimize the power losses). Both terms depend mainly of the number and type of wind turbines, the tower height and geographical position, electrical layout, among others. Besides, other auxiliary costs must be to keep in mind to calculate the initial investment such as the cost of auxiliary roads or tower foundations. The complexity of the problem is mainly due to the fact that there is not analytic function to model the wind farm costs and most of the main variables are linked.**

Keywords-wind farms, genetic algorithm, evolutive algorithm, optimization, risk managment

I. Introduction

The use of wind energy to generate electricity is becoming more and more important in most countries. Actual interest in renewable energy resources, such as wind power, is due mainly to a double support. On one side are the economic and political aspects, such as the upward trend in fossil fuel prices and insecurity of supply. On the other are social and environmental aspects, resulting from the ever increasing social awareness about the harmful impacts of the emission of greenhouse gases responsible for global climate change.

Wind power installed worldwide by the end of 2009 amounts to a total of 157.90 GW, of which 76.15 GW correspond to Europe, and of these, 19.15 GW, to Spain. The growth rate of total installed capacity in the world has been of 31% in 2009, a rate that has remained at similar values during the last decades and nothing seems to indicate that much will change in coming years.

The design of a wind power project aimed at generating electricity and its proper operation, over the facility life span, is a complex and multidisciplinary task that involves many different areas from engineering to other sciences.

When an investor decides to address the construction and operation of a wind farm, have to face a number of difficulties. It is not only a complex enterprise, from a technological standpoint, but also presents a degree of uncertainty, in terms of return or profitability of operation during its lifetime, rather higher than desirable. There are many factors that influence the uncertainty (that in the end becomes a risk) in the returns on investment [1,2]. Among all of them, the main are:

• *Future prices and costs*. The future prices of goods, such as the price of the energy or the discount rate of money, are obviously unknown. But, in order to estimate the present return from selling the electricity produced (along the life span of the wind farm) is necessary to know the selling price of the energy and the discount rate, along the whole service life of the park (a time horizon of about 20 years). In this chapter could be included the costs of various factors that influence the normal development of the project, during their construction (such as construction costs of civil work or implementation delays), operation (turbine unavailability, losses in the distribution network or due to wake effect, or maintenance cost) and also in their final phase of decommissioning. This section could also include the risk of possible future regulatory changes that could affect the economic or financial scenario.

• *The wind*. The income from the sale of generated electric energy is the main source of return on investment in the wind farm. Therefore, the random nature of wind (speed distribution and directions) introduces some degree of uncertainty in annual energy production. In this sense is worth noting that the optimum positioning of each of the turbines within a wind farm is one of the factors that more influence the profitability of the installation throughout its operating life cycle. This is due to the turbine wake effect (the screening effect produced by the rotor of a turbine on another located behind it, downstream). The wake effect makes that when a turbine is located in the wake of another turbine produces less energy than if it were exposed to the free air stream. Wake effect losses are the result of interaction of two main factors: the wind (wind rose and speed, not controllable) and the layout of the turbines in the wind farm (controllable at the project stage).

From the above factors, only the losses due to wake effect are controllable to some extend, since they depend on the geographic location of the individual turbines. It is also the individual factor that accounts for the major losses from the theoretical production potential.

This work was partially supported by the Spanish MCYT under research projects ENE2007-66072/ALT and ENE200768032-C04-02, and Andalusia Government under projects Ref. P06-TEP-01882 and TEP-5170.

On the one hand, from the standpoint of minimizing infrastructure costs, it is desirable to minimize the distance between the turbines. This type of compact wind farm design would present a reduced initial cost, but it would produce a large amount of wasted (no generated) electrical energy, due to wakes. On the other hand, a dispersed wind farm design reduces interference between the wakes of turbines but increases the infrastructure costs. Accordingly, a dispersed wind farm design (with the same turbines) would have a higher initial cost (infrastructures), but could produce (and sell) a greater amount of electricity, as it would have less losses due to wake effect. As shown, the role of the designer of wind farms is to set a turbine layout that results in a balance between the initial investment (as low as possible) and the expected net profit from the sale of energy, after subtracting the normal operation and maintenance costs (as large as possible).

As an example, Fig. 1 shows changes in the wind rose at List/Sylt (Germany), measured in 1969 and 1972 [3]. Figure 2 shows the variations in Weibull distribution parameters (C and K), mean wind speed and estimated yearly generation of energy along 30 years on Hong Kong (adapted from [4]).

In this paper, the problem of the optimum location of the turbines in a wind farm, taking into account the uncertainty in the statistical characterization of the wind, is analyzed. The uncertainty from the wind information, in both wind direction and intensity (speed), becomes uncertainty in the estimation of the yearly generated energy. It is therefore the factor that most directly affects the profitability of investment. But, fortunately, at the same time is the most controllable factor in the design stage of the wind farm (optimizing the turbine layout).

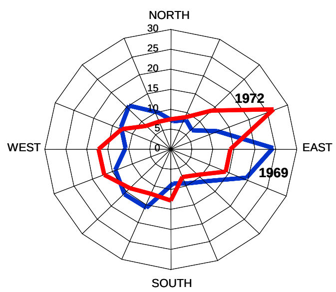

Figure 1. Example of annual variation in the compass rose. Wind rose from List/Sylt (Germany) for the years 1969 and 1972 [3].

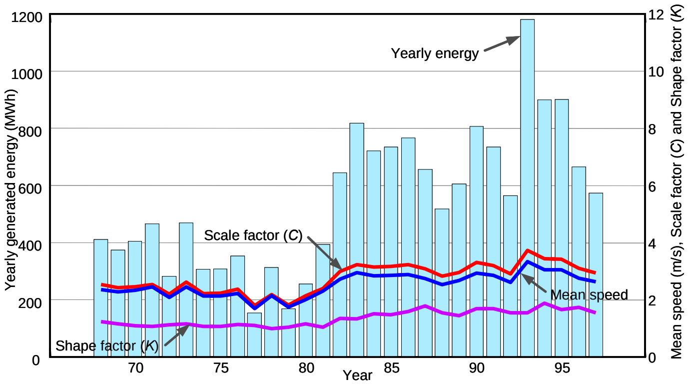

Figure 2. Change in Weibul parameters, mean wind speed and estimated yearly generation of energy in Hong Kong since 1968 until 1997 [4].

The objective is to determine the optimal configuration of the wind farm, so that the profitability uncertainty is set to a level of risk acceptable for investors. Moreover, the study should allow the investor to know the maximum and minimum levels of profitability of the project, which is an essential piece of information in the investor decision making, in order to undertake or reject the project.

After this introduction, the remainder of the work is organized as follows. The economic formulation of the problem is discussed in Section II. Once stated the purpose of the developed tool, the economic variables of the problem and how they are affected by the initial investment and the operation and maintenance costs are shown. The decision-making process is introduced in this section too. Section III addresses the codification of the evolutionary algorithm, showing the main operators and performance sequence. To show some of the main features of the algorithm, the results of a test case under a suit of nine different wind scenarios are shown in Section IV. Finally, Section V summarizes the main conclusions of this work.

II. Wind Farm Cost Model

As often done in the investment analysis, the Net Present Values is used as a figure of merit to compare the profitability of a wind farm investment. A wind farm with a certain turbine configuration (turbine rated capacity, type, height and location), x, requires an initial capital investment to build and put the facility in production, $I_{WF}(x)$. This initial investment is necessary mainly to afford the wind turbine acquisition costs, as well as the civil and the electrical infrastructure costs. The wind farm, once in operation, delivers a stream of both financial benefit (profits from the generated electric energy selling), $N_{ESk}(x)$, and ordinary operation and maintenance costs, $N_{O\&Mk}(x)$, year after year, during the installation life time or production period, LT. A final present cost for the installation decommissioning, $C_D(x)$, and a present residual value, $V_R(x)$, after the production period, must also be considered. This way, the net present value of the wind farm initial capital investment, $I_{WF}(x)$, for an installation live spam of LT years with an equivalent discount rate, r, can be written as:

$$NPV(x) = -I_{WF}(x) - C_D(x) + V_R(x) + \sum_{k=1}^{LT} \frac{N_k(x)}{(1+r)^k} \qquad (1)$$

Where the net cash flow, N_k, represents the net incomes produced by the wind farm during the k-th year. This term is only the difference between the income resulting from the energy sale and the operation and maintenance cost, $N_k(x) = N_{ESk}(x) - N_{O\&Mk}(x)$. Therefore, the maximization of the NPV means a balance between the minimization of the investment and the maximization of the net cash flows (to maximize the net generation of energy) (1). Both terms depend on the number and type of wind generators, the tower height, geographical position, position substation, electrical layout, among other. Table I shows a typical cost distribution of an inland wind farm, adapted from [5].

In order to obtain a wind farm NPV as realistic as possible, the evolution of the prices of the sold energy as well as the increment of the operation and maintenances cost must be considered. Assuming that $E_k(x)$ is the annual net amount of electric energy produced and sold at year k, p_{kWh} is the price of the kilowatt-hour of sold energy, Δp_{kwh} is its annual increment, $C_{O\&Mk}(x)$ is the yearly cost of operation and maintenance at year k, and $\Delta C_{O\&M}$ is its annual increment, then the NPV of the cash flow along the wind farm life span yields:

$$NPV(x) = -I_{WF}(x) - C_D(x) + V_R(x) + \sum_{k=1}^{LT} \frac{E_k(x) p_{kWh} (1+\Delta p_{kWh})^{k+1}}{(1+r)^k} - \sum_{k=1}^{LT} \frac{C_{O\&M\,k}(x)(1+\Delta C_{O\&M})^{k+1}}{(1+r)^k} \tag{2}$$

TABLE I. TYPICAL INITIAL COST STRUCTURE OF A WIND FARM.

Item			**%**
Wind turbines			65-75
Substation and electrical infrastructure			10-15
	Inner electrical distribution installation	*6-9%*	
	Substation and evacuation line	*4-6%*	
Civil work			5-10
Component installation			0-5
Other			5
Overall wind turbine cost (€/kW)		800-1200	

To properly evaluate the potential energy supplied by the wind farm during a year, the wake speed decay effect must be considered due to the perturbation of the wind speed profile due to the operation of the turbines located upstream [4-7]. The actual net energy produced and sold by a set of turbines in a wind farm is lower that the sum of the energies of the turbines if they were isolated. This is due to three kinds of losses, the wake effect previously mentioned, the electrical losses in the wind farm distribution network and the unavailability loss of production must be considered to foresee the days where the turbines are out of production for maintenance, repair or technical restrictions.

The three main economic components of the wind farm -initial investment, operation costs and sale of the energy- are rather difficult to evaluate, even simplifying the problem, because there are many interrelated variables that affects each other. For instance, the type, height and location of a turbine determine the maximum amount of electrical energy that can be obtained, but this energy must be reduced due to interferences in the wind speed field derived from the presence of other near turbines.

III. OPTIMIZATION ALGORITHM

Genetic algorithms are robust optimum search techniques that find the minimum or the maximum of a function based on principles inspired from the natural genetic and evolution mechanisms observed in the nature [10-12]. These algorithms use multiple paths of search instead of single point, using encoded solutions to the problem (variable values or genotypes), instead of their real values. Their main principle is the maintenance of a set of encoded solutions that evolves along the time, guiding the population towards the optimum.

The initial population can be settled both randomly or heuristically [13,14]. Genetic reproduction is performed by means of a few basic genetic operators, mainly crossover and mutation that recombine highly fit individuals (best solutions). The evaluation of the population (potential solutions) is performed by means of a specific objective function (fitness) that depends on each particular optimization problem. The objective function guides the evaluation-selection-optimization process, playing a similar role to the gradient (derivative) in the conventional optimization methods. Individual selection is performed according to a selection strategy that chooses parents with probability proportional to their relative worth (fitness) and explores the solution space looking for better and better solutions.

The type and height of the wind turbines are discrete variables that are not easily managed by traditional numerical algorithms due to the non-differentiable nature of the problem. Therefore, integer codification has been used in the algorithm implementation, which has been also applied to the locations of the potential wind turbines.

The integer codification used represents every possible solution of the problem by means of a matrix where the columns refer to the turbines of an individual and every row codifies the characteristics for each turbine: position of the wind generator in Cartesian coordinates (X_i,Y_i), type of wind generator (T_i) and tower height (H_i). The type of turbine is codified with a number, which will be the index in the generator database that uses the algorithm as an input. The aforementioned database contents all the necessary information of the wind generators that can be installed in the wind farm (i.e. maximum and minimum height of the towers, turbine and tower costs, foundation cost, and curve power-wind speed). Therefore, these matrixes have a variable number of columns, depending on the number of generators required by the codified individual solution [15-18].

Evolutive algorithms make use mainly of two kinds of operators to generate new individuals (potential solutions): crossover and mutation. The crossover operator is applied on two selected individuals, called parents, to generate new individuals, called sons, with a mix of chromosomes (characteristics) from the parents. The selection method used is known as roulette wheel, where the individuals with highest NPV (objective function) are more likely to be selected. Five types of crossover operators that are applied in a randomly way have been developed to be used in the algorithm [15-18]. The mutation operator is applied on one individual to generate another by randomly changing one or more chromosomes. When the population is confined in a local maximum, this operator leads to the creation of individuals out of this zone of local attraction. This way the algorithm can evolve towards the global maximum.

Usually, after the operation of crossover or mutation, not valid solutions can be created. In this case, a regenerative algorithm goes through the individuals removing the turbines that are wrongly placed and reducing the number of generator to the imposed limit.

When addressing the problem within the framework of a deterministic approach, once the input variables values are set (the deterministic scenario), an optimization algorithm, based on genetic algorithm techniques, determines the optimal configuration of the wind farm (Fig. 3a). But, when addressing the problem with a risk approach, the uncertainty in the input variables must be considered. Now, for every set of input variables, an scenario (S_1, S_2, ... S_N), characterized by its probability of occurring (p_1, p_2,…p_N), must be considered (Fig. 3b). In this case, Table II shows the corresponding matrix results. As can be seen, the *ij* element of this matrix (NPV_{ij}) shows the NPV related to the *i-th* potential wind farm configuration (individual *i-th*), considering the *j-th* scenario (S_j). With the Maximum Expected Value (MEV) approach, the objective is to find the wind farm configuration with maximum expected value of NPV. To reach that goal, the NPV for each individual corresponding to each one of the considered scenarios, must be calculated with the expression:

$$MEV_i = \sum_{j=1}^{m} NPV_{ij} p_j$$

Figure 4 shows a block diagram of the methodology used in this work to determine the optimal configuration of a wind farm, taking into account the risk associated with the uncertainty of the input information.

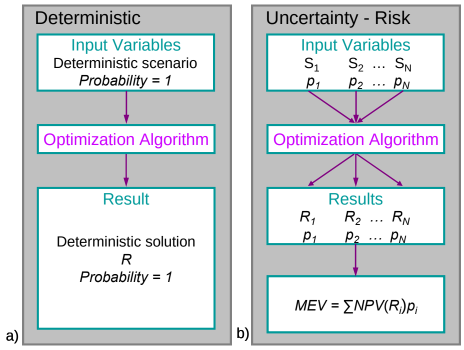

Figure 3. Optimization process a) Deterministic approach; b) Risk approach: A set of uncertainty scenarios results in a set of optimum configurations. The MEV approach leads to the optimum for the set of scenarios.

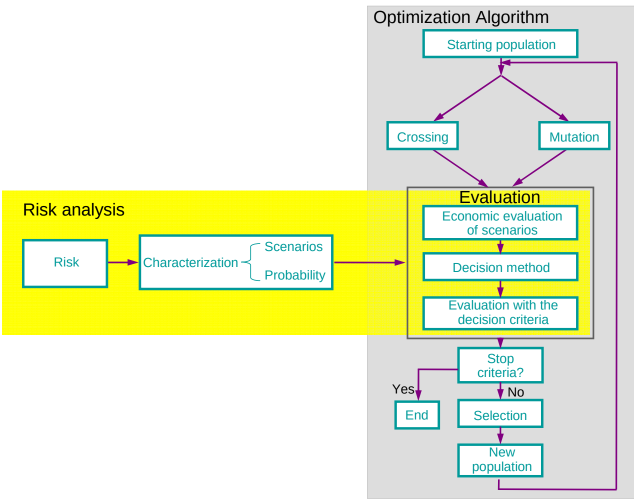

Figure 4. Optimization algorithm incorporating uncertainty (risk) scenarios.

TABLE II. RESULTS MATRIX. NPV OF EACH SOLUTION (POTENTIAL WIND FARM CONFIGURATION) FOR EVERY SCENARIO

Scenario	S_1	…	S_j	…	S_m	*MEV*
Scenario probability	$p(E_1)$	…	$p(E_j)$	…	$p(E_m)$	$MEV_1 = \sum_{j=1}^{m} NPV_{1j} p_j$
Individual *1st*	NPV_{11}		NPV_{1j}		NPV_{1m}	$MEV_2 = \sum_{j=1}^{m} NPV_{2j} p_j$
…	…	…	…	…	…	…
Individual *i-th*	NPV_{i1}	…	NPV_{ij}	…	NPV_{im}	$MEV_i = \sum_{j=1}^{m} NPV_{ij} p_j$
…	…	…	…	…	…	…
Individual *n-th*	NPV_{n1}	…	NPV_{nj}	…	NPV_{nm}	$MEV_n = \sum_{j=1}^{m} NPV_{nj} p_j$

The algorithm's optimization process is guided (driven) by a global cost model of the wind farm taking into account both the initial investment as the present value of the yearly net cash flow during the whole life span of the wind farm. The optimization problem was formulated as a mixed-integer nonlinear problem and was solved by using a specific evolutive algorithm based on Matlab.

IV. TEST CASE

As an example, the optimization of a wind farm on a 2.5 km × 2.5 km) square terrain is considered. The terrain is subdivided into 10 × 10 cells for possible wind turbine location. The considered terrain includes three kinds of restrictions such as the presence of a main road crossing the wind farm from north to south, over its west border, a forbidden zones and a low load-bearing capacity zone, where the considered foundation costs are higher. Tables III and IV summarized the input parameters and the main characteristics of the wind turbines used in the considered test case. The cost information used is typical values, e.g. the price of energy is based on the mean yearly value at the Spanish market in 2009. Figure 5 shows the power-speed characteristic of these wind turbines.

TABLE III. MAIN IMPUT ALGORITHM PARAMETER

Life time span (year)	17
Interest rate (%)	3.0
Price of energy (€/kWh)	0.09
Maximum number of turbines	10
Auxiliary roads cost (€/m)	80
Foundation cost increase-Tower more than 50 m high (%)	50
Foundation cost increase-Low bearing terrain (%)	45
Terrain roughness length (mm)	5.5
Availability factor (%)	95
Present cost of decommissioning (%)	3.0
Present residual value (%)	3.0

As mention previously, the uncertainty is considered in the wind distribution information (direction and speed). Table V summarizes the 9 wind scenarios considered each of them with a different probability. In all of them, a Weibull distribution with shape parameter $K = 2$ is considered, but the value of C are depending on each scenario. For example, scenario S1 has an occurrence probability of 9.75%, a Weibull distribution with $K = 2$ and $C = 7.5$ for all wind directions. The last three columns show the frequency of each wind direction for this scenario. As a result of a balance between the complexity of the optimization of the wind farm's electrical infrastructure and its small percentage on the investment (Table I), in this case, the cost of electricity infrastructure has been considered equal to those of civil works. This investment in civil infrastructure work is calculated taking into account the total length of the auxiliary road network and the turbine foundations.

TABLE IV. MAIN CHARACTERISITCS OF THE CONSIDRED WIND TURBINES

	WT 1	WT 2	WT 3
Rated capacity (MW)	2.00	2.00	1.67
Minimum height (m)	60	60	60
Maximum height (m)	100	100	80
Turbine cost (M€)	2.10	2.00	1.67
Tower cost (k€/m)	1.5	1.5	1.5
Foundation cost (k€)	80	80	80

Figure 6 shows the optimum solution found by the algorithm, considering the maximum expected value criterion (MEV). As shown, the optimal solution consists of 10 turbines of type 1 (WT1), 100 m in height, arranged in two diagonal rows, separated 884 m each other, with a staggered turbines layout, plus a turbine next to the main road. Table VI summarizes the most relevant economical results obtained for this optimum configuration.

TABLE V. CONSIDERED WIND SCENARIOS AND PROBABILITIES

Scenario	Probability (%)	Scale factor C (m/s)	Directions (%)		
S1	9.75	7.5	WSW (20%)	SW (55%)	SSW (25%)
S2	39.00	8.0	WSW (20%)	SW (55%)	SSW (25%)
S3	16.25	8.5	WSW (20%)	SW (55%)	SSW (25%)
S4	3.00	7.5	W (20%)	WSW (55%)	SW (25%)
S5	12.00	8.0	W (20%)	WSW (55%)	SW (25%)
S6	5.00	8.5	W (20%)	WSW (55%)	SW (25%)
S7	2.25	7.5	SW (20%)	SSW (55%)	S (25%)
S8	9.00	8.0	SW (20%)	SSW (55%)	S (25%)
S9	3.75	8.5	SW (20%)	SSW (55%)	S (25%)

Figure 7 shows the solution obtained using the deterministic approach for Scenario 2, the scenario with the greatest probability of occurrence. As can be seen, the distance between the two diagonal rows is now 530 m. Therefore, the mean distance between turbines is lower in the deterministic solution than with the risk approach. The risk approach leads wind farms with a more sparse wind turbine layout, since in this way (by increasing the distance between turbines) losses due to the effect of the wakes are reduced for the whole set of possible scenarios.

TABLE VI. MAIN ECONOMIC RESULTS FOR THE MEV APPROACH (EXPECTED VALUES) AND THE DETERMINISTIC SOLUTION

Expected Value	MEV		Deterministic
NPV (M€)	77.98	NPV (M€)	77.24
IRR (%)	102.49	IRR (%)	102.35
Payback (years)	4.77	Payback (years)	4.78
Total investment (M€)	25.68	Total investment (M€)	25.60
WT investment (M€)	*22.50*	*WT investment* (M€)	*22.50*
Civil work cost (M€)	*1.59*	*Civil work cost* (M€)	*1.55*
Electrical infrastr. (M€)	*1.59*	*Electrical infrastr.* (M€)	*1.55*
Yearly gen. energy (GWh)	67.71	Yearly gen. energy (GWh)	67.16

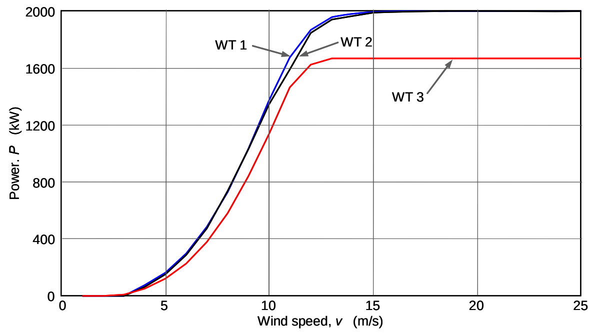

Figure 5. Wind turbines power-speed characterirtics.

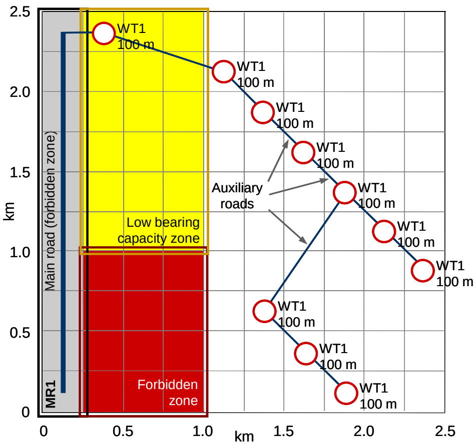

Figure 6. Optimum wind farm configuration. Maximum Expected Value approach.

Table VII compares the NPV that would be obtained for the considered scenarios using both deterministic and risk approaches, as well as their corresponding expected values (EV). The solution obtained by the risk approach is less sensitive to changes in the characterization of the wind than the corresponding deterministic solution. In addition, the risk approach leads to a higher EV that the deterministic solution. On the contrary, the deterministic approach yields a maximum value of the NPV for Scenario 2. Table VIII shows the expected values of the average power broken down by wind directions. The expected losses due to wake effect in the risk approach solution (MEV) are significantly lower (0.12%) than the corresponding to the deterministic solution (0.48).

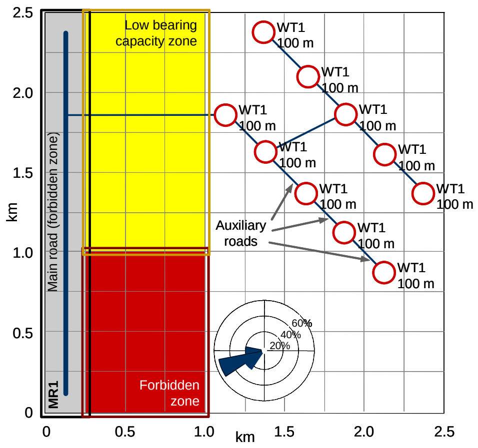

Figure 7. Optimum wind farm configuration. Deterministic approach.

TABLE VII. NPV FOR EACH ONE OF THE CONSIDERED SCENARIOS

Scenario	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*	*S9*	EV
MEV (M€)	66.27	77.16	87.49	66.27	77.16	87.49	65.47	76.33	86.65	77.98
Determin. (M€)	66.34	77.24	87.56	65.29	76.15	86.45	64.60	75.42	85.71	77.69

TABLE VIII. EXPECTED VALUES OF THE AVERAGE POWER BROKEN DOWN BY WIND DIRECTIONS

Wind rose direction		W	WSW	SW	SSW	S	Total
Available mean power (kW)		310	1857	3385	1896	290	7738
MEV	Mean power (kW)	310	1857	3385	1896	281	7729
	Wake effect losses (%)	0.00	0.00	0.00	0.00	3.22	0.12
Deterministic	Mean power (kW)	293	1857	3385	1896	270	7701
	Wake effect losses (%)	5.24	0.00	0.00	0.00	6.99	0.48

This difference is due to the fact that when the wind blows from W and S, the wake losses increases in the deterministic solution to 5.24% and 6.99% respectively, as a result of the shorter distance between wind turbines along these directions.

V. CONCLUSIONS

Wind power expansion is limited because of high investment cost. Wind farms have very small operation costs, but they are very intensive in funding requirements to cover the initial investment needs. The random nature of wind is a major risk and becomes a critical factor on investment decision. This work introduces a new procedure to optimize the wind farm configuration by evaluation of the expected energy production. The objective of the algorithm is to find the optimum layout that maximizes the expected profit, considering the risk from uncertainty in wind direction and speed.

The design a wind farm involves a large number of variables. At the project stage, the behavior of many of these variables is difficult to characterize either due to errors in the estimation of costs and uncertainty in economic behavior, or due to the random nature of some of the variables. Among all the variables that influence the profitability of a wind farm project, the characteristics of the wind have the greatest influence on the plant configuration and its economic efficiency. Therefore, in this work, the risk analysis and decision making has focused on the uncertainty in wind resource (direction and speed) characterization.

The performance of the proposed method has been successfully verified by analyzing a test case, with a set of nine different wind scenarios, with probability assigned. As a result, when the risk analysis is included, the optimization process of the wind farm leads to solutions (plant configurations) less sensitive to the uncertainty than the deterministic solution.

REFERENCES

[1] Paul R. Garvey. Analytical Methods for Risk Management. A Systems Engineering Perspective. 2009 Taylor & Francis Group, LLC.

[2] Garvey, P. R., January 2005. System-of-Systems Risk Management: Perspectives on Emerging Process and Practice, The MITRE Corporat.

[3] L. Jarass, L. Hoffmann, A. Jarass, G. Obermair, *Wind energy*, Springer-Verlag, Berlin, 1981.

[4] Isaac Y.F. Lun, Joseph C. Lam. *A study of Weibull parameters using long-term wind observations*. Renewable Energy, 2000.

[5] M. Junginger, A. Faaij, W.C. Turkenburg, "*Cost reduction prospects for offshore wind farms*", Wind Engineering Vol. 28-1, 2004, pp. 97–118.

[6] I. Katic, J. Høstrup, and N.O.Jensen, "A simple model for cluster efficiency", in EWEC'86, Rome, 1986.

[7] S. Frandsen, R. Barthelmie, S. Pryor, O. Rathmann, S. Larsen, J. Højstrup, and M. Thøgersen, "Analytical modelling of wind speed deficit in large offshore wind farms", Wind Energy, vol. 9, No. 1, pp. 39–53, Jan. 2006.

[8] S. T. Frandsen, "Turbulence and turbulencegenerated structural loading in wind turbine clusters", Ph.D. dissertation, Technical University of Denmark, January 2007.

[9] A. Crespo, J. Hernández, and S. Frandsen, "Survey of modelling methods for wind turbine wakes and wind farms", Wind Energy, vol. 2, pp. 1–24, 1999.

[10] R. Spillman, "Genetic algorithms, nature´s way to search for the best". Dr. Dobb´s J 1993:26-30.

[11] J.J. Grefenstette, "Optimization of Control Parameters for Genetic Algorithms", IEEE Trans. On Systems Man, And Cybernetics, vol. SMC-16, pp. 122-128, January/February 1986.

[12] D. Goldberg, Genetic algorithms in search, optimization and learning. Addisson-Wesley Pub. Co. Inc, 1989.

[13] Grady SA, Hussaini MY, Abdullah MM. Placement of wind turbines using genetic algorithms. Renewable Energy. 2005.

[14] Mosetti G, Poloni C, Diviacco B. Optimization of wind turbine positioning in large wind farms by means of a genetic algorithm. J Wind Eng Ind Aerodyn 1994.

[15] J. Serrano González, A.G. González Rodríguez, J. Castro Mora, J. Riquelme Santos, M. Burgos Payán. *A New Tool for Wind Farm Optimal Design*. 2009 IEEE Bucharest Power Tech Conference, June 28th - July 2nd, Bucharest, Romania.

[16] José Castro Mora. *Optimización Global de Parques Eólicos Mediante Algoritmos Evolutivos*. Tesis doctoral. Departamento de Ingeniería Eléctrica. Universidad de Sevilla. Available at: http://fondosdigitales.us.es/tesis/tesis/863/optimizacion-global-de-parques-eolicos-mediante-algoritmos-evolutivos/.

[17] J. R. Santos, M. B. Payan, J. Calero, and J. C. Mora, *An evolutive algorithm for wind farm optimal design*, Neurocomputing, vol. 70, no. 16-18, pp. 2651–2658, 2007.

[18] J. Serrano González, A.G. González Rodríguez, J. Castro Mora, J. Riquelme Santos, M. Burgos Payán. *Optimization of Wind Farm Turbines Layout Using an Evolutive Algorithm.* Renewable Energy (ISSN: 0960-1481), Vol. 35, Issue 8, August 2010, pp. 1-11.