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Corso di Dottorato in Ingegneria Matematica e Simulazione

Ciclo XXX

Tesi di Dottorato

How to evaluate the investment and management economic sustainability for different photovoltaic plant installations

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Chapter 1

Introduction

The public attention for Renewable Energy Sources has grown around the world in recent years, and the issue has become increasingly prominent.

The phenomenon has roots that date back to the late nineties, precisely to 1997, when the Kyoto Protocol was defined. It was the main tool developed by the international community to face climate changes and to reconcile the environmental interests with the economical ones.

This document was signed in the Third Session of the Conference of the Parties (COP3) on climate, of the United Nations Framework Convention on Climate Change (UNFCCC). To date, it has been signed by more than 180 countries and it entered into force on February 16th 2005, following ratification by Russia. In fact, the treaty could enter into force only if it had been ratified by at least 55 signatory nations and if the nations that had ratified would produce at least 55% of polluting emissions. The latter condition was reached only in November 2004 when also the Russian Federation has completed its accession.

The Kyoto protocol stipulates the duty on developed countries to reduce the greenhouse gases emissions, in 2008-2012, by at least 5% compared to 1990. The protocol does not provide, for developing countries, commitments to reduce greenhouse gas emissions. This in observance of the equity principle, in order to avoid restricting their economic growth requiring them particularly heavy obligations. The Kyoto protocol stipulates that member countries can acquire emission credits through a system of market mechanisms: the Emissions Trading (ET), the Clean Development Mechanism (CDM) and the Joint Implementation (JI). The purpose of these tools is to maximize the reduction of greenhouse gas emissions at least cost.

The first mechanism requires that the different participating countries can assign or acquire each other emission credits; thus, countries that are unable to meet their commitments in terms of reducing greenhouse gas emissions immediately, can acquire excess credits from countries that have exceeded their goals. The Clean Development Mechanism requires that industrialized countries can acquire emission credits by implementing initiatives aimed at generating environmental benefits in developing countries, in terms of both reducing greenhouse gas emissions and developing the socio-economic status.

The European Commission, in January 2008, has focused, again, the awareness of enterprises and economic operators on the issue, with the so-called 20-20-20 package. This package approved a set of legislative proposals to face climate changes.

The proposals are, in particular, the achievement, by 2020, of a 20% reduction in CO_2 emissions, a 20% improvement in energy efficiency and a 20% share of energy from renewable sources.

By the same measure it was also defined the extent to which each member state would have to contribute to the results' achievement. For example, Italy has to reduce by 13% carbon dioxide emissions in sectors that are not included in the emissions' trading system and it has to increase production from renewable energy sources to the 17% of domestic consumption (compared with 5.2% in 2005). These are ambitious goals, which led member countries to adopt national plans to promote investments in renewable energy sources.

In December 2015, then, at the UN Climate Change Conference held in Paris, a climate agreement has been defined and it provided the following:

- temperature rise below 2-Celsius degrees: at the climate conference held in Copenhagen in 2009, the 200 participating countries gave themselves the target of limiting the rise in global temperature above pre-industrial values. The Paris agreement states that this increase should be contained below 2-Celsius degrees, trying to stop to + 1.5 degrees. To hit the target, emissions must start to decline from 2020.
- Global Consensus: worldwide joined this agreement, including the four biggest polluters. In addition to Europe,

also China, India and the United States have agreed to reduce emissions.

- Five-year checks: the text provides an objectives' review process that must be held every five years. However, in 2018 it will be already asked to the countries to reduce emissions, to get ready in 2020. Therefore, the first five-year monitoring will be in 2023.
- Funds for clean energy: the old industrialized countries will deliver one hundred billion per year (from 2020) to spread around the world green technologies and decarbonise the economy. A new financial goal will be fixed at the latest in 2025.
- Refunds to the most exposed countries. The agreement kicks off a mechanism of reimbursement to offset the financial losses caused by climate changes in the most geographically vulnerable countries, often the poorest ones.

1.1 Some of the current challenges

The renewable energy sector is characterized by not having yet obtained the so-called grid parity. The generation cost of the produced energy is still significantly higher than for conventional energy and therefore it requires an incentive, determined by the regulator. It is a sector that, in reality, has two kinds of criticalities.

First, there are considerable difficulties in financing due to the uncertainty of the economic-financial performance. To this, the significant discontinuities in regulations that have occurred and are still ongoing must be added.

At a time like the present one, in which the Governments of all major western economies are forced to pursue aggressive strategies of reorganization and cuts in public spending, the question of whether to continue or not to fund the development of green technologies represents a topic of current interest.

With the austerity phase that is going through, creative strategies will probably be necessary to support the development of this sector. Certainly renewable energy can be a clean engine to boost innovation. Not surprisingly, this sector has generated new sectors, with the start up of industrial companies, with partnerships between industrial and financial companies, or with spinoff derived from the traditional energy sector.

The development of renewable energies and the reconversion process that goes with it can be a great opportunity and a possible driver to boost growth in the name of a more sustainable development model.

In this context, the investments' economic evaluations focused on the peculiarities of this sector become increasingly important; as well as the economic analysis used as a support during the construction phase of renewable energy installations; the location identification for new plants maximizing the economic investment and the definition of co-existence logics between traditional and renewable energies. These issues are addressed in this thesis.

Chapter 2

Simulation

Simulation is a powerful tool to describe and analyze complex systems in all the real situations in which it is extremely difficult to identify the best strategy among different alternatives. It allows analyzing different scenarios in order to select the one that best expresses the proposed objectives.

The simulation models can provide valuable support to:

- in-depth understanding of the system and of the interactions among all its components;
- long-term assessments: cost/benefit analysis regarding decisions that involve structural aspects of the company (fleet-sizing, location-plant, plant-sizing, new markets expansion, etc.).
- tactics assessments: "what-if" analysis on the risks assessment due to environmental factors and process criticalities, or induced by strategy changes;
- short-term decisions: decision support system able to act in emergency situations (plants breaking, strikes, peak demand, etc.).

In short, simulation is a low-cost technique, which does not imply big risks and represents a valuable support in the decision-making process.

Simulation consists of creating a model, which represents reality and allows evaluating and predicting the dynamic of a series of events linked to particular conditions. The model must faithfully represent real phenomena through the conversion from a qualitative view to a quantitative vision of the system.

Usually, the model describes the estimated evolution of a phenomenon or of a physical system based on initial data, returning final data.

It should be noted that simulation is not the only type of modelling approach to a problem. The canonical modelling approach, for many disciplines, in fact, is that one which allows providing phenomenal representations in the form of mathematical propositions from which it is possible to obtain quantitative data on which assessments on the object system are based.

However, when reality is overly complicated, this kind of approach would lead to the introduction of heavy simplifications, with the risk of getting incorrect results and misleading analysis.

An important distinction, in the definition of simulation models, is the one between deterministic and stochastic systems.

A deterministic system is a system in which the evolution is led by a cause-and-effect law. This means that all effects can be associated with the cause that generated them.

A stochastic system is a system whose evolution can be estimated only by a probabilistic point of view. It follows the introduction of an error that can be more or less significant depending on the goodness of the model and of the carried out validation. In these models, in fact, the moment when an event occurs is not certain but it can be determined, to the maximum, a probability distribution that describes the possibilities that this event will occur at a given moment.

By introducing the input data to a deterministic model, a predetermined result is obtained. In a stochastic model, instead, when probabilistic data are introduced, a random result is obtained, which represents an estimation of the real system.

In the study of logistic/production systems the choice of stochastic models is often necessary to take account of different aspects of variability and unpredictability.

Once the system has clearly been defined, it is necessary to identify the involved variables, to collect data, to define the objective functions and to build the model. When the model is completed, before considering reliable the obtained results, it is necessary to proceed with the model validation.

2.1 Simulation models' validation

The "goodness" of a simulation model depends not only on the construction of the model (i.e., the system analysis, the data survey and the transcription logic), but also on performing a complete experimental activity, which should include the experimental error measurement, which is generally a normal distribution (NID (0, σ^2)) [1-3].

σ^2 can be estimated using Cochran's theorem [3] through the measurement of the Mean Square Pure Error (MSPE), its unbiased estimator. It is an intrinsic characteristic of each model and it is strictly connected to the investigated reality because it is directly dependent on the overall stochasticity of which the real system is affected.

In other words, any system displays its stochasticity level conditioning the behaviour of the output variables and producing a characteristic error which cannot be set aside. In the experimental phase, the real problem is not the error which is strictly connected to the system stochasticity, but the possibility to add to it a second important error source, which, contrariwise, can be controlled and, if necessary, even removed. This second source is determined by an inadequate number of extractions from the random variables' distributions that does not allow obtaining the whole adherence to the actual probability distributions.

The MSPE trend in the simulated time, for all systems displaying a time evolution characterized by a sufficiently high number of extractions from the model frequency distributions, shows that the real system error can be separated from the total error, with all the subsequent positive consequences on the reliability analysis of the model output results.

On the contrary, there are systems that cannot be managed in the experimental phase according to the MSPE evolution scheme in the simulated time.

This problem occurs each time the number of extractions from the frequency distributions that characterize the model is limited to a single value or, in any case, to a limited sample, which is not adequate to obtain an effective description of the distributions.

This class includes the main part of the systems analysed in this thesis.

In this case, both the variance of the mean response ($MSPE_{MEAN}$) and the variance of the standard deviation ($MSPE_{STDEV}$) must be monitored. Using these two parameters, the optimal number of runs necessary to obtain an unbiased evaluation of the experimental error afflicting the objective function can be chosen.

With this methodology, it is possible to graphically illustrate the evolution of the experimental error variance as a function of the sample size.

The methodology allows identifying the number of replicated runs required to minimize the error generated by inadequate overlapping of the variables' probability density functions with Monte Carlo extraction.

In this way, the experimenter is able to choose the best ratio between experimental cost and expected results.

The MSPE method can be divided in the following phases:

- set a number K > 2 of simulation runs, carried out in parallel, in which the independent model variables are maintained the same;
- establish, for each run, a number N >> 1 of replications so that one can construct the matrix Y, whose generic entry y_{ij} is the simulator output at run j∈{1,…, K} and replication i∈{1, …, N};
- calculate, for each n = 1,…, N, and j = 1,…, K the means matrix and the standard deviation matrix

$$\overline{y_{nj}} = \frac{\sum_{i=1}^{n} y_{ij}}{n} \tag{2.1}$$

$$\sigma_{nj} = \begin{cases} 0 & n = 1 \\ \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(y_{ij} - \bar{y}_{nj}\right)^2} & n \geq 2 \end{cases} \tag{2.2}$$

- calculate the N means of means and of standard deviations (for any n = 1,…, N)

$$\bar{y}_n = \frac{1}{K}\sum_{j=1}^{K}\bar{y}_{nj} \tag{2.3}$$

$$\bar{\sigma}_n = \frac{1}{K}\sum_{j=1}^{K}\sigma_{nj} \tag{2.4}$$

- calculate N values of $MSPE_{MEAN}$ and of $MSPE_{STDEV}$

$$MSPE_n^{MEAN} = \frac{1}{K-1}\sum_{j=1}^{K}\left(\bar{y}_{nj} - \bar{y}_n\right)^2 \tag{2.5}$$

$$MSPE_n^{STDEV} = \frac{1}{K-1}\sum_{j=1}^{K}\left(\sigma_{nj} - \bar{\sigma}_n\right)^2 \tag{2.6}$$

The results, transferred onto the plane (i, $MSPE_{MEAN}$), show the mean square pure error curve trend in the replicated runs. Therefore, it is possible to know the error variance that affects each objective function step-by-step.

According to Cochran's theorem, $MSPE_{MEAN}$ represents the best estimators of the experimental error variance (σ^2) and, consequently, gives a measure of the experimental error in the mean value of the means distributions.

Figure 2.1 shows the $MSPE_{MEAN}$ concept:

- for each of the K runs, given N replications, a frequency distribution is obtained with a mean $\overline{y_{\mathrm{N\,j}}}$;
- the K means $\overline{y_{\mathrm{N\,j}}}$, where 1 ≤ j ≤ K, opportunely sampled, produce the mean frequency distribution with a mean $\overline{Y_N}$ and unbiased variance estimate by $MSPE_{MEAN}$.

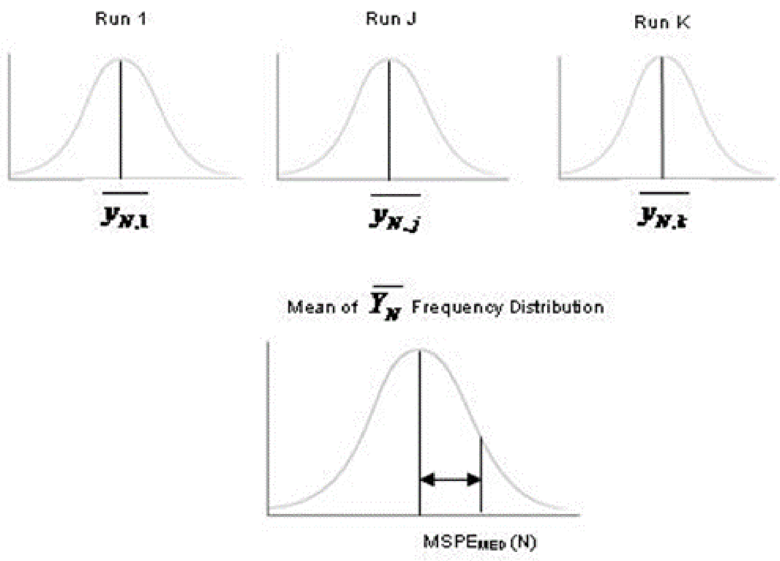

Fig. 2.1: $MSPE_{MEAN}$ generation

The same approach is also valid for the standard deviation. For each of the K runs, N standard deviations are calculated $stdev_{ij}$ ($y_{1j}, y_{2j}, \dots y_{ij}$) where 1 ≤ i ≤ N from which N means of standard deviation are obtained as follows:

$$\overline{stdev_n} = \frac{\sum_{j=1}^{K} stdev_{nj}}{K} \tag{2.7}$$

Then, N MSPESTDEV are calculated:

$$MSPE_{STDEV}(i) = \frac{\sum_{j=1}^{K} (stdev_{ij} - \overline{stdev_i})^2}{K-1} \tag{2.8}$$

where 1 ≤ j ≤ K and 1 ≤ i ≤ N.

Each MSPE carries knowledge that yields important inferences to the behaviour of the actual experimental responses because, according to Cochran's Theorem, this identifies the interval in which there is a 99.7% probability that the value y* of a single simulation lies in it.

In the time-based evolution systems, usually managing small, the generic expression of this interval is:

$$\bar{y} - 3\sqrt{MSPE_{MED}} \leq y^* \leq \bar{y} + 3\sqrt{MSPE_{MED}} \tag{2.9}$$

In the runs-based evolution systems:

$$\bar{y} - 3\sqrt{MSPE_{MED}} - 3\sqrt{\overline{VAR} + MSPE_{STDEV}} \leq y^* \leq \bar{y} + 3\sqrt{MSPE_{MED}} + 3\sqrt{\overline{VAR} + MSPE_{STDEV}} \tag{2.10}$$

where $\overline{VAR}$ is the square of $stdev_n$.

Moreover, when each of the experimental responses resulting from K parallel runs have a sufficiently great wideness to allow an exhaustive description of the population behaviour, the two MSPE values evolving in the simulations would crash on the x axis (MSPE = 0):

$$\lim_{n\to\infty} MSPE_n^{MEAN} = \lim_{n\to\infty} MSPE_n^{STDEV} = 0 \tag{2.11}$$

The problem is not to obtain a theoretical MSPE = 0, but to limit the number of runs through a careful check of the experimental error evolution in terms of both magnitude and convergence, to also limit its impact on y* to acceptable values.
As previously shown, for each replication, the parameter N influences the number of runs necessary to perform the calculation of the dependent variables' statistical parameters.
With respect to the K runs performed in parallel, the interest to choose a high K can be correct. As K increases, the sample becomes wider. In many cases, therefore, it could happen that, as K increases, the MSPE calculation time rapidly increases.

2.2 Design of Experiments

Frequently, the simulation models' analysis power decreases during the traditional experimentation phase. What-if analysis generates partial and inhomogeneous scenarios, related to punctual situations.
This gap may be overcome using some experimental techniques that come from Design of Experiments (DOE) approach and Response Surface Methodology (RSM) by which it is possible to obtain state equations from the analysis of experimental data.
DOE has an important role when developing new products or improving existing ones.
Some applications of DOE include:

- design configurations' evaluation and comparison

- alternative materials' evaluation
- determination of the key parameters which have an influence on the systems' performance

2.2.1 Effects' analysis

Basing on the DOE methodology, the effects' analysis has to be applied after the MSPE analysis and before the definition of experimental plan.

The DOE literature assigns two objectives to this phase, a conceptual and an utilitarian one:

1. conceptual objective: when a complicated system is considered, it is not possible to disregard one or more independent variables which may influence at least one of the analysis' objective functions. Consequently, during the independent variables definition, all the independent variables able to influence the objective functions, or to have a conditioning effect on them, must be considered.

   The need to avoid this risk implies to increase the number of independent variables. Considering that the Response Surface Methodology simulation runs grow exponentially, every additional variable creates a multiplicative effect on the runs number.

   This process allows to find out the ability of the independent variables to influence every objective function and to define a priority ranking for each one.

2. Utilitarian objective: basing on DOE theory, a fixed value can be assigned to all independent variables which have a low influence on the objective functions. The specific value has to be evaluated into an established range of variability. The importance of this objective is clear when considering the number of experimental points necessary to conduct, for example, a Central Composite Design:

$$N = 2^k + n_c + 2 \cdot K \tag{2.12}$$

where k is the number of independent variables used in the project.

The importance of an independent variable is not an absolute concept but it is related to the value that it may assume into the pre-defined variability range and it is related to the considered objective function.

The effects' analysis allows evaluating the capability, for every independent variable, to influence the objective functions not only as a single variable but also considering the interactions with the other independent variables [4,5].

During the effects' analysis phase, it is very important taking into consideration the following considerations:

- generally, not only the first order effects can be significant but also the second order ones. The effects from the third order on, instead, are rarely significant;

- two independent variables A and B can have significant first order effects without generating an interaction effect AB;
- two independent variables with no significant effects, could generate a relevant interaction effect.

2.2.2 2^k factorial designs

The 2^k factorial designs are a particular kind of experiments where each factor is considered at two different levels (high level A or low level B). These projects are the most used because they permit to analyse a lot of factors without using a high number of data.

Factorial designs' advantages are:

- they allow to analyse the combined effect of two or more factors on the objective function by simultaneously changing the factors' values
- every test provides information on all the design factors allowing to save resources and time
- simultaneously changes of a lot of factors are applicable to different conditions

As already stated, in the 2^k factorial designs each independent variable can assume any value within the assigned range. The main "effect" of an independent variable (A) for an objective function is the variation between the mean of the dependent variable values with a high level of A and the mean of the same values for a low level of A.

In other words, the main "effect" is the measure of the independent variable ability to influence a dependent variable by changing his value from low to high.

The "effect" values allow elaborating the ranking of independent variables ability to influence the dependent variables.

For instance, if A effect is equal to 1000, B effect is 1 and AB interaction effect is 0,5, it is possible to assume that:

- in this experiment factor A is more important than B, considering the defined objective function and of variability ranges
- B is not able to generate a relevant effect on the objective function (as a single variable or combined with A). For this reason, this variable can be considered as a constant equal to one of the values which are contained within its variability range.

Instead, if the B effect was 10 and the AB interaction value was 5, it would not be immediately clear if B is not relevant for the project.

In this case, it is necessary to proceed with the Analysis of Variance (ANOVA) methodology to obtain a statistically reliable analysis.

2.3 Analysis of Variance

Simulations provide in output a lot of experimental data, which may be used to obtain scientifically acceptable conclusions. To reach this purpose, one of the most commonly used statistical techniques is the ANOVA.

The aim of this methodology is to evaluate the importance of the different variability sources on the experiment variability:

- systematic variation sources, which are under the experimenter control as they are the input data
- random variation sources (intrinsic stochastic variability, environment conditions, measurement errors)

Mathematically, it means elaborating a H_0 null hypothesis and its negation, called alternative hypothesis H_a. H_0 considers the equality of all the groups' means. This means that belonging to a particular group is not influent on the result, that all groups' data come from the same population and that the differences among the groups only depend on random variation sources.

H_a, instead, is often what the experimenter wants to demonstrate, i.e. the considered factors are significant and there is at least one group which has a different mean value.

If H_a is true, systematic variation sources will be added to the random ones.

ANOVA is based on contrast concept. The contrast allows to obtain the sum squares and the mean squares through which it

is possible to determine a statistic parameter to be compared with the corresponding tabled Fisher value.
To start the ANOVA methodology it is necessary to consider that the sum square total (SS_T) is equal to the sum of the sum square of the treatments (SS_{TREAT}) with the sum square error (SS_E):

$$SS_T = SS_{TREAT} + SS_E \tag{2.13}$$

This means that the total statistic variability is based on two main components:

- $SS_{TREAT} = \sum_{i=1}^{k} SS_{EFFi}$ where EFF_i is the effect of order *i.* SS_{TREAT} provides an evaluation of the part of statistic variability which is linked to the independent variables.
- SS_E, which represents the error, linked to different sources, which influence the experiment without a statistical reliable explanation.

  SS_E is composed, for instance, by non-systematic measurement errors, endogenous/exogenous interference effects which influence the dependent variables without the possibility to measure their results. The more SS_E is high the less independent variables are able to explain the dependent variable behaviour. When the experiment is converted into a meta-model, SS_E can be divided into two different components.

The first one is related to the experimental phase and is called Sum Square Pure Error (SSP_E) and the other one is related to the model and is called Sum Square Lack of Fit (SS_{LOF}). The meaning of these values will be detailed in Paragraph 2.2.5 when considering the ANOVA tests.

In order to obtain an evaluation of SS_{PE}, it is necessary to add central tests (tests conducted in the project centre).

In this thesis the ANOVA methodology has been applied using a specific statistical tool called Design Expert.

2.4 Response Surface Methodology

It consists of some techniques which permit to interpolate and approximate the information obtained using the results of different DOE runs.

The main purpose of this technique is to establish the objective function trend within the project range.

The simulation conducted for each test of the experimental design provides the output parameters, generating a “cloud” of experimental points.

The evaluation of the factors’ effect on the objective function is obtained applying the regression analysis. In this kind of analysis, the experimental data are used, through the application of a specific model (for example a factorial design or a central composite design), to quantify the link between the output and the input variables.

The dependence is expressed by equation 2.14:

$$y = \Phi(x_1, x_1 ... x_p) + \varepsilon \qquad (2.14)$$

where:

y is the output variable

φ is the set of regression coefficients

x_p is the p^{th} input variable

ε is the error.

It is necessary to provide an estimation of the regression coefficients (βi).

The aim is to define an analytical equation which passes through the considered points or at a reduced distance obtaining a good level of data fitting. In this way, for different input variable values, the output variable can be evaluated, with a low error level, as a function of the input values, following the defined equation and without repeating the simulation.

This function is called response surface or meta-model or regression model and may be obtained for every output variable.

The RSM advantages consist in:

- the possibility to graphically evaluate the area where the input variables provide an optimal value for the objective function
- considering that the surface is an analytic function As a consequence, its optimization is easy and it is not necessary to conduct other simulations.

The results' reliability prerequisites are that the objective function is quite regular and that the conducted DOE runs provide sufficient information.

There are various RSM techniques, based on different analytic forms and interpolation/approximation logics.

The most commonly used methodology is the method of Least-Squares which is also the default technique of different statistical software.

2.4.1 Least-Squares method

The base element for this methodology is the error:

$$e_i = y_i - \bar{y} \tag{2.15}$$

where

y_i is the real value of the objective function

$\bar{y}$ is the value obtained by the regression curve application

The regression curve fitting goodness is evaluated by equation 2.16:

$$e_1^2 + e_2^2 + \ldots + e_i^2 + \ldots + e_n^2 \tag{2.16}$$

The best interpolating curve is the one that is able to minimize this quantity and it is defined the least-squares regression curve.

When choosing the regression model, it is necessary to start from the lower order model, i.e linear model. In fact, the more the order model is increased, the more the risk to lose sight of the regression purpose (definition of the trend in a set of points) is increased, because the model is more affected by the system noise.

The methodology based on the best regression surface research consists in the definition of subsequent regression meta-models with an increasing order level until the best-fit model is obtained. The analysis sequence proceeds in the following order:

1. First order model: is used to describe systems which can be studied with factorial designs (for instance a 2^k).

   For a 2^2 factorial design, for example, the model is:

$$\bar{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 \tag{2.17}$$

   where β_i, β_{ij}, can be evaluated from the effect values and with β_0 which is equal to the mean of all the experimental data.

   Every coefficient represents the curve's gradient which links each β_i with its x_i, considering the other x_{i-1} at a prefixed value. In this case the response surface takes the form of a plane, or of a twister plane in case there is a significant interaction term $x_i x_j$.

The pure curvature test allows understanding if the influence of $x_i x_j$ term makes it necessary to go through with a second order model or if it is possible to consider a twister plane. It is based on the introduction of central test points (n_c) and on the evaluation of the statistical difference between the main test points' mean and the central test points' one [3].

2. Second order model: sometimes the linear model is not sufficient to represent the considered reality. It is necessary to apply quadratic models. Generally the Central Composite Design (CCD) is used. When considering two factors the model is:

$$\bar{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_2^2 + \beta_5 x_1 x_2 \qquad (2.18)$$

The regression coefficients to be determined in this case are six, so it is necessary to have at least 2 additional test points, to be added to the 4 points of the factorial design. The number of total test for this kind of model is:

$$N = 2^k + n_c + 2 \cdot K \qquad (2.19)$$

It is necessary to choose the additional project points in order to grant a uniform precision in each area, without a focus in a particular surface part.

For symmetry reasons, the number of added points, called axial tests, cannot be different from 2K. The problem is establishing the most convenient position in terms of information contribution for the regression model. Generally, points located outside of variability range are considered in order to obtain a uniform precision.

If two variables are considered, the axial tests will be on a circumference, whose radius is equal to the semi diagonal of the factorial design. If more than two variables are considered, the same approach can be applied having spheres and hyperspheres instead of circumferences (Figure 2.2).

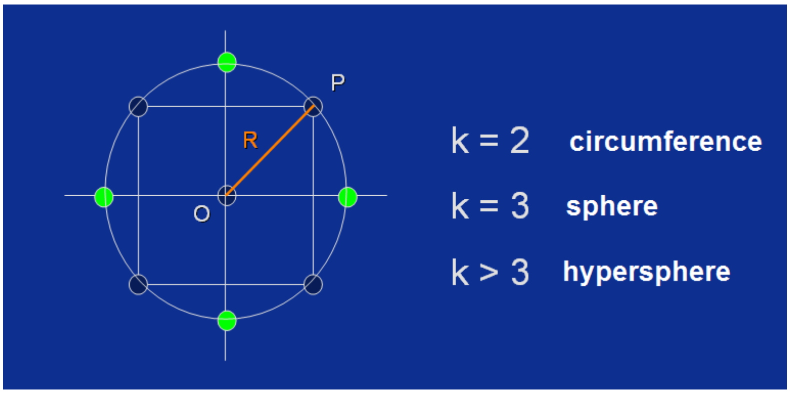

Fig. 2.2: axial points

If, for design reasons, it is not possible to obtain axial tests outside the independent variables variability range, the Face-Centred Central Composite Design (FC-CCD) is used. In the FC-CCD the axial 2K points are "squashed" on the border of the variability region (Figure 2.3).

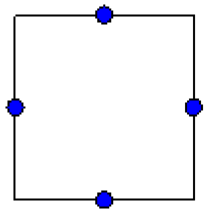

Fig. 2.3: FC-CCD axial points

The use of a FC-CCD instead of a classic CCD, however, involves the loss of the project rotatability, statistical property with which the variance of the predictive model (V_x) has the same value in any position located at equal distance from the project centre (for a more detailed explanation see [1,2]).

These points do not add anything about the direct knowledge of the model but they allow to know the tangents in the extreme points and to correct the trend of the regression surface by decreasing its variance.

3. Models with an order greater than 2: the number of tests needed increases exponentially, this type of project is therefore very expensive and is only used when strictly necessary.

Therefore, the starting point is generally a first order model. To understand if the model successfully approximates the considered set of points or if it is necessary to increase the model order, there are specific tests on regression which can be conducted. These tests are to see if the equation found by estimating β_i is actually able to evaluate the link between dependent and independent variables:

- the first test has the aim of assessing the regressive approach accuracy. The test is conducted by comparing a value of F appropriately evaluated, with a tabulated F Fisher value.

  This test should be independent from the type of regressive model, since it aims to understand if the regressive approach is able to identify a connection between the dependent variable and the regressor's values in the considered data.

  Actually, since the Sum Squares still depend on the model, it may happen that the test does not pass because of the chosen model and it may be convenient to modify the model and conduct again the test.

- the second test is the Lack of Fit one. It is designed to assess the model's lack of fit on the experimental data. This test is conducted only if the first test has a positive outcome. It should be noted that, in order to perform this test, it is necessary to have multiple values of the y response in, at least, one project point (it is advisable to have 4-5 central tests). As already stated, SS_E can be divided into SS_{PE} and SS_{LOF}. The SS_{LOF} is the error component due to the model's lack of fit, namely, the error component due to the regressive approach, while the SS_{PE} is the component of pure experimental error and it is not under the experimenter control. The meaningfulness of the factors is verified using the Fisher test. This test is based on the calculation of parameter $F_0 = \frac{MS_{TREAT}}{MS_E}$ and on its comparison with $F_{v1,v2}$. If:

- $F_0 > F_{v1,v2}$ H_0 hypothesis is rejected
- $F_0 < F_{v1,v2}$ H_0 hypothesis is accepted

Figure 2.4 shows the ANOVA table structure.

	Freedom Degrees	Mean Squares	F_o
SS_{TREAT}	a - 1	$MS_{TREAT} = \frac{SS_{TREAT}}{a-1}$	$F_o = \frac{MS_{TREAT}}{MS_E}$
SS_E	N - a	$MS_E = \frac{SS_E}{N-a}$	
SS_T	N - 1		

.

Fig. 2.4: ANOVA table structure

Finally, it must be remembered that the model for which the lack of fit test is positive, presents a good fit to the data solely and exclusively within the range of values for which it was built. It is not possible to make extrapolations from the model and, therefore, it is not possible to conclude anything out of the analysis range. The Design Expert software performs both these tests automatically.

Chapter 3

Study of a photovoltaic plant economic sustainability

The production of electricity from renewable sources plays a strategic role in the energy future because it helps to effectively manage climate changes through an energy generation portfolio with lower emissions of greenhouse gases. Photovoltaic solar energy is safe and sustainable and is characterised by a growing trend. Economic sustainability analysis are one of the main tools to understand the real actual sustainability of such kind of plants and, even more important, to identify the factors that have, or can have in the future, the main roles in their development.

In this Chapter the study of a photovoltaic plant economic sustainability is presented by initially explaining the state of the art and, then, showing the proposed methodology and the results obtained by applying it to a test case.

These studies and results have also been published in [6].

3.1 State of the art

The research done on photovoltaic plants (or in general on renewable energy) has, often, focused on the sustainability and environmental efficiency of such plants. For example, Cicea [7] specifically focuses on an analysis of the renewable energy investments' environmental efficiency at a macroeconomic level, while Cucchiella and D'Adamo [8] examine the energy and environmental impact of a photovoltaic plant located on a building rooftop, considering several possible locations.

However, it is becoming increasingly important to assess the economic viability of such plants, which is why the literature has recently grown with many works added in this vein.

Numerous Authors take into account the classic investment assessment parameters, in support of various arguments.

Cucchiella [9] analyses the Net Present Value (NPV), Internal Rate of Return (IRR), Discounted Payback Period (DPBP) and Discounted Aggregate Cost-Benefit Ratio (BCR) in order to determine the number of photovoltaic plants necessary to achieve a pre-set production goal with this type of plant in Italy.

Paudel and Sarper [10] conduct an economic analysis with regard to an investment in a photovoltaic plant located in a semi-desert area of Colorado.

Peerapong and Limmeechokchai [11], as well as Spertino [12], perform an economic analysis of various photovoltaic plants and conclude that government incentives are significant for the sustainability of such investments.

Stevanovic and Pucar also [13] point out the non-sustainability of investments in photovoltaic plants with decreased incentive rates. In this case, however, only the incentive rate's impact on investment parameters is assessed, without considering other input factors.

Mahesh and Jasmin [14] focus initially on the importance of renewable energy in reducing CO_2 emissions but they also come to the conclusion regarding the indispensability of substantial government incentives designed to support investments of this nature.

Dusonchet and Telaretti [15] perform a comparative economic analysis of the key policies supporting the dissemination of energy production by means of photovoltaic plants in several European countries. As economic analysis outputs, they consider the NPV and the IRR and they identify several important factors. Among the primary inputs having an impact, the value of solar radiation and incentive policies are those highlighted. Talavera [16] performs an economic analysis of a photovoltaic plant in southern Spain. He investigates the NPV, the IRR and the Levelized Electricity Cost (LEC) but, realizing the importance of one parameter change in relation to the others, also performs a sensitivity analysis. The limit of such analysis consists in the fact that a change in the main parameter, i.e., LEC, is considered, by modifying the other parameters taken one at a time.

Ren [17] considers the problem of the optimal dimensioning of a residential photovoltaic plant with the aim of minimizing costs. He also performs a LEC sensitivity analysis that demonstrates the same weakness as the analysis carried out by Talavera [16].

The main difference between the approach proposed in this Chapter and the analysed works is the analysis methodology.
In my research work, the aim was to analyse the impact of the economic variables, which were considered to have the most influence on the investment's key assessment parameters, by exploiting the most of RSM's significant descriptive capabilities. In particular, NPV, IRR, Pay Back Period (PBP) and LEC were taken into account. In tackling this analysis, two unique issues related to the location of the plant were brought to the fore: one concerning the incentive rates provided by the national government and the other linked to the plant's geographical location. By considering these two particular parameters it was then necessary to define a Country (Italy) in which to conduct the analysis in order to have a unique incentives policy and not too wide geographical regions. The incentives focus was due to the fact that the incentive level had gradually decreased along with an increase in the number of plants installed, resulting in significant consequences on investment profitability.

3.2 Methodology

For the economic sustainability analysis, a dynamic business plan was created. The business plan was flexible, dynamic and capable of analysing the economic viability of a photovoltaic plant in relation to the regulatory environment (reference country, incentive amount, duration, etc...), the type of climatic conditions at the site (DNI, etc...) and the financial environment (inflation, interest rates, etc...). After defining the input variables, it was possible to populate the business plan structures and to calculate the main indicators of economic sustainability. After the business plan was created, an analysis of the investment's economic viability was set up through the use of the RSM.

The first step, according to RSM theory, was to select the most suitable experimental design in order to verify the significance of the factors on the Key Performance Indicators (KPIs).

The choice fell on the 2^k factorial design that made it possible to describe, through a first-order regression meta-model, the possible link between the independent and dependent variables (objective functions). To verify the accuracy of the chosen meta-model order, it was still necessary to gather additional information through the measurement of the objective functions value in the design centre. This made it possible to confirm (or not) the validity of the hypothesized first-order meta-model. In the case of non-confirmation, it became necessary to raise the meta-model order, through the addition of further tests (axial points) specially positioned according to the theory. It was, then, possible to carry out the ANOVA, for each indicator, to understand if the meta-model was capable of providing a satisfactory approximation and, in this case, to determine the factors' influence on the objective functions.

3.3 Test case

The plant, which was taken into account (Figure 3.1), was a 1 MW solar photovoltaic plant, partially integrated, located in the backcountry of Savona.

Fig. 3.1: plant

The plant delivered 100% of the energy produced in the network via dedicated withdrawal.

Table 3.1 shows the data related to:

- Plant size
- Facility costs
- Solar radiation data
- Efficiency losses
- Plant technical data
- Financial Metrics

Plant technical data	
Nominal power (kWp)	864
Annual DNI on horizontal surface (kWh/m²)	1,295.45
Exposure:	45° (south)
Annual DNI on exposed surface (kWh/m²)	1317.04
Estimated yield (%)	76.75
Theoretical annual energy production (kWh)	1,137,924.00
Expected annual energy production (kWh/kWp)	1,010.83
Expected annual energy production (kWh)	873,356.67
Decrease in annual energy production (%)	0.9%
Self-consumption (%)	0.0%
Energy delivered to the network (%)	100.0%
Feed-In Tariff (€/kWh)	0.384
Energy purchase price (€/kWh)	0.08
CTR Fee (€/kWh)	0.00416
Injection coefficient for Medium voltage transmission	0.042

PERFORMANCE RATIO	76%

Financial Metrics:	
Depreciation coefficient	9%
Financing term (years)	18
Interest rate on debt	6%
Collateral with equity	20%
Discount rate	4%

Operating assumptions	
Number of maintenance operations (select)	2
Impact of single maintenance operation on performance	1.5%
Annual energy dissipation	3%
Impact of maintenance on performance	0%

Plant size	
Total number of modules	3840
Number of strings	192
Number of modules per string	20
Number of inverters	3

Facility costs	
Cost of modules per string	€ 73,440.00
Total cost of modules	€ 1,468,800.00
Unit cost of inverter	€ 70,000.00
Total cost of inverters	€ 210,000.00
Cost of design, installation and Supply of components	€ 921,200.00
Maintenance operation cost	€ 12,500.00
Inverter replacement cost	€ 1,000.00
Total cost of turnkey plant	€ 2,600,000.00

Loss of plant efficiency (%)	
Mirroring	2.00
Shading	3.50
Mismatching	4.75
Temperature effect	4.00
Continuous DC system	2.00
Inverter	2.00
Alternating AC system (cables and transformer)	3.00
Pollution/filters	2.00
Total system losses	23.25

Table 3.1: Plant data

In particular, the annual Direct Normal Irradiance (DNI) on horizontal and exposed surfaces, indicated in the plant's technical specifications, were calculated from the corresponding monthly average daily radiation shown in Table 3.2.

Average daily radiation reported monthly on a horizontal surface (kWh/m^2)	
January	1.53
February	2.31
March	3.33
April	4.34
May	5.00
June	5.53
July	6.11
August	4.91
September	3.82
October	2.64
November	1.68
December	1.39

Average daily radiation reported monthly on an exposed surface (kWh/m^2)	
January	1.61
February	2.40
March	3.42
April	4.38
May	5.02
June	5.53
July	6.13
August	4.96
September	3.89
October	2.72
November	1.76
December	1.48

Table 3.2: Monthly average daily radiation

These data were used as input data for the business plan through which, the main indicators of economic sustainability were calculated. In particular, it was decided to use as economic and financial indicators the NPV, PBP, IRR and LEC.

After the business plan was created, a 2^4 design was set, considering the following input factors:

- incentive rate (factor A);
- discount rate (factor B);
- number of cleaning operations (factor C);
- interest rate on medium/long (M/L) term debt (factor D).

Each factor was varied in a range delimited by the two canonical low and high levels, with the addition of a further centre-point design. The variation levels for the four variables are shown in Table 3.3.

	Low Level	Midrange Level:	High Level
Incentive rate (€)	0.16	0.27	0.38
Discount rate (%)	4	5	6
Number of cleaning operations	0	1	2
Interest rate on M/L debt	6	8	10

Table 3.3: input factors and respective variation ranges

Technically, the chosen RSM design was a mono replicated factorial design that was studied using Daniel's method [5] to calculate the experimental error. The resulting factorial design was a 2^4 with a centre-point design, represented in the IR^4 space with a hypercube on whose vertices the experimental tests to be performed were found.

The financial and economic indices taken into account for the purpose of assessing the investment were:

1. Net Present Value: is the algebraic sum of the cash flows (OFCF) over several years of the analysis horizon discounted at an interest rate (WACC)

$$NPV = \sum_{t=0}^{n} \frac{FCFO_t}{(1+WACC)^t} - FCFO_0 \tag{3.1}$$

2. Internal Rate of Return: is the interest rate at which the NPV is zero:

$$\sum_{t=0}^{n} \frac{FCFO_t}{(1+IRR)^t} - FCFO_0 = 0 \tag{3.2}$$

3. Levelised Energy Cost: is the price at which electricity must be generated from a specific source to break even over the lifetime of the project. It includes all costs over project lifetime: initial investment, operations and maintenance, cost of fuel, cost of capital.

$$LEC = \frac{AnnualizedInvestmentExpenditure + O\&M + Fuel}{AnnualElectricityGeneration(kWh_e / year)} \tag{3.3}$$

4. Pay Back Period: is the point of temporal equilibrium of the cash in and cash out discounted at the WACC rate

$$\sum_{t=1}^{PBP} \frac{FCFO_t}{(1+WACC)^t} - FCFO_0 = 0 \tag{3.4}$$

In order to carry out the ANOVA analysis for each indicator, the Design Expert software of Stat Ease Inc. was used.

The result obtained was that, for all of the investigated objective functions, the first-order meta-models were not capable of providing a satisfactory approximation:

- IRR and PBP did not pass the F test on Regression (Figure 3.2)
- NPV and LEC passed the F test on Regression (Figure 3.3) but they had significant curvature.

PBP Response

ANOVA for selected factorial model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	459.00	15	30.60	6.42	0.3013	not significant
A-Incentive r.	441.00	1	441.00	92.56	0.0659	
B-Discount r.	0.000	1	0.000	0.000	1.0000	
C-Number of	9.00	1	9.00	1.89	0.4004	
D-Interest rat	0.000	1	0.000	0.000	1.0000	
AB	0.000	1	0.000	0.000	1.0000	
AC	9.00	1	9.00	1.89	0.4004	
AD	0.000	1	0.000	0.000	1.0000	
BC	0.000	1	0.000	0.000	1.0000	
BD	0.000	1	0.000	0.000	1.0000	
CD	0.000	1	0.000	0.000	1.0000	
ABC	0.000	1	0.000	0.000	1.0000	
ABD	0.000	1	0.000	0.000	1.0000	
ACD	0.000	1	0.000	0.000	1.0000	
BCD	0.000	1	0.000	0.000	1.0000	
ABCD	0.000	1	0.000	0.000	1.0000	
Residual	4.76	1	4.76			
Cor Total	463.76	16				

IRR Response

ANOVA for selected factorial model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.021	15	1.418E-003	38.58	0.1258	not significant
A-Incentive r.	0.021	1	0.021	571.88	0.0266	
B-Discount r.	0.000	1	0.000	0.000	1.0000	
C-Number of	1.000E-004	1	1.000E-004	2.72	0.3470	
D-Interest rat	2.500E-005	1	2.500E-005	0.68	0.5610	
AB	0.000	1	0.000	0.000	1.0000	
AC	1.000E-004	1	1.000E-004	2.72	0.3470	
AD	2.500E-005	1	2.500E-005	0.68	0.5610	
BC	0.000	1	0.000	0.000	1.0000	
BD	0.000	1	0.000	0.000	1.0000	
CD	0.000	1	0.000	0.000	1.0000	
ABC	0.000	1	0.000	0.000	1.0000	
ABD	0.000	1	0.000	0.000	1.0000	
ACD	0.000	1	0.000	0.000	1.0000	
BCD	0.000	1	0.000	0.000	1.0000	
ABCD	0.000	1	0.000	0.000	1.0000	
Residual	3.676E-005	1	3.676E-005			
Cor Total	0.021	16				

Fig. 3.2: First-order Model ANOVA for PBP and IRR

Response LEC

ANOVA for selected factorial model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	9.946E-003	2	4.973E-003	64649.00	< 0.0001	significant
B-Discount r.	7.921E-003	1	7.921E-003	1.030E+005	< 0.0001	
C-Number of	2.025E-003	1	2.025E-003	26325.00	< 0.0001	
Curvature	5.294E-007	1	5.294E-007	6.88	0.0210	
Residual	1.000E-006	13	7.692E-008			
Cor Total	9.948E-003	16				

Response NPV

ANOVA for selected factorial model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	1.241E+013	7	1.773E+012	3.84	0.0392	significant
A-Incentive r.	1.108E+013	1	1.108E+013	24.02	0.0012	
C-Number of	1.123E+009	1	1.123E+009	2.435E-003	0.9619	
D-Interest ra	3.944E+011	1	3.944E+011	0.85	0.3822	
AC	2.078E+011	1	2.078E+011	0.45	0.5211	
AD	1.349E+011	1	1.349E+011	0.29	0.6034	
CD	2.850E+011	1	2.850E+011	0.62	0.4545	
ACD	3.060E+011	1	3.060E+011	0.66	0.4390	
Curvature	1.334E+009	1	1.334E+009	2.891E-003	0.9584	
Residual	3.691E+012	8	4.614E+011			
Cor Total	1.610E+013	16				

Fig. 3.3: First-order Model ANOVA for LEC and NPV

Consequently, it was necessary to use higher order (second order) meta-models. According to RSM theory, higher quality meta-models were obtainable with the CCD and the FC-CCD. After the first tests attempted with the new designs, the use of FC-CCD designs was chosen.

By analysing the results obtained with the FC-CCD for each of the four economic variables, it was seen how second-order regression meta-models were capable of adequately describing the behaviour of the indices by modifying the considered inputs.

3.3.1 Results' analysis

From the ANOVA table for the NPV objective function (Figure 3.4), only factors A and B were identified as significant.

In other words, only the incentive rate and the discount rate, within their respective variability ranges, were capable of creating an impact on the NPV.

Response 1 NPV

ANOVA for Response Surface Reduced Linear model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	1.489E+013	2	7.444E+012	50.39	< 0.0001	significant
A-Incentive r.	*1.292E+013*	*1*	*1.292E+013*	*87.45*	*< 0.0001*	
B-Discount r.	*1.969E+012*	*1*	*1.969E+012*	*13.33*	*0.0014*	
Residual	3.250E+012	22	1.477E+011			
Cor Total	1.814E+013	24				

The Model F-value of 50.39 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise.

Values of "Prob > F" less than 0.0500 indicate model terms are significant.
In this case A, B are significant model terms.
Values greater than 0.1000 indicate the model terms are not significant.
If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model.

Fig. 3.4: ANOVA for NPV

From an analysis of the response surface (Figure 3.5), it was possible to note that the maximum variation of NPV was € 3,000,000. In particular, a change in the discount rate from 4% to 6% determined small deviations in the NPV (in the case of a minimum incentive rate, it was impossible to attain a positive NPV even with a minimum discount rate), while an increase in the incentive rate led to significant changes in the NPV (from about - € 1,000,000 to approximately + € 1,500,000).

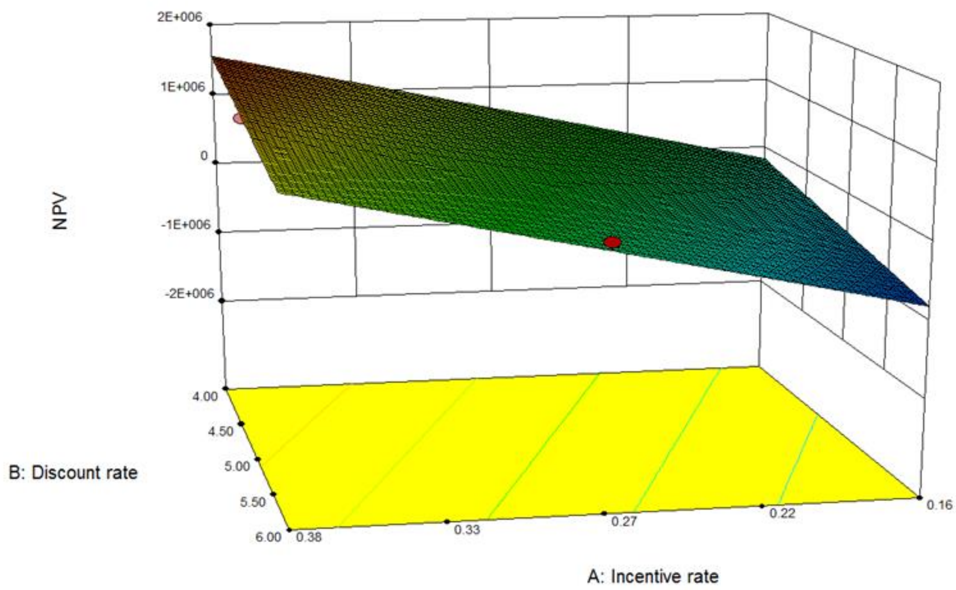

Fig. 3.5: Response surface showing NPV as a function of factors A and B

From the ANOVA table for the IRR objective function (Figure 3.6), factors A, C, D and AC and AD interactions were identified as significant.

They were the incentive rate, the number of cleaning operations and the interest rate on the M/L debt, as well as the interaction between the incentive rate and number of cleaning operations and the interaction between the incentive rate and interest rate on the M/L debt that were capable of creating an impact on the IRR of the investment.

Response 2 IRR

ANOVA for Response Surface Reduced Quadratic model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.024	6	4.054E-003	3753.24	< 0.0001	significant
A-Incentive r	*0.024*	*1*	*0.024*	*22064.14*	*< 0.0001*	
C-Number of	*1.389E-004*	*1*	*1.389E-004*	*128.57*	*< 0.0001*	
D-Interest ra	*2.222E-005*	*1*	*2.222E-005*	*20.57*	*0.0003*	
AC	*1.000E-004*	*1*	*1.000E-004*	*92.57*	*< 0.0001*	
AD	*2.500E-005*	*1*	*2.500E-005*	*23.14*	*0.0001*	
A^2	*2.057E-004*	*1*	*2.057E-004*	*190.44*	*< 0.0001*	
Residual	1.944E-005	18	1.080E-006			
Cor Total	0.024	24				

The Model F-value of 3753.24 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise.

Values of "Prob > F" less than 0.0500 indicate model terms are significant.
In this case A, C, D, AC, AD, A^2 are significant model terms.
Values greater than 0.1000 indicate the model terms are not significant.
If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model.

Fig. 3.6: ANOVA for IRR

As in the case of the NPV, it was possible to perform a more thorough analysis because of the response surfaces.

The surface in Figure 3.7 shows how the IRR increased with an increase in the incentive rate while the same parameter was unchanged by a change in the interest rate on the debt. It followed, therefore, that a change in the interest rate on the debt had very little impact on the IRR, whereas, while keeping the same interest rate on the debt, a change in the incentive rate entailed considerable variations of the IRR (from about 4% to about 11% in the transition from low level to high level).

Taking, then, into account the link that existed between the number of cleaning operations and the incentive rate (Figure 3.8), it was possible to identify the maximum IRR, which was obtained in correspondence to the maximum incentive rate and the minimum number of cleaning operations.

Considering the combined effect of the two variables it was shown that, for the same incentive rate, a change in the number of cleaning operations had very little impact on the IRR, whereas, for the same number of cleaning operations, a change in the incentive rate entailed considerable variations (from about 4% to about 12%).

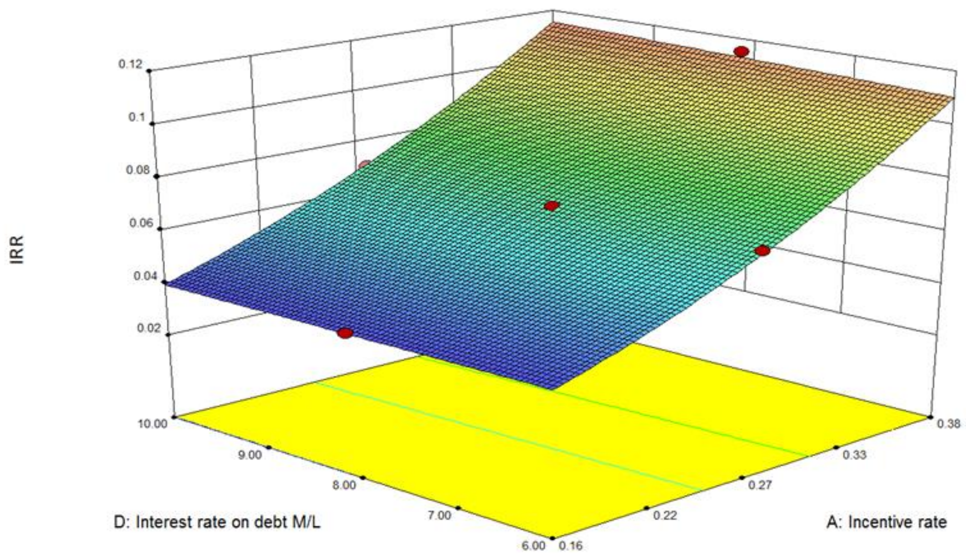

Fig. 3.7: Response surface showing IRR as a function of factors A and D

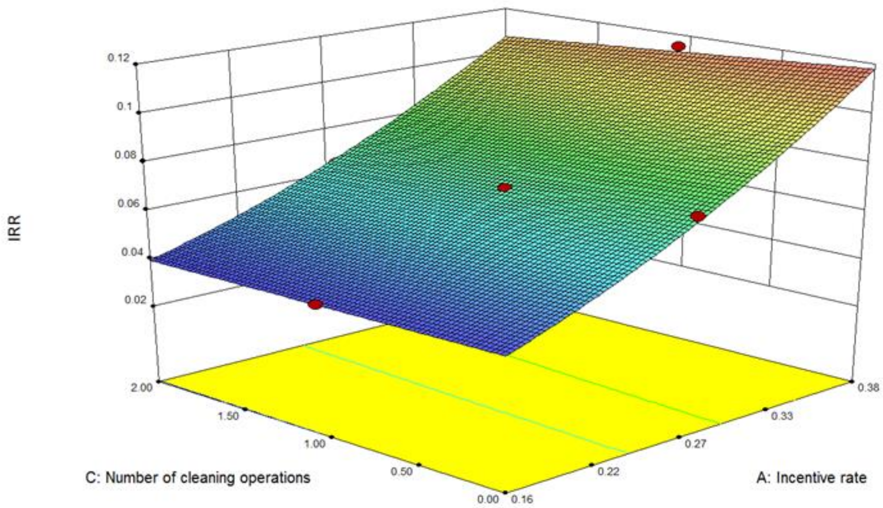

Fig. 3.8: Response surface showing IRR as a function of factors A and C

From the ANOVA table for the LEC objective function (Figure 3.9), always within the predetermined variability ranges, factors B, C, and the BC interaction were identified as significant.

They were the discount rate and the number of cleaning operations, as well as the interaction between the discount rate and the number of cleaning operations that were capable of creating an impact on the LEC.

Plotting the LEC according to the discount rate and number of cleaning operations (Figure 3.10), it was possible to see how the maximum LEC was equal to € 0.33.

The number of cleaning operations affected the LEC to a lesser extent (with a maximum variation from 0.27 to 0.29), while a variation in the discount rate entailed changes in the LEC from 0.27 to 0.31.

Response 3 LEC

ANOVA for Response Surface Reduced Quadratic model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.011	9	1.242E-003	68247.09	< 0.0001	significant
A-Incentive r	*0.000*	*1*	*0.000*	*0.000*	*1.0000*	
B-Discount r	*8.889E-003*	*1*	*8.889E-003*	*4.883E+005*	*< 0.0001*	
C-Number of	*2.289E-003*	*1*	*2.289E-003*	*1.258E+005*	*< 0.0001*	
D-Interest ra	*0.000*	*1*	*0.000*	*0.000*	*1.0000*	
BC	*1.000E-006*	*1*	*1.000E-006*	*54.93*	*< 0.0001*	
A^2	*1.434E-007*	*1*	*1.434E-007*	*7.88*	*0.0133*	
B^2	*1.482E-006*	*1*	*1.482E-006*	*81.38*	*< 0.0001*	
C^2	*1.758E-007*	*1*	*1.758E-007*	*9.66*	*0.0072*	
D^2	*1.434E-007*	*1*	*1.434E-007*	*7.88*	*0.0133*	
Residual	2.731E-007	15	1.820E-008			
Cor Total	0.011	24				

The Model F-value of 68247.09 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise.

Values of "Prob > F" less than 0.0500 indicate model terms are significant.
In this case B, C, BC, A^2, B^2, C^2, D^2 are significant model terms.
Values greater than 0.1000 indicate the model terms are not significant.
If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model.

Fig. 3.9: ANOVA for LEC

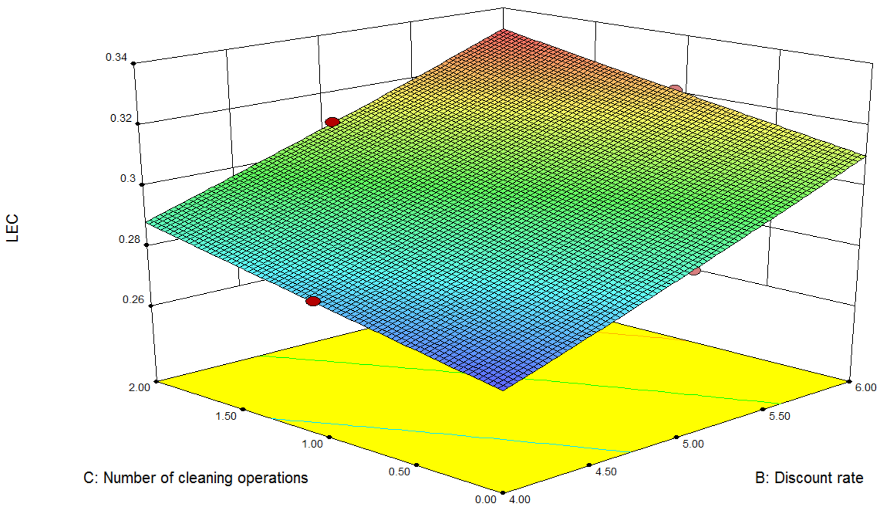

Fig. 3.10: Response surface showing LEC as a function of factors B and C

From the ANOVA table for the PBP objective function (Figure 3.11), factors A, C, and the AC interaction were identified as significant. They were the incentive rate and the number of cleaning operations, as well as their interaction, that were capable of creating an impact on the PBP.

Plotting the PBP according to the incentive rate and number of cleaning operations (Figure 3.12), it was shown that the PBP varied between 8 and 20 years. In particular, for the same incentive rate, a change in the number of cleaning operations had relatively little effect on the PBP, while, for the same number of cleaning operations, a change in the incentive rate entailed considerable changes from 20 years to 8 years due to the rate's transition from the low level to the high level.

Response 4 PBP

ANOVA for Response Surface Reduced Quadratic model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	531.49	5	106.30	7432.66	< 0.0001	significant
A-Incentive r	*490.89*	*1*	*490.89*	*34324.46*	*< 0.0001*	
C-Number of	*9.39*	*1*	*9.39*	*656.50*	*< 0.0001*	
AC	*9.00*	*1*	*9.00*	*629.31*	*< 0.0001*	
A^2	*11.11*	*1*	*11.11*	*776.79*	*< 0.0001*	
C^2	*0.42*	*1*	*0.42*	*29.28*	*< 0.0001*	
Residual	0.27	19	0.014			
Cor Total	531.76	24				

The Model F-value of 7432.66 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise.

Values of "Prob > F" less than 0.0500 indicate model terms are significant.
In this case A, C, AC, A^2, C^2 are significant model terms.
Values greater than 0.1000 indicate the model terms are not significant.
If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model.

Fig. 3.11: ANOVA for PBP

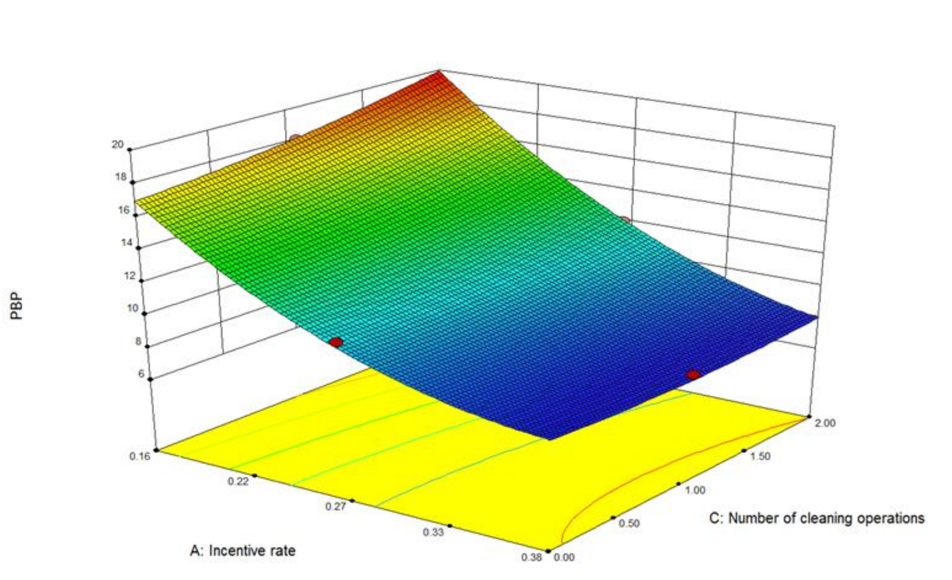

Fig. 3.12: Response surface showing PBP as a function of factors A and C

From the carried out analysis it was possible to observe that one of the major factors having an impact on the investment's sustainability indicators (NPV, IRR and PBP) was the incentive rate. The studied plant came into operation in May 2011, when the so-called "Third Feed-In Tariff" [18] was in force in Italy, with a new incentive rate of 0.335 €/kWh.
With this incentive level the investment's NPV was positive, the PBP is decidedly low (under 10 years) and the IRR (between 8% and 10%) was higher than the current discount rate regardless of the level of the other variables. This phenomenon is shown in Figures 3.13 - 3.15 which represent the sections of Figures 3.5, 3.8 and 3.12 at an incentive rate equal to 0.335 €/kWh, with relative confidence intervals at 95%.

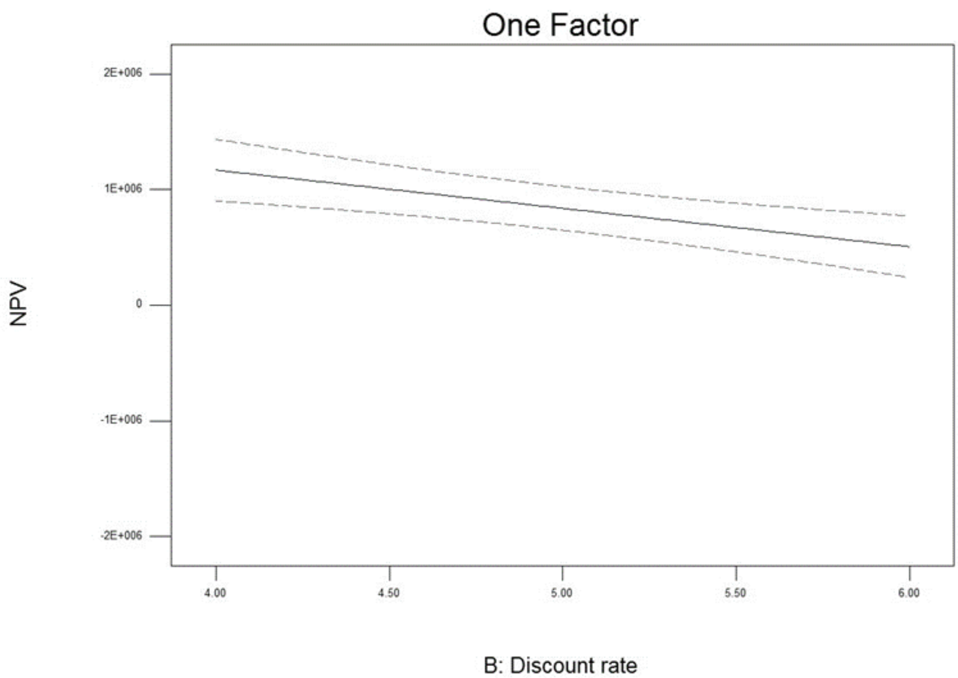

Fig. 3.13: NPV change with incentive rate equal to 0.335 €/kWh

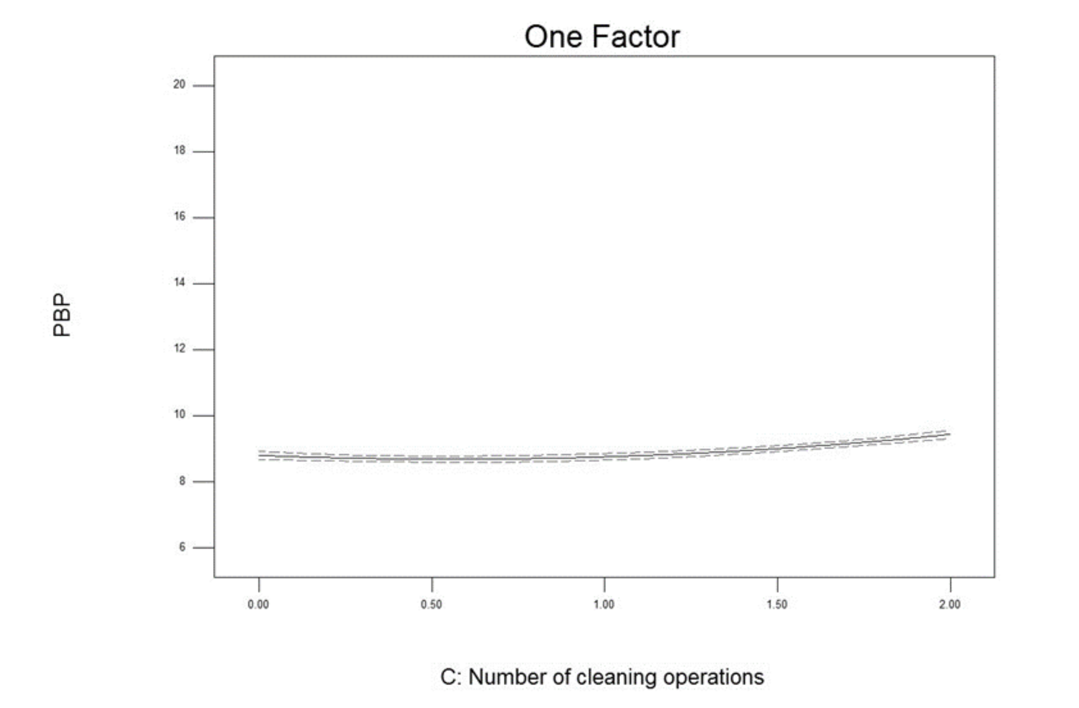

Fig. 3.14: PBP change with incentive rate equal to 0.335 €/kWh

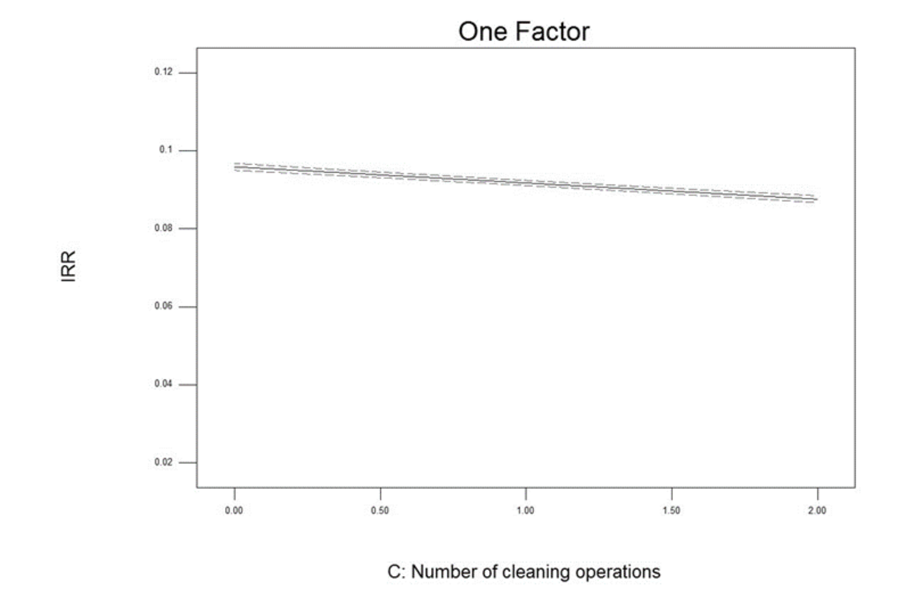

Fig. 3.15: IRR change with incentive rate equal to 0.335 €/kWh

It should be noted, however, that, over the years, Italy's policies about photovoltaic incentives led to a gradual reduction of incentive rates [12].

In particular, the last government decree [18] ordered a retroactive reduction of incentives extending the duration of the incentive period against a rate reduction.

At the time of this study the policy was to reduce the incentives basing on the remaining number of funding years according to the schedule shown in Table 3.4.

Residual period	reduction %
12	25%
13	24%
14	22%
15	21%
16	20%
17	19%
18	18%
19 or more	17%

Table 3.4: Incentives reductions

The plant studied in this test case, at that time, had a remaining term of 17 years. Therefore, a 19% reduction in the incentive rate (which fall to 0.27 €/kWh) had to be considered.

The effects of this reduction on the investment's economic result were:

- the NPV, with an increased discount rate, got very close to zero, with the risk of even becoming negative (Figure 3.16);

- the PBP was strongly affected by the number of cleaning operations and rose to around 12 years, which was more than half the length of the overall investment (Figure 3.17);
- the IRR’s variation range decreased by two percentage points, from 10% - 8% to 8% - 6%, in the transition from 0 to 2 cleaning operations/year (Figure 3.18).

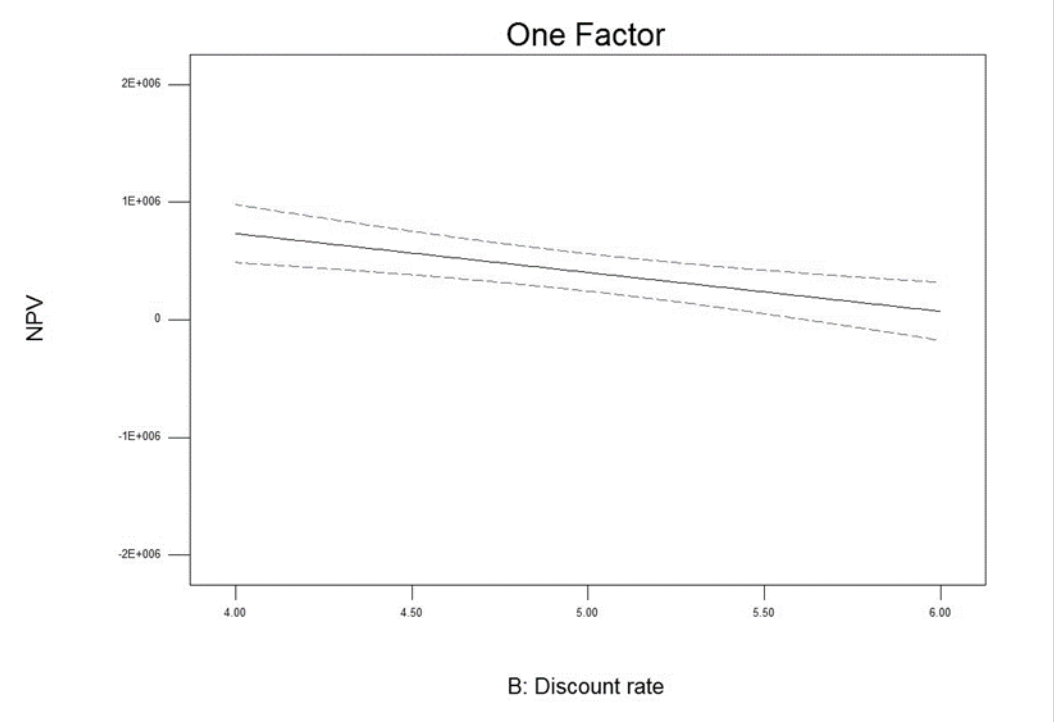

Fig. 3.16: Change in the NPV with incentive rate equal to 0.27 €/kWh

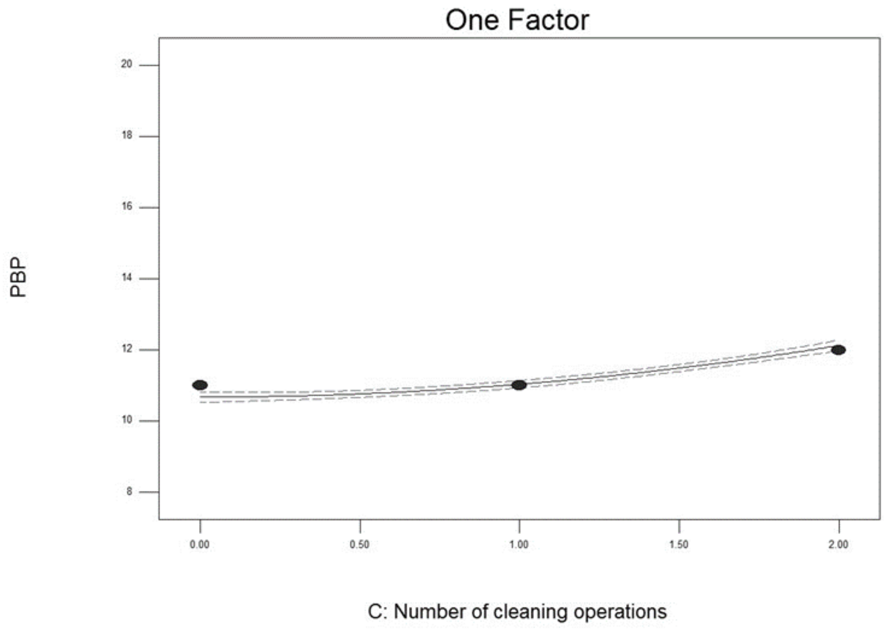

Fig. 3.17: Change in the PBP with incentive rate equal to 0.27 €/kWh

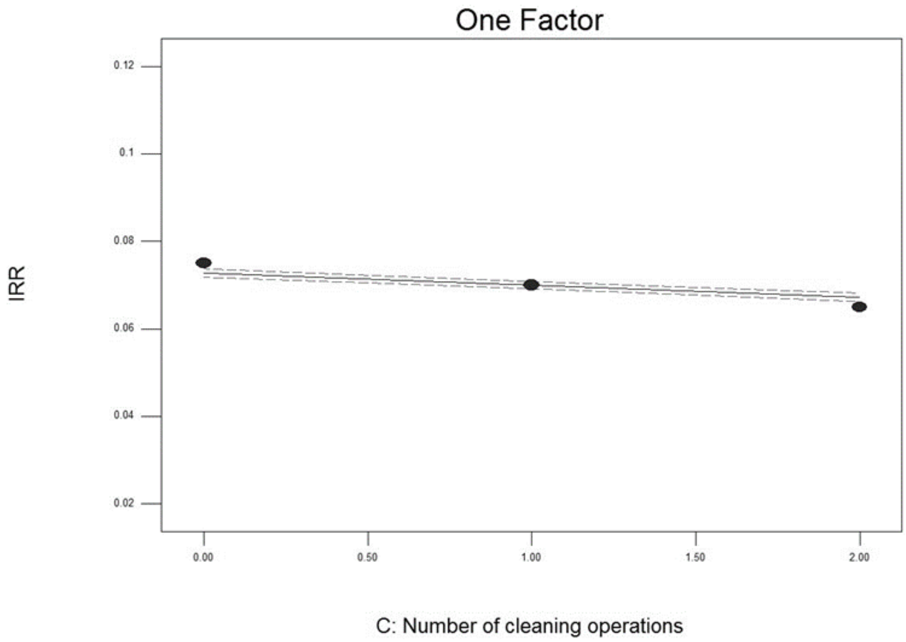

Fig. 3.18: Change in the IRR with incentive rate equal to 0.27 €/kWh

It followed that the sustainability of an investment of this type was quite critical and very dependent on the feed-in tariff.

The situation would have been even more difficult for Italian plants with a lower residual time or considering other subsequent reduction policies leading also to negative NPVs; PBPs greater than plants' duration and IRRs even lower than the considered discount rate.

Another sensitive aspect, which determined higher or lower economic results for these kind of plants, was the geographic position.

To make this point clear, in Figures 3.19-3.23, the economic outputs that would have been obtained if a plant, identical to the previous one, were installed in Palermo (a city with one of the highest solar radiation levels) are shown.

This allows a direct and intuitive comparison between the two locations.

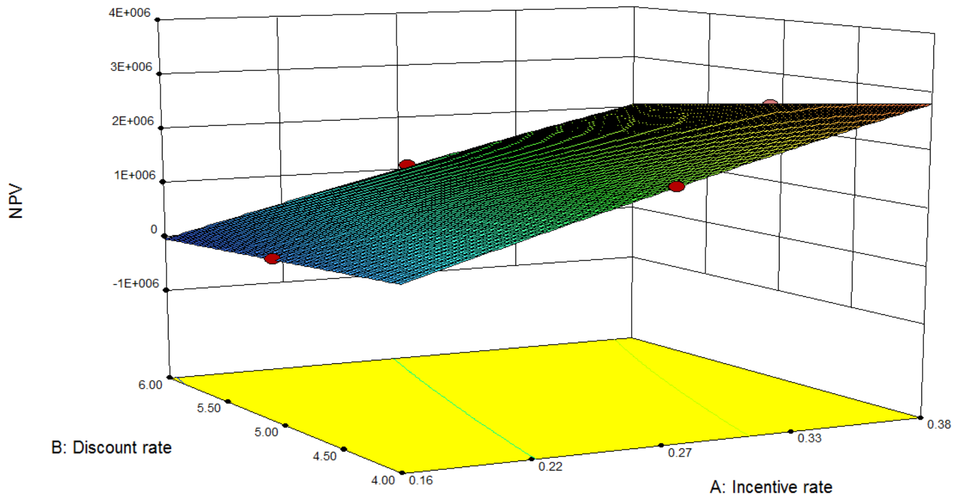

Fig. 3.19: Response surface showing NPV as a function of factors A and B

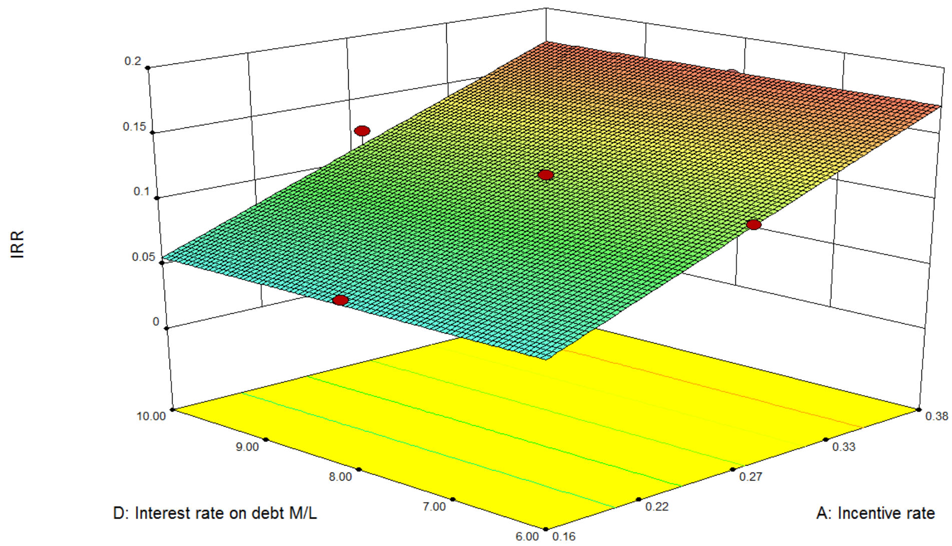

Fig. 3.20: Response surface showing NPV as a function of factors A and D

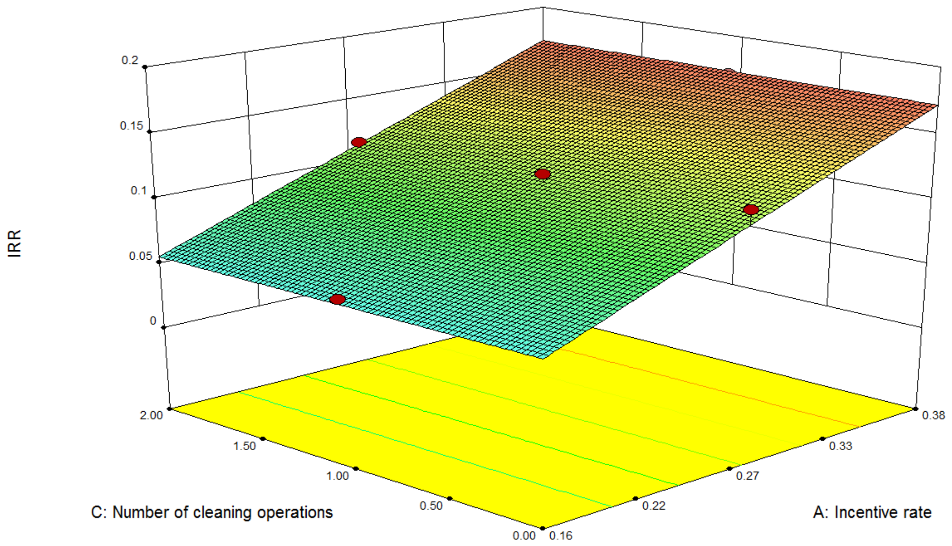

Fig. 3.21: Response surface showing IRR as a function of factors A and C

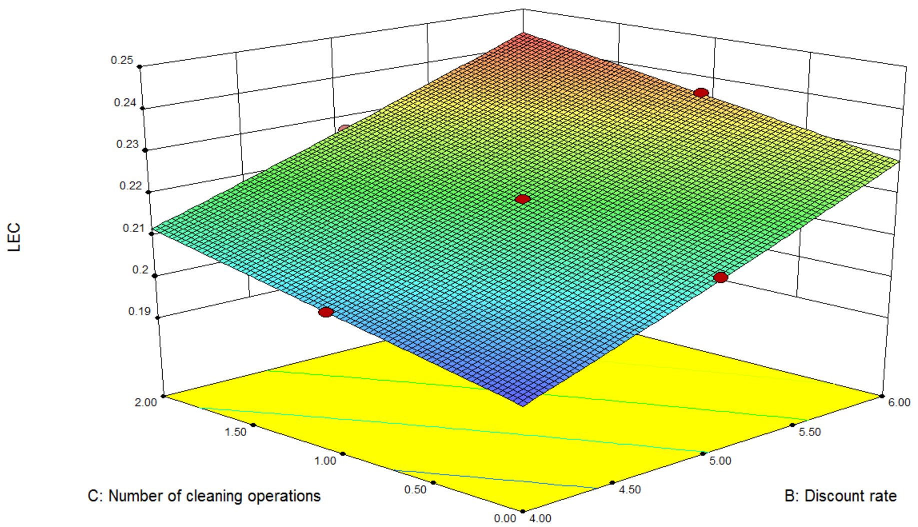

Fig. 3.22: Response surface showing LEC as a function of factors C and B

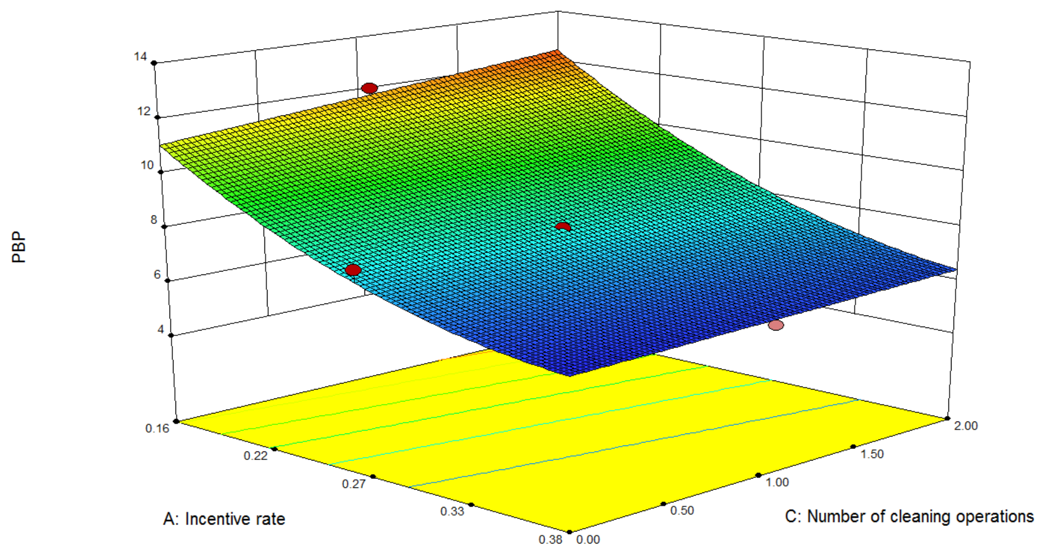

Fig. 3.23: Response surface showing PBP as a function of factors A and C

With reference to the new location, it was noted that:

- The NPV was again strongly influenced by the incentive rate but, irrespective of the latter's value, it was almost always positive and had a maximum value (about € 2,800,000) significantly higher compared to the previously considered plant (approximately € 1,500,000);
- The IRR increased, in an obviously positive direction, from 4% to 5% in its minimum and from 12% to 16% in its maximum value;
- The LEC obtained a reduction of about 20% under all analysed conditions;

- The PBP never exceeded 13 years, while in the previous case it could also reach a value equal to the entire duration of the investment.

It followed how, through a careful choice of the installation site, even in the presence of government policies aimed at reducing incentive rates, the economic sustainability of photovoltaic plants investments can be maintained.

3.4 Discussion

The use of RSM to analyse the sustainability of an investment in a solar PV system showed how, by defining a suitable variability range of input parameters, it was possible to:

- identify which of them had a real ability to impact the investigated parameters;
- find out which regression meta-models were capable of describing the behaviour of the financial result by modifying the input parameters.

In such a way, instead of obtaining an accurate snapshot of the system, it was possible to obtain homogeneous information usable for a dynamic analysis of the investment. With a static analysis, in fact, it was only possible to observe that the NPV, with an incentive rate of 0.38 €/kWh and a discount rate of 4%, was equal to € 1,500,000. With a dynamic analysis, instead, it was possible to achieve a response surface that described the behaviour of the NPV by modifying the incentive rate and the discount rate in a range respectively of 0.16 €/kWh - 0.38 €/KWh and 4% -8%.

The approach of analysing an investment using RSM made it also possible to monitor the investment's economic sustainability by modifying the amount of government support in the future. To reach this goal the business plan played an important role to obtain data to populate the RSM. Its use allowed the RSM approach being more flexible and able also to analyse different and/or hypothetical situations.

The methodology proposed in this Chapter is generally valid and can be applied to any kind of plant or system. This approach can also be further improved by moving from a deterministic model to a stochastic one using both input data (such as the DNI, inverter breakdowns, etc.) in the form of a Probability Density Function (PDF) and also making proper use of the Monte Carlo method.

This stochastic development is presented in Chapter 4.

Chapter 4

Stochastic techno-economic assessment of a CSP system

Combining technological solutions with investment profitability is a critical aspect in designing both traditional and innovative renewable power plants. The introduction of new advanced-design solutions, although technically interesting, does not often generate adequate revenue to justify their utilization. In this Chapter, an innovative methodology is proposed that aims to satisfy both targets. It allows performing the investment's analysis, in stochastic regime, using the Monte Carlo method and considering all the feasible plant configurations. It also allows evaluating the impact of every technical solution on the economic performance indicators by using regression meta-models built according to Response Surface Methodology. This approach enables the design of a plant configuration that generates the best economic return over the plant entire life cycle.

In this Chapter the stochastic techno-economic assessment of a Concentrated Solar Power (CSP) system is presented by initially explaining the state of the art and then showing the proposed methodology and the results obtained by applying it to an innovative linear Fresnel Concentrated Solar Power system.

These studies and results have also been published in [19].

4.1 State of the art

To date, most techno-economic analyses applied to renewable power plants have focused on the deterministic regime.

G.C. Bakos et al. performed a techno-economic study of an integrated solar combined-cycle power plant in Southern Greece [20]. They determined the investment yearly cash flows, considering all of the connected direct and indirect costs, and they calculated the primary financial indexes, such as the IRR, the NPV and the LEC. Finally, they presented a traditional sensitivity analysis on the effect of the contribution rate on the investment profitability.

M. Chandel et al. examined a solar photovoltaic power plant site at Jaipur (India) and determined the primary economic KPIs, such as the IRR, the NPV, the PBP and DPBP, and the LEC [21].

M. Horn et al. presented an investment evaluation, determining the NPV and the LEC of an integrated solar combined-cycle system in Egypt [22].

R. Hosseini et al. performed a comparative study of different traditional and solar power plants using the levelized electricity cost as the reference metric [23]. A comparison, in terms of the LEC, between linear Fresnel and parabolic trough collector power plants was performed by G. Morin et al. [24]. Comparative analyses using the LEC among different renewable electricity generation technologies have been developed by Varun et al. [25] and by S. Giuliano et al. [26].

A. Poullikkas has implemented a parametric study of different parabolic trough solar thermal technologies [27]. For this purpose, a simulation software package was used to analyse the investment in terms of NPV, IRR, PBP and LEC. The parameters considered included the plant capacity, the capital cost, the operating hours, the CO_2 ETS price and the annual land leasing.

W.T. Chong et al. performed a techno-economic analysis of an innovative wind–solar hybrid renewable energy generation system by applying the life cycle cost (LCC) method [28]. They considered the cash flows generated by the investment and they calculated the NPV for the 25-year lifetime of the system.

D.L. Talavera et al. presented an investment analysis of PV systems located in buildings or public areas, including a sensitivity analysis of the NPV, the DPBP, the IRR and the LEC [16].

All of these studies provided evaluations that were not exhaustive in terms of stochasticity, which characterized many of the involved factors. The uncertainty connected to these variables was not considered in the above-mentioned studies.

For this reason, recently, some researchers have begun to develop studies in stochastic regime, considering, for some of the variables, probability distribution functions rather than deterministic values and using Monte Carlo simulations to determine the economic KPIs.

Falconett et al. developed a probabilistic model to assess the effects of different governmental support mechanisms on the financial return (NPV) of small-scale hydroelectric, wind energy and solar PV systems. The model considers 17 random input variables, represented as probability distributions, such as the hours of sunshine, the wind regime, the installation cost, and the operating and the maintenance costs. The simulations were performed using Monte Carlo techniques [29].

Cun-bin et al. presented an investment risk analysis of a wind farm project in China. The authors simulated the NPV using the Monte Carlo method and analysed the investment PBP and IRR [30].

Guanche et al. performed an analysis of the uncertainty that influences wave energy farm financial returns. They performed a statistical analysis of IRR, NPV and PBP by simulating the life-cycle production. The considered uncertainty sources include climate conditions, political environment and current legislation issues [31].

E.J. da Silva Pereira et al. presented a methodology that uses the Monte Carlo method to estimate the behaviour of some economic parameters (NPV and produced energy cost). They applied the methodology to analyse a grid-connected photovoltaic system (GCPVS) and a stand-alone photovoltaic system (SAPVS). The random variables considered include the total initial cost, the interest rate and the value of the energy produced and sold to the grid [32].

The study presented in this Chapter belongs to this second research line, i.e., the implementation of the economic analysis in the stochastic regime. However, in the current work, a methodology that supports the technical decision makers in the selection of different technological solutions according to the overall economic impact is presented.

Rather than considering a predefined and fixed structure, this approach optimizes the choice among different technological solutions to maximize the economic result.

To achieve this goal, the dynamic business plan previously presented was developed by introducing a stochastic approach. It analysed, by using the Monte Carlo method, the behaviour of the primary economic variables related to the investment while varying specific technical and performance parameters.

Moreover, using the RSM technique, different design solutions were compared, considered both individually and combined.

In this way, a techno-economic optimization of the plant was obtained, in which all of the possible design decisions were made, considering the economic return of the investment.

4.2 Methodology

The first phase of the study was the development of the dynamic business plan (presented in Chapter 3) in a dynamic and stochastic business plan. The model was used to compare different design solutions and to identify the best economic plant configurations.

The model included drivers such as the regulatory context (the reference Country, the amount of governmental subsidies, the duration of the subsidies, etc.), the weather-environmental conditions at the site (the direct normal irradiance, etc.) and the financial context (the discount rate, loans, the interest rates, etc.). After the input variables were defined, the structures of the income statement, the balance sheet and the financial statement were set up to calculate the KPIs for the economic sustainability of the investment. These KPIs from the business plan model were arranged into a decisional dashboard with visual alerts to provide an at-a-glance summary of a specific technological choice.

To include the stochasticity related to the model input parameters, appropriate statistical distributions were defined to describe some of the identified exogenous variables. Such distributions were obtained from a historical database (e.g. DNI) or were identified through public databases (e.g. macroeconomic trends and interest rates).

A Monte Carlo simulation tool, @Risk Software of Palisade Inc., was integrated into the business plan model to simulate the behaviour of the input variables and to obtain reliable simulation outputs, associated with occurrence probabilities.

An important topic in the experimental phase was the response accuracy. To determine the responses accuracy, the MSPE in replicated runs [33] evaluation method was applied to each financial KPI.

Increasing the number of simulations resulted in a better fit to the statistical distributions. The MSPE methodology was used to evaluate both the stabilization phase of the curve and the residual error in the results.

Using this methodology, the sample size of the simulation runs which provides an unbiased estimation of the related population parameters was calculated, and the effect of the tolerance interval on the result was estimated.

After the correct number of simulations was identified, any scenario could be analysed using the model.

When the business plan was completed and validated using the MSPE technique, the RSM technique was used to compare the available design alternatives.

Using data from the stochastic business plan model, RSM was used to investigate the behaviour of the primary economic KPIs, varying the different plant configurations related to the components.

The first step was the choice of the most suitable experimental design to verify the components significance (and their potential interaction). Thanks to the ANOVA analysis it was, then, possible to determine if the choice correctly fitted the analysed system. At the end, by analysing the resulting meta-models and response surfaces, the best technical solutions could be chosen.

4.3 Test case

The case studied was an innovative linear Fresnel Concentrated Solar Power system for which it was necessary to analyse two specific plant components (the reflecting surface and the absorber tube), for which different solutions were proposed by technology partners during the design phase.

The studied plant was composed of 16 modules. Each module included 160 mirrors organized in 8 rows of 20 mirrors in each row. The dimensions of each mirror were 0.6 m by 5.85 m. The features of the plant are shown in Table 4.1.

Electric power peak	1 MWe
Thermal power peak	6 MWth
Solar collector field area	8986 m2
Total plant area	17500 m2
Total plant length	500 m
Total plant width	35 m
Heat transfer fluid	water

Table 4.1: Plant features

The proposed technology differed from that based on linear parabolic connectors for the use of almost flat mirrors arranged in lines. The mirrors concentrated the light on a linear absorber tube located above the solar field. To compensate for the angular spread, an additional surface was placed above the absorber tube to re-concentrate the solar rays (Figure 4.1). The annual efficiency of the solar collector (solar to thermal) was approximatively 42%.

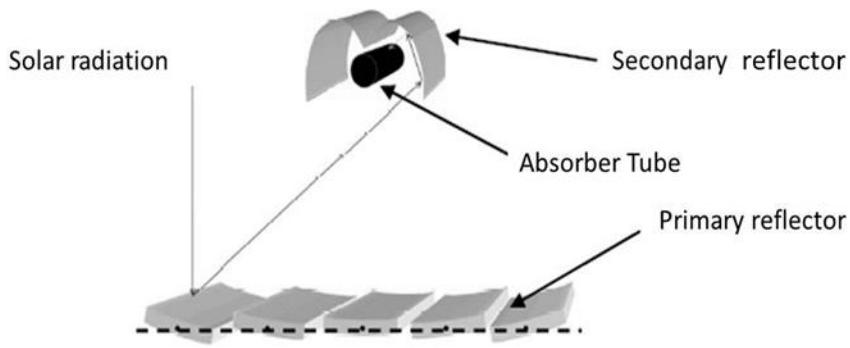

Fig. 4.1: Plant representation

The heat produced by the solar field was converted into electrical power using an organic Rankine cycle (ORC). A dry and spray cooler was used for the cooling part of the cycle. This cooler was equipped with fans that were usually powerful enough to ensure the heat removal. However, when the external temperature was too high, some of the nozzles spray demineralized water onto the heat exchangers of the cooler to assist in lowering the temperature.

The design temperature for the steam was 270°C at 55 bar (saturated steam). The thermal to electrical net efficiency at the design point was 23%, with 25°C/35°C inlet/outlet temperature of the cooling water.

The storage time was not long; there was a buffer storage of 15 minutes at full load to manage the transient behaviour (shut down, short low irradiation period, etc.).

The ORC developed for this power plant produced low pressure steam with a high conversion efficiency; therefore, the strategy was similar to the sliding pressure mode of a steam Rankine turbine, i.e., it was not mandatory to maintain a fixed temperature (pressure) at the outlet of the solar field.

A schematic process flow diagram of the power plant is provided in Figure 4.2.

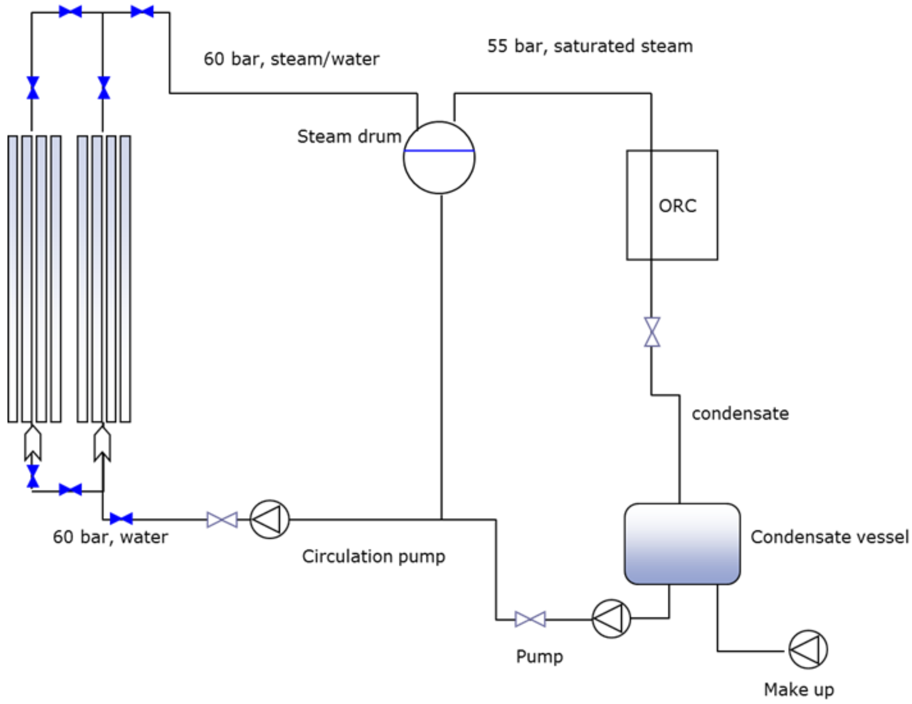

Fig. 4.2: Plant schematic

The use of limited temperatures allowed the minimization of heat loss and a simultaneous increase in the efficiency of the collector. Water was used as the heat transfer fluid, instead of oil, to simplify plant safety efforts and to eliminate the oil to water heat exchanger, typically implemented in most solar plants, thus reducing costs.

The Fresnel facets rotated around their own axes. The support mechanism was on a continuous axis on which the heliostat rotated. It bore a significantly lighter structure compared with the ones in use for other existing technologies. Moreover, the reduced dimensions of each mirror (3.51 m^2) offered reduced exposure to wind. However, if the wind strength was not in line with the mirror supports, the mirrors went to their stow position. Because of these technological features, both investment and maintenance costs were strongly reduced compared to equivalent parabolic plants. However, the average working efficiency was 5-7 percentage points lower than that of parabolic troughs (8-10% versus 15%) [32].

Other performance improvements could be made by the design of new materials for the reflecting surfaces and the absorber tube, and by the optimization of the sizing parameters of the plant.

Regarding these aspects, the design focused on two main components:

- reflecting surfaces with good reflection features, precision of shape, resistance, and mechanic stability at high temperatures (secondary surface). In particular, the duration of the reflective surfaces was studied by using superficial coating and protective painting on the reflective parts and glasses;
- absorber tube with high absorption properties and low emissivity through the study of a selective coating with high resistance and stability at 300°C that did not require a vacuum;

The proposed methodology was, then, applied to these two main technical solutions.

4.3.1 Filling in and validating the business plan

As a first step the business plan input variables were identified:

- technical variables: e.g. the installed power, the components employed, the features of the components, the efficiency;
- weather-environmental condition variables: e.g. the DNI, the parameters defining the wind;
- regulatory context variables: e.g. the amount of governmental subsidies, the duration of the subsidies;
- economic-financial variables: e.g. the cost of the components, the discounted rates, the interest rates;

Tables 4.2 and 4.3 show the main economic-financial variables taken into account and their values.

	Cost Interval	UOM
Reflecting surface	8-16	€/m2
Mirror supports	30-55	€/m2
CPC	55-100	€/m
Absorber tube	120-300	€/m
Metal structures	13-20	€/m2
Foundations	15	€/unit
Tracking system	4000-10000	€/unit
Power block	1300	€/kWe
Piping and wiring	120-300	€/m

Table 4.2: plant cost initial assumptions

Discount rate (%)	4
Long-term loan (% of capital cost)	30
Interest rate (%)	6
Time for loan repayment (yr)	15
Depreciation coefficient (%)	9
O&M costs (% of capital cost)	3
Overhead (% of capital cost)	1.5
Annual increase in overhead (%)	2

Table 4.3: economic parameters

It was now necessary to define the main KPIs to be measured as business plan's outputs:

- NPV, PBP, DPR, IRR and LEC (as already defined in Chapter 3)
- Discounted Profitability Ratio (DPR): is the ratio between the NPV and the initial investment. It provides the percentage return of the investment expenditure for the lifetime of the project as follows:

$$DPR = \frac{NPV}{I_0} * 100 \tag{4.1}$$

- Project Cover Ratio (PCR): is the ratio of the present value of the cash flows over the remaining full life of the project to the remaining debt in the period:

$$PCR_t = \sum_{t=1}^{n} \frac{FCFO_t}{debt_t} \tag{4.2}$$

- Return On Investment (ROI): measures, per period, the rate of return on invested money:

$$ROI = \frac{NetProfit}{Investment} * 100 \tag{4.3}$$

These KPIs were arranged into a decisional dashboard from the business plan model (Figure 4.3) with visual alerts to provide the decision maker with an at-a-glance summary of a specific technological choice.

Fig. 4.3: decisional dashboard

To determine the responses reliability, as explained in the methodology section, the MSPE evaluation method in replicated runs was applied to each financial KPI. In Figure 4.4 the analysis of the NPV index is shown.

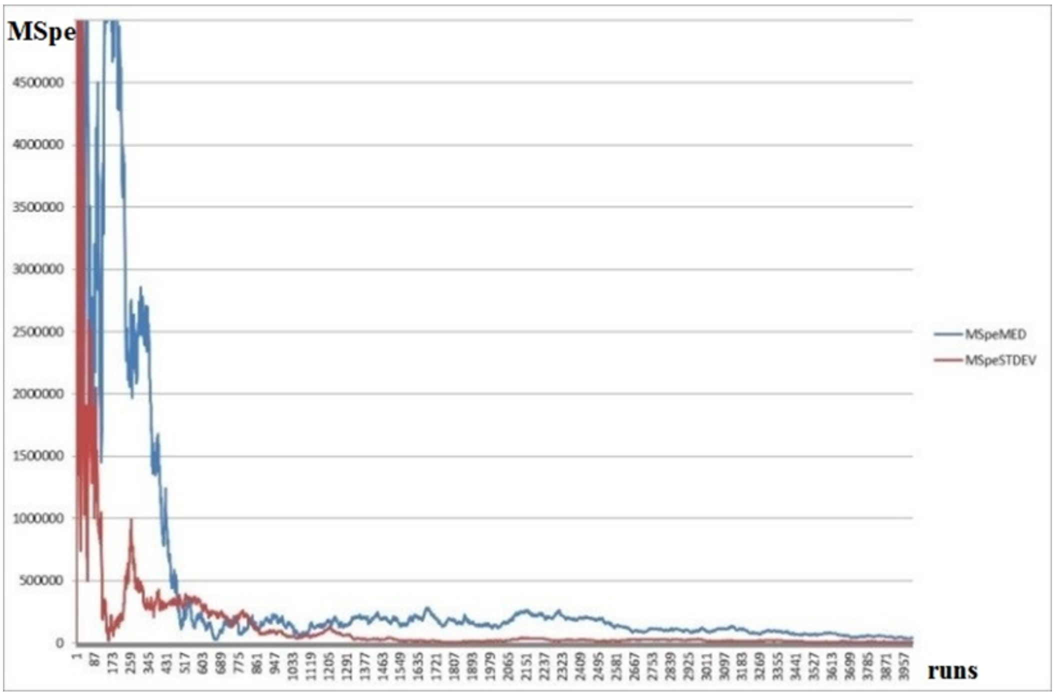

Fig. 4.4: MSPE evolution curve of the NPV index

The MSPE curves evolutions showed that 4000 was the number of replicated runs necessary to obtain an accurate solution. The same analysis was carried on for all the KPIs. It was, now, possible to analyse any scenario by using the business plan model.

4.3.2 Location analysis

Two possible plant locations were analysed, one site in northern Italy (Savona, Liguria) and one in the south of Italy (Palermo, Sicily), with different DNIs. In Figure 4.5, the yearly DNI profiles (annual average) used for both locations, derived from the database of the Italian National Agency for New Technologies, Energy and Sustainable Economic Development (ENEA), are shown.

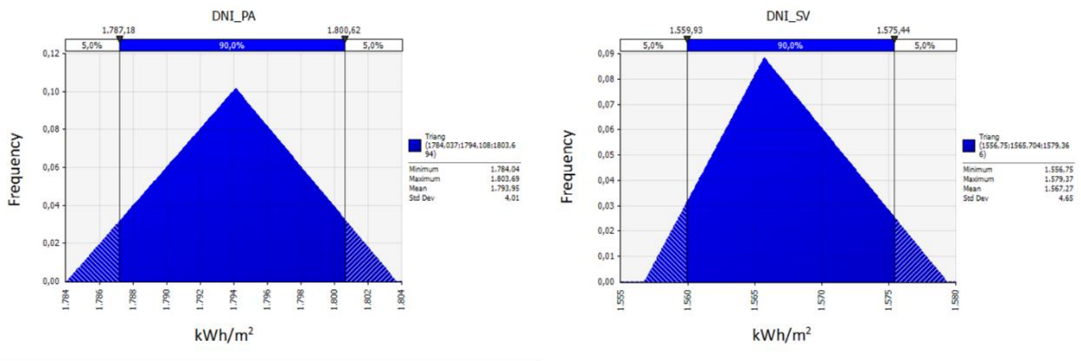

Fig. 4.5: DNI probability density functions (annual average)

For each site, the KPIs related to two possible configurations, one with a high conversion efficiency and one with a lower efficiency (see Table 4.4), were evaluated.

Investment Cost (€)	Conversion Efficiency (%)
5.860.079	7,9
5.933.183	9,1

Table 4.4: plant configurations

Combining the two selected sites with the configurations of Table 4.2, four economic scenarios were generated:

- Scenario 1: Savona, Low Efficiency
- Scenario 2: Savona, High Efficiency
- Scenario 3: Palermo, Low Efficiency
- Scenario 4: Palermo, High Efficiency

For each of the four, the business plan model was used to determine the probability density function of the economic KPIs. The kWh price used in this model included governmental incentives. In particular, as an example, Figures 4.6-4.9 show the probability profiles related to NPV and LEC.

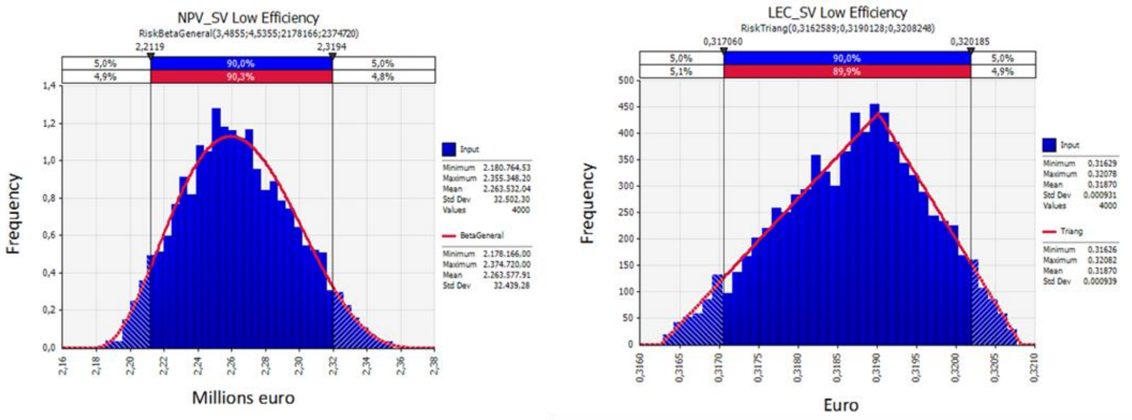

Fig. 4.6: NPV and LEC for Scenario 1

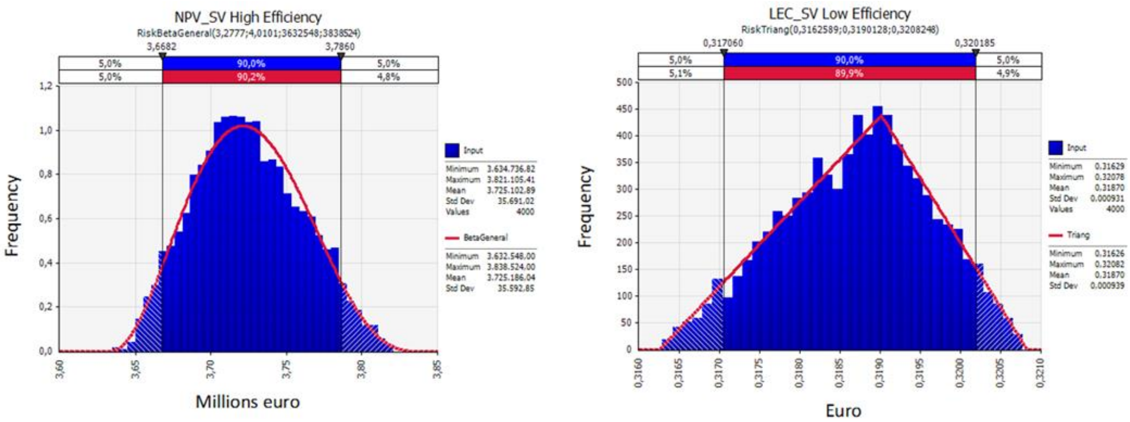

Fig. 4.7: NPV and LEC for Scenario 2

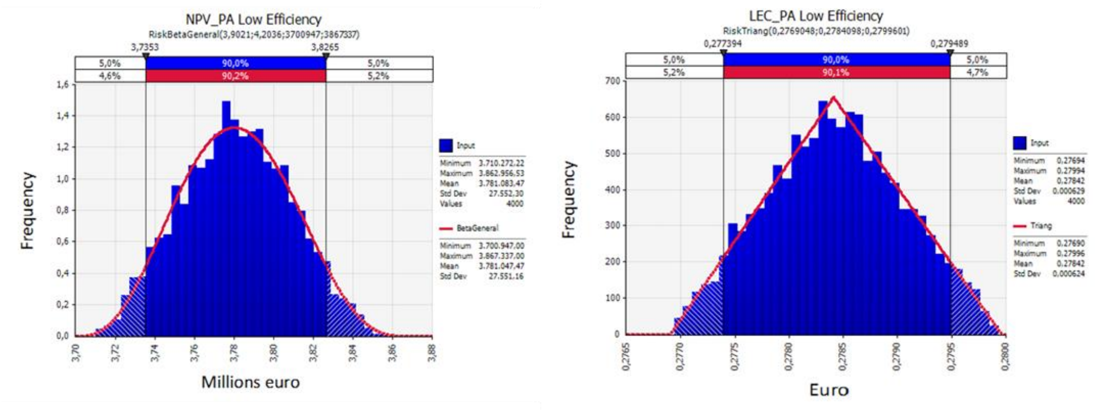

Fig. 4.8: NPV and LEC for Scenario 3

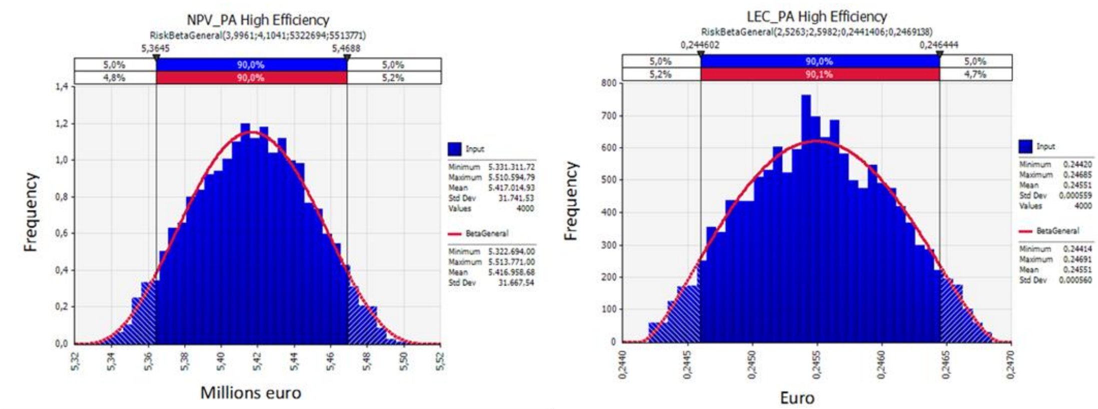

Fig. 4.9: NPV and LEC for Scenario 4

In Figures 4.6-4.9, the frequency histograms were obtained using the business plan model. Then, the probability density functions, represented by the red curves, were rebuilt. Using a statistical fitting model, the pdfs that provide the best fit were chosen from among those that passed the chi-square test.

The results of the 4 scenarios showed that Scenario 4 (Palermo High Efficiency) had the highest NPV (mean value equal to € 5,417,000 with a standard deviation of € 31,741), a lower LEC (mean value equal to 0.24551 and a standard deviation of 6E-4) and a higher DPR (mean value equal to 0.9130 and a standard deviation of 0.0053). The location of Savona, on the contrary, was not competitive for any of the analysed KPIs. For example, the NPV in scenario 2 (high efficiency) had a lower mean value than the one obtained from the low efficiency configuration in Palermo (3,725,000 € vs 3,781,000 €).

The results of the comparative analyses of all of the KPIs showed that Palermo was the preferred location for the 1 MW experimental plant. Therefore, the following analyses refer to the Sicilian site.

4.3.3 Technological solutions to be analysed

After the business plan was completed and validated, using the MSPE technique, the RSM was used to compare the available design alternatives.

In particular, sensitivity analyses were performed for the following two constructive components:

- the reflecting surface (Factor A), considering the reflection of different reflective surfaces (e.g., a glass mirror at 93% and aluminium coated at 88%)
- the absorber tube (Factor B), considering the thermal losses of different receivers (e.g., an evacuated pipe at -5% and a glass enclosure without a vacuum at -10%)

Depending on the combination of those parameters, the annual power plant performance was simulated.

4.3.3.1 Reflecting surface

The selected materials for the fabrication of the reflecting surface should have good reflectance, low superficial micro-roughness and must not graze the protective layer, to avoid diffraction losses.

The candidate materials were glass and aluminium. To hold the weight, glass was usually matched with plastic or steel supports and aluminium was always matched with aluminium supports.

The three technical alternative designs were the following:

- a reflecting surface fabricated of thin glass (0.85 mm) with a plastic support;
- both the reflecting surface and support fabricated with aluminium;
- a reflecting surface fabricated of thick glass (3 mm) with a steel support.

The normal reflectance used during the simulation was 93% for 3-mm glass, 96% for 0.85-mm glass, and 88% for the aluminium–coated surface.

The morphology of the reflective surface for the aluminium-coated or thin glass case was better than for the thick glass because of a higher flexibility; the difference, however, was slight, approximately 0,5% between the different treatments.

A qualitative analysis of the advantages and disadvantages of each type of reflecting surface is shown in Table 4.5.

	Advantages	Disadvantages
Glass	Highly transparent (low optical loss)	Fragile
	High performance over time	
	Resistant to UV rays	
	Relatively hard (resistant to abrasion)	
	Chemically inactive	
Aluminium*	Low weight	High cost
	Good resistance	

* The aluminium used for the reflecting surfaces was anodized aluminium, not treated aluminium, which had a very pliable surface and was susceptible to physical damage and to chemical corrosion.

Table 4.5: Advantages and disadvantages of each type of reflecting surface

4.3.3.2 Absorber tube

The absorber tube was one of the most important components of the solar thermodynamic conversion. The external pipe diameter was 70 mm and the thickness of the pipe wall was 3 mm. A good absorbing system significantly improved the photo-thermal conversion efficiency. The three technical solutions proposed in this study were:

- tube in air with a glass lock (non-evacuated pipe);
- tube in air with an annular glass jacket (non-evacuated pipe);
- vacuum-sealed tube (evacuated pipe).

The solar absorbance was 96% for the evacuated pipe and 94% for the non-evacuated pipe.
In the first case (Figure 4.10), the absorber tube was surrounded by air contained in the cavity formed by the coupling between the secondary reflecting surface and the horizontal glass plate.

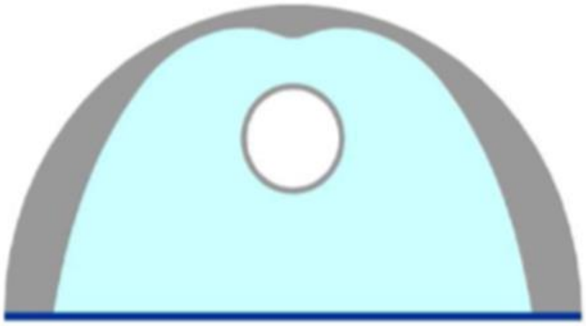

Fig. 4.10: Tube in air with a glass lock

The primary assumptions for this case were:

- the temperature in the absorber tube was assumed constant: the solar power plant under study was a direct steam generation (DSG) plant, wherein the water was boiled directly in the receiver tubes; therefore, most of the pipe was involved in the evaporation stage with a constant temperature along the receiver;
- the thermal flux carried by the primary and the secondary reflecting surfaces was uniformly distributed on the external surface of the absorbing tube;
- the motion of the air was induced by buoyancy;

- the absorber tube exchanges heat, even by radiation, with the secondary reflecting surface and with the glass plate;
- the boundary surfaces of the system exchanged heat, by convection and by radiation, with the external environment.

In the second configuration (Figure 4.11), the absorber tube was surrounded by air contained in a coaxial pipe made of glass.

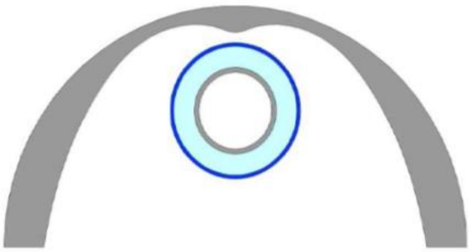

Fig. 4.11: Tube in air with a glass jacket

The primary assumptions for this case were:

- the temperature in the absorber tube was assumed constant;
- the thermal flux carried by the primary and the secondary reflecting surfaces was assumed to be uniformly distributed on the external surface of the absorber tube;
- the motion of air into the blue circular ring was caused by the thermal floating;
- the absorber tube exchanged with the glass jacket by radiation;

- the boundary surface of the system (glass jacket) exchanged heat through convection and radiation with the external environment.

In the third case (Figure 4.12), the absorber tube was contained in a coaxial pipe (jacket) made of glass and the annular cavity was maintained at a vacuum.

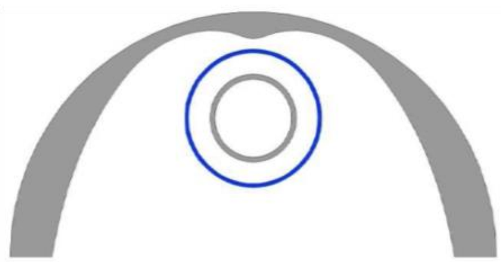

Fig. 4.12: Vacuum-sealed tube

The primary assumptions for this case were:

- the temperature of the internal surface was constant;
- the thermal flux through the primary and the secondary reflecting surfaces was uniformly distributed on the external surface of the absorber tube;
- the absorber tube exchanged heat with the glass jacket by radiation only;
- the boundary surface of the system (glass jacket) exchanged heat with the external environment through convection and radiation.

4.3.4 Economic assessment

Using data from the stochastic business plan model, RSM was used to investigate the behaviour of the primary economic KPIs, varying the different plant configurations related to the two considered components.

The first step was the choice of the most suitable experimental design to verify the significance of the two components (and their potential interaction).

A two-level factorial design with two factors, reflecting surface (A) and absorber tube (B), was chosen.

Four extra central points were added to evaluate the experimental error and to conduct appropriate statistical tests to validate the model (test for lack of fit, pure quadratic curvature, etc.).

The scheme of the experimental design is shown in Figure 4.13.

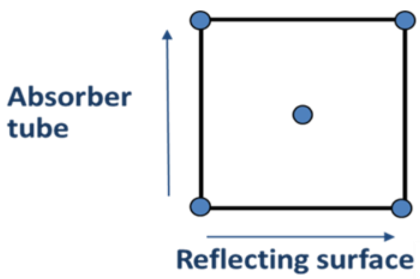

Fig. 4.13: Scheme of the two-level factorial design

To assign the lower level (-1), the central level (0), and the higher level (+1) to the factors, cost analyses, with application of the different technologies, were conducted (Tables 4.6 and 4.7).

The levels were, then, assigned, considering the cost of the adopted solution.

For example, in the case of the reflecting surface, the low level corresponded to the lowest cost, while the opposite was for the absorber tube, as shown in Table 4.8.

Reflecting Surface	€/m2	Efficiency losses (%)
Glass + Steel	48	9.5
Alum. + Alum.	70	12.5
Glass + Plastic	81	7.5

Table 4.6: reflecting surface - cost assumptions and influence on efficiency

Absorber Tube	€/m2	Efficiency losses (%)
Vacuum-sealed tube	39.3	5
Tube in air with a glass jacket	32.6	14
Tube in air with a glass lock	27	10

Table 4.7: absorber tube - cost assumptions and influence on efficiency

	Reflecting Surface	Absorber Tube
Lower level (-1)	Glass + Steel	Vacuum-sealed tube
Central level (0)	Alum. + Alum.	Tube in air with a glass jacket
Higher level (+1)	Glass + Plastic	Tube in air with a glass lock

Table 4.8: factors' levels

A regression model for NPV, LEC and DPR were, then, applied. The results from the experimental campaign conducted on the business plan model provided, for each configuration, the KPIs shown in Table 4.9.

A: reflecting surface	**B: absorber tube**	**NPV (€)**	**LEC (€/kWhe)**	**DPR (%)**
(-1)	(-1)	5.904.500	0.2280	1.097
1	(-1)	7.328.830	0.2144	1.241
(-1)	1	4.799.640	0.2492	0.878
1	1	6.223.280	0.2324	1.039
0	0	2.966.490	0.2982	0.5112
0	0	2.966.610	0.2978	0.5118
0	0	2.966.340	0.2989	0.5110
0	0	2.966.320	0.2994	0.5080

Table 4.9: 2^2 factorial design experimental data

To find the regression model for each dependent variable, the software Design Expert, by Stat Ease, Inc., was used.

The 2^2 factorial design provided a first-order meta-model, which did not describe the existing relations between the economic variables and the various technological solutions (see Paragraph 2.3).

The following step fitted a second-order meta-model using a FCC design (Table 4.10).

A: reflecting surface	B: absorber tube	NPV (€)	LEC (€/kWhe)	DPR (%)
(-1)	(-1)	5.904.500	0,228	109,7
1	(-1)	7.328.830	0,2144	124,1
(-1)	1	4.799.640	0,2492	87,8
1	1	6.223.280	0,2324	103,9
(-1)	0	3.992.830	0,2655	73,8
1	0	5.416.430	0,2455	91,3
0	(-1)	4.885.860	0,253	84,52
0	1	3.780.730	0,2784	64,5
0	0	2.966.490	0,2982	51,12
0	0	2.966.610	0,2978	51,18
0	0	2.966.340	0,2989	51,10
0	0	2.966.320	0,2994	50,80

Table 4.10: FCC design experimental data

The scheme of FCC design is reported in Figure 4.14.

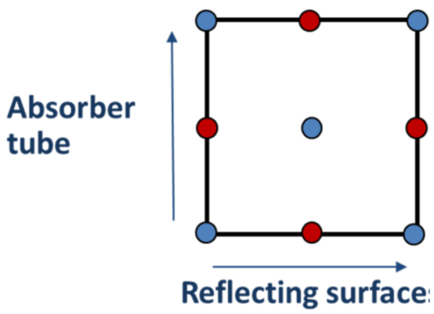

Fig. 4.14: Scheme of the FCC design

The FCC showed that second-order meta-models correctly described the behaviour of the three variables. For example, in Figure 4.15, the ANOVA for the NPV shows that both Fisher's regression tests passed.

Response 1 NPV

ANOVA for Response Surface Reduced Quartic model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	2.420E+013	7	3.457E+012	1.332E+008	< 0.0001	significant
A-Reflecting	*3.041E+012*	*1*	*3.041E+012*	*1.172E+008*	*< 0.0001*	
B-Absorber	*6.107E+011*	*1*	*6.107E+011*	*2.353E+007*	*< 0.0001*	
AB	*1.165E+005*	*1*	*1.165E+005*	*4.49*	*0.1015*	
A^2	*4.028E+012*	*1*	*4.028E+012*	*1.552E+008*	*< 0.0001*	
B^2	*2.491E+012*	*1*	*2.491E+012*	*9.597E+007*	*< 0.0001*	
A^2B	*1702.18*	*1*	*1702.18*	*0.066*	*0.8105*	
A^2B^2	*3.674E+007*	*1*	*3.674E+007*	*1415.45*	*< 0.0001*	
Residual	1.038E+005	4	25956.90			
Lack of Fit	*49272.39*	*1*	*49272.39*	*2.71*	*0.1983*	*not significant*
Pure Error	*54555.21*	*3*	*18185.07*			
Cor Total	2.420E+013	11				

Fig. 4.15: FCC design ANOVA results for the NPV

The second-order meta-models and the related response surfaces for NPV, LEC and DPR are respectively shown in Figures 4.16-4.18:

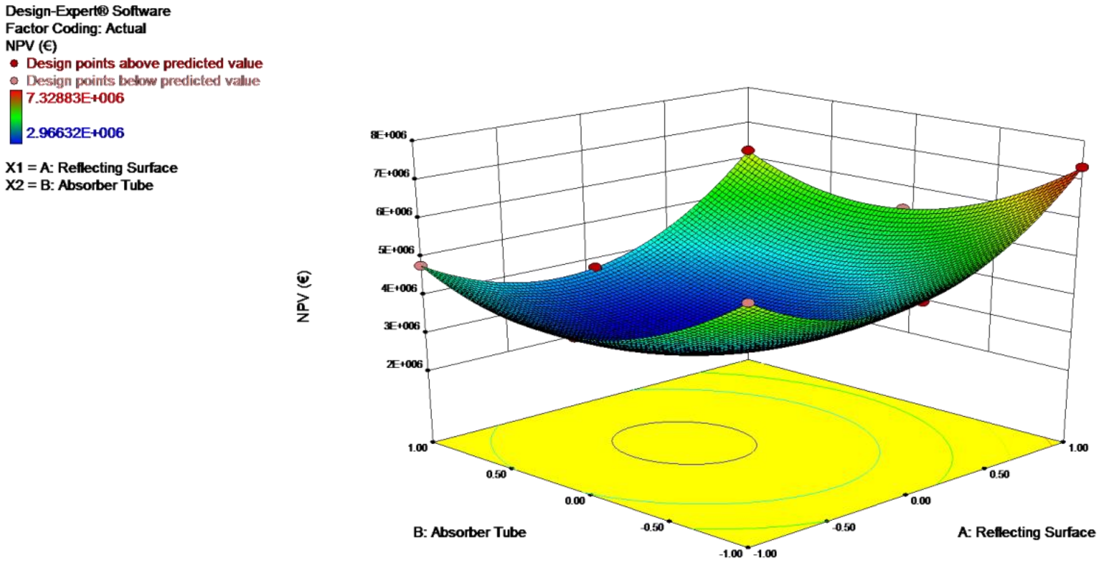

Fig. 4.16: Response surface of the NPV

Equation 4.4 shows the corresponding NPV meta-model equation.

$$NPV = 2.966E006 + 7.119E005A - 5.526E005B - 170.69AB + 1.738E006A^2 + 1.367E006B^2 - 35.73A^2B - 7423.68A^2B^2 \quad (4.4)$$

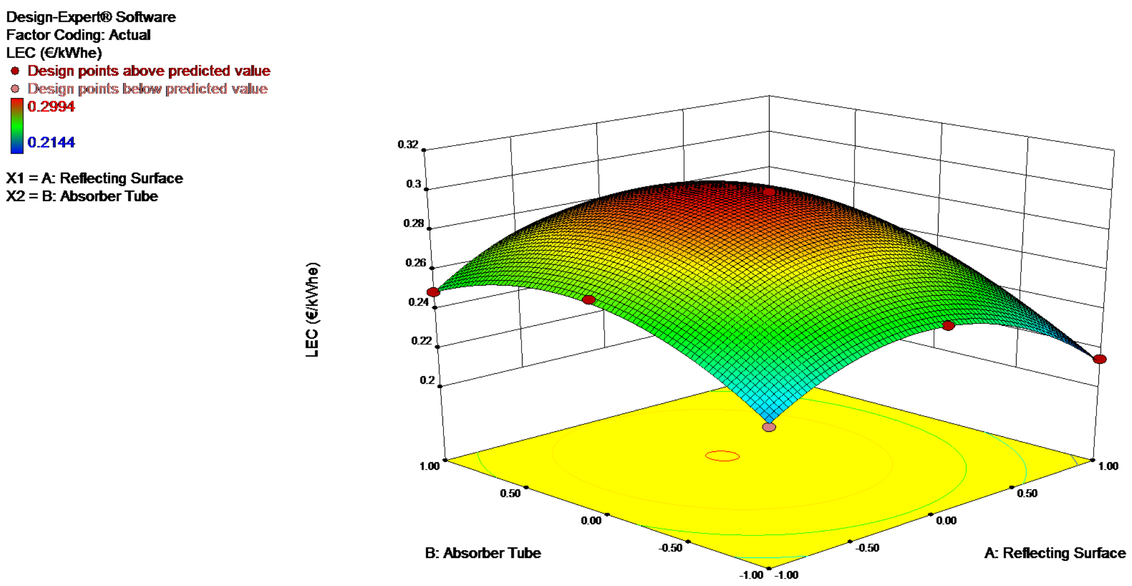

Fig. 4.17: Response surface of the LEC

Equation 4.5 shows the corresponding LEC meta-model equation.

$$
\begin{aligned}
LEC &= 0.30 - 8.40E - 003A + 0.013B - 0.043A^2 - 0.033B^2 + \\
&- 2.90E - 003A^2B + 8.375E - 003A^2B^2
\end{aligned}
\tag{4.5}
$$

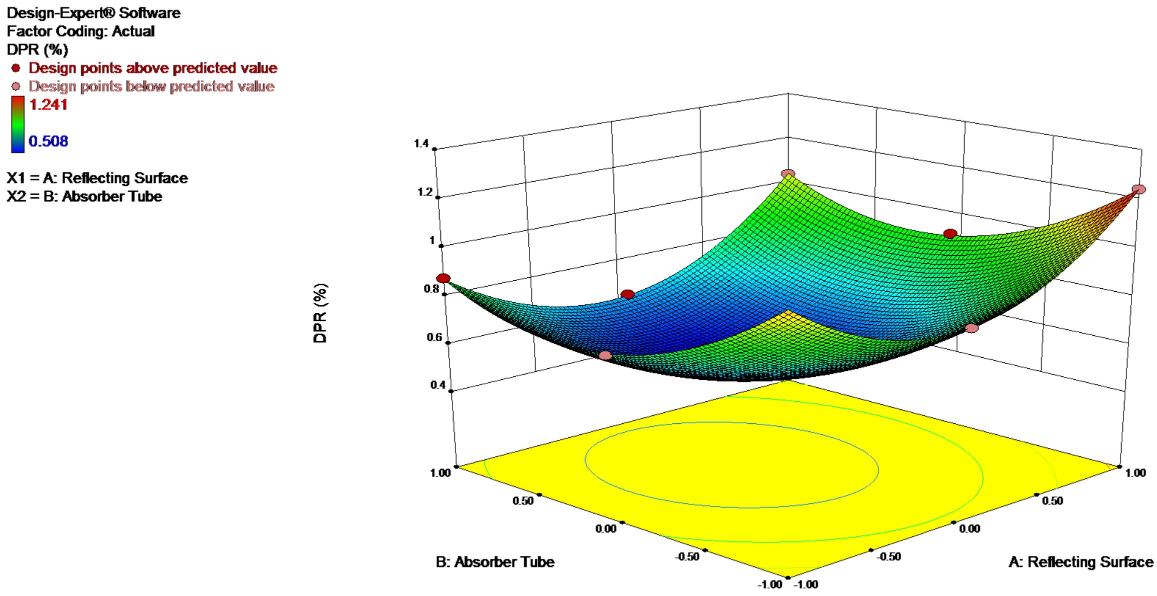

Fig. 4.18: Response surface of the DPR

Equation 4.6 shows the corresponding DPR meta-model equation.

$$DPR = 0.51 + 0.087A - 0.10B + 4.25E-003AB + \\ +0.32A^2 + 0.24B^2 - 5.15E003A^2B - 0.011AB^2 \quad (4.6)$$

The regression meta-model results showed that, from the economic point of view, the best technological configuration was the glass reflecting surface with plastic supports and the vacuum-sealed tube.

This configuration yielded the highest NPV, the highest DPR and the lowest LEC. It was the high conversion efficiency (10,4%) that most positively influenced the result.

On the contrary, the less favourable configuration was one that was recommended by the technologists, i.e., the aluminium reflecting surface with aluminium supports and the tube in air with a glass jacket.

That particular solution was less expensive, if only the components' cost was considered.

However, a lower conversion efficiency (7,4%) drastically impacted the total production, thus impacting the overall economic result.

The confidence intervals were calculated for all of the regression models (Tables 4.11-4.13).

A: reflecting surface	**B: absorber tube**	**NPV (€)**	**NPV inferior limit**	**NPV superior limit**
(-1)	(-1)	5.904.500	5.904.140	5.905.000
1	(-1)	7.328.830	7.328.340	7.329.100
(-1)	1	4.799.640	4.799.270	4.800.130
1	1	6.223.280	6.222.790	6.223.650
(-1)	0	3.992.830	3.992.340	3.993.070
1	0	5.416.430	5.416.190	5.416.920
0	(-1)	4.885.860	4.885.410	4.886.310
0	1	3.780.730	3.780.280	3.781.170
0	0	2.966.490	2.966.210	2.966.660

Table 4.11: NPV confidence interval 95%

A: reflecting surface	B: absorber tube	LEC (€/kWhe)	LEC inferior limit	LEC superior limit
(-1)	(-1)	0,228	0,226	0,232
1	(-1)	0,2144	0,2097	0,2158
(-1)	1	0,2492	0,2462	0,2522
1	1	0,2324	0,2294	0,2354
(-1)	0	0,2655	0,2609	0,2669
1	0	0,2455	0,2441	0,2501
0	(-1)	0,253	0,2493	0,2567
0	1	0,2784	0,2747	0,2820
0	0	0,2982	0,2963	0,2999

Table 4.12: LEC confidence interval 95%

A: reflecting surface	B: absorber tube	DPR (%)	DPR inferior limit	DPR superior limit
(-1)	(-1)	109,7	109,1	110
1	(-1)	124,1	123,6	124,5
(-1)	1	87,8	87,3	88,1
1	1	103,9	103,4	104,3
(-1)	0	73,8	73,5	74,3
1	0	91,3	91,0	91,8
0	(-1)	0,8452	0,842	0,851
0	1	0,645	0,642	0,650
0	0	0,5112	0,508	0,512

Table 4.13: DPR confidence interval 95%

Figure 4.19 shows the interval for the LEC in the median section of the domain with the B factor set to the central level (tube in air with a glass jacket).The data showed that the size of the confidence interval on the average response was sufficiently stationary along the entire variability range of factor A (reflecting surface).

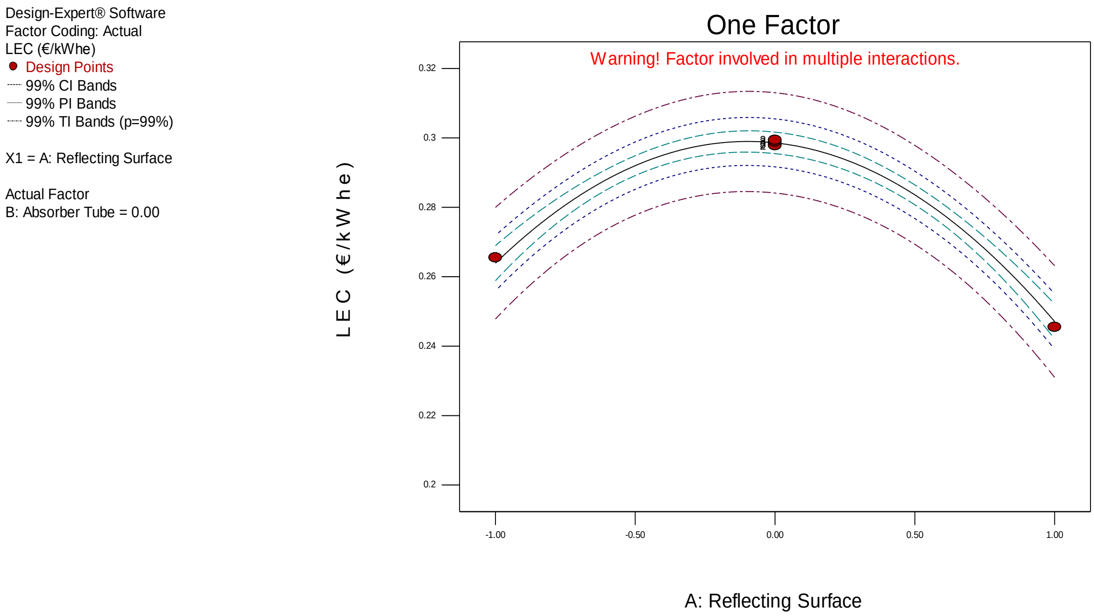

Fig. 4.19: Confidence intervals for the mean response of the LEC

4.4 Discussion

A methodology for the renewable energy investment evaluation in stochastic regime was defined to allow the designers choosing the plant components in accordance with the investment economic parameters.

The Monte Carlo method was used to obtain the occurrence probability for every economic and financial index. In addition to this phase of preliminary investigation, an economic and comparative analysis of the technological alternatives was performed, basing on the RSM technique.

Contrary to the traditional sensitivity analysis, the sensitivity analysis in this study investigated the variability of more elements at the same time, by considering each single factor and their interactions.

The case study validated the proposed approach and demonstrated that the technical solution, identified at the beginning by the technology partners, would have generated a decrease in the investment parameters. Throw the use of the methodology a new solution was, then, proposed to obtain both technological and economic goals.

Furthermore, the presented methodology was generalized, and therefore it is applicable to any type of innovative plant design.

Chapter 5

A stochastic methodology to evaluate the optimal multi-site investment solution for photovoltaic plants

The problem addressed in this Chapter is the location and size identification for a certain number of photovoltaic systems in order to maximize the NPV of the overall investment.

Having set an upper limit for the investment, the methodology identifies, among the sites with different DNIs, those where many photovoltaic systems can be installed and the optimal size within predefined ranges.

In this Chapter a stochastic methodology to evaluate the optimal multi-site investment solution is presented by initially explaining the state of the art and then showing the proposed methodology and the results obtained by applying it to a test case.

These studies and results have also been published in [34].

5.1 State of the art

The economic evaluation of investments in plants producing electricity from RES is traditionally dealt once the site location is selected, almost always deterministically.

Alongside the traditional methods, in recent years, more advanced methodological approaches have gained ground, developed in stochastic regime. The new concept introduced by these approaches is identifying meta-model regression to describe the behaviour of economic variables as a function of the values assumed by the project variables [35-38].

The problem addressed in this Chapter is conceptually very different from the work in the literature, although it is the assessment of investments in plants producing electricity from solar energy.

It involved, in fact, developing a methodology that allowed identifying the location and power of a certain number of photovoltaic systems in order to maximize the NPV of the overall capital. In addition to the NPV, the methodology measured the impact of other parameters so that the investor can have a broader view than the creation of new capital.

In particular, the project coverage ratio and the amount of CO_2 emitted into the atmosphere were considered.

The question then became, from a mathematical point of view, the optimum value of a function in an N-dimensional domain (N being the possible site locations). The reference function described the NPV behaviour for the chosen sites, the percentage of investment for each site and the resulting plant power. The stochasticity was linked to design elements such as the DNI, the number and the year the inverters were replaced, the annual energy production, the feed-in tariffs and the energy purchase price. The decision-making element, however, was the overall profitability of the investment and was generated as a combination of the NPV at the individual sites.

The heart of the problem became, therefore, the search for the optimal point of a function, which was not known a priori, so it was necessary to proceed by suitably combining, in an organized sequence of methodological steps, a series of mathematical techniques: DOE, RSM and the Monte Carlo method.

The result was a rigorous approach that, as demonstrated in the case study, was able to deal with this kind of problem with good results.

The novelty of the proposed approach was the possibility to reach, with a single methodology, the economic optimization of an a priori not known function, considering the real stochastic nature of all the involved variables.

5.2 Methodology

The proposed approach followed 5 main steps:

- Step 1: building a business plan (as in the methodology described in Chapter 4) where a number of PDFs interacted and described the behaviour of the system in a stochastic way. The business plan was appropriately sought from the values assigned to technical and location-related variables and provided mean output and NPV variance values for a particular investment combination. It was, then, essential to implement a particular control on the experimental error impacting the business plan results.

- Step 2: under certain conditions, it was possible to reduce the size of the experimental domain. This was accomplished by eliminating the variability of the independent variables in the assigned range that had no real ability to impact on the objective function.
- Step 3: research based on an excellent feeling/experience/intuition was not possible because of the vastness of the experimental domain. It, therefore, became necessary to use a specific methodology that identified, first, the objective function and its dependence with the main variables function and, then, identified the optimal point. The RSM is the methodology that allows to obtain regression meta-models to respond to this kind of requirements on limited domains. On the other hand, when the size of the domain is the size of that investigated, the classic RSM becomes impractical. It is, in fact, impossible to find meta-models to adapt excessively large domains. The problem could be overcome by using special calculus methods (mathematical analysis) that, in direct research, have conceptual limitations but, if properly adapted, could locate the optimal area of the domain for the location. These included the Steepest Ascent method [39, 40] and the Simplex Method of Spendley [41-43].

- Step 4: once the limited domain with the optimum area was found, it was possible to build the objective function's meta-model and the optimal point could be identified.

5.3 Test case

As part of an investment diversification policy, a financial company considered it appropriate to undertake a study to assess the possibility of setting up new solar energy production facilities. The plants had to be located in Southern Italy in four different sites, and the maximum total outlay was estimated at 240M€.

By respecting these constraints, it was necessary to define where it was worth investing and how much of the total outlay was worth to be used. This with the aim of maximizing the investment results in terms of NPV and DPR and considering, also, the environmental impact in terms of reduction of CO_2 emissions.

The company indicated five reference sites in four different regions of Southern Italy: Ragusa, Sassari, Bari, Foggia and Reggio Calabria.

The main data considered for each site were:

- the DNI
- the availability of the land to be assessed at 7000/8000 mq/MWe

- the possible financing from local or national government agencies. In particular, for sites Sassari and Bari, unsecured loans were provided for 15M€ each one.

As far as the types of equipment was concerned, the choice was photovoltaic solar panels with polycrystalline silicon.

Depending on the overall size of the power to be installed, the price per square meter of land was almost identical for each location; turnkey cost was 1M€/MWe.

The variability ranges for the investment values in the 5 locations (decision variables) that were taken into consideration in the model were:

- Ragusa (factor A): 0≤ A ≤ €100M
- Sassari (factor B): 0≤ B ≤ €30M
- Bari (factor C): 0≤ C ≤ €30M
- Foggia (factor D): 0≤ D ≤ €20M
- Reggio Calabria (factor E): 0≤ E ≤ €60M.

As far as the objective function was concerned, the NPV was selected as the main one.

It is important to underline that the CO_2 emissions reduction and the DPR threshold were also taken into account as an important result of the multi-site investment policy.

5.3.1 Step 1: preparation of the business plan and error analyses

The method's first step involved entering input data (both deterministic and PDF) in the business plan. The PDFs for all the stochastic data were determined using statistical analysis on data collected on similar plants/systems.

For example, in Figures 5.1-5.5, the DNI's PDFs for the 5 sites are shown.

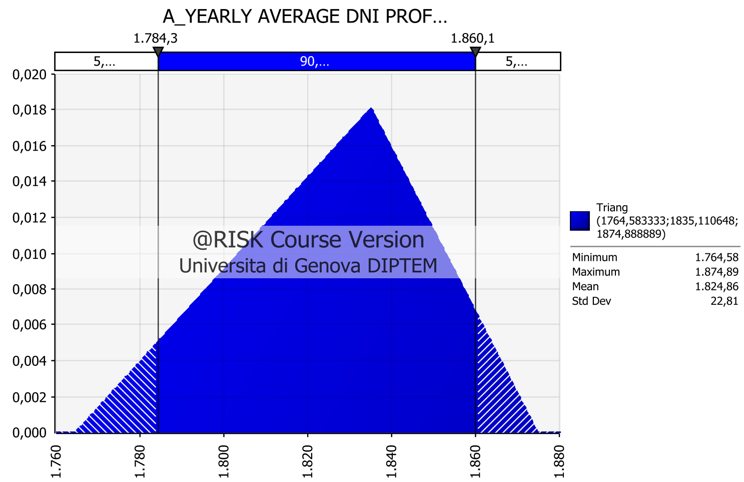

Fig. 5.1: yearly average DNI profile for Ragusa

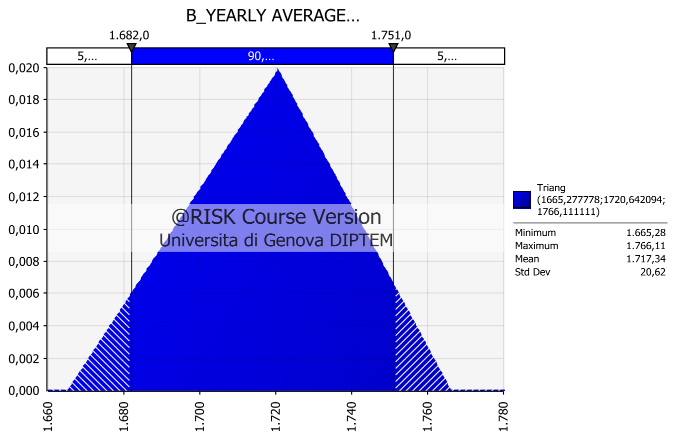

Fig. 5.2: yearly average DNI profile for Sassari

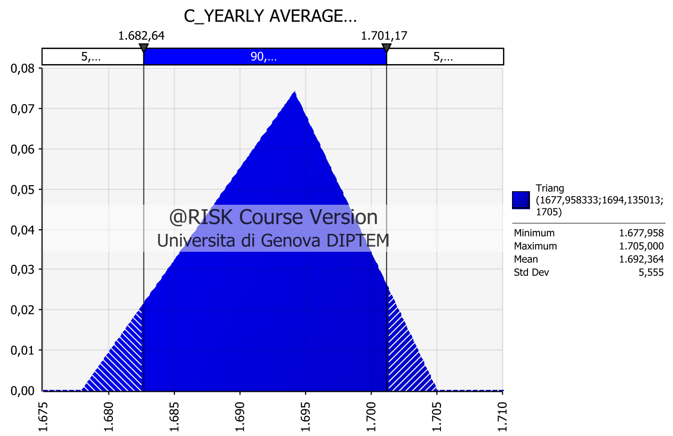

Fig. 5.3: yearly average DNI profile for Bari

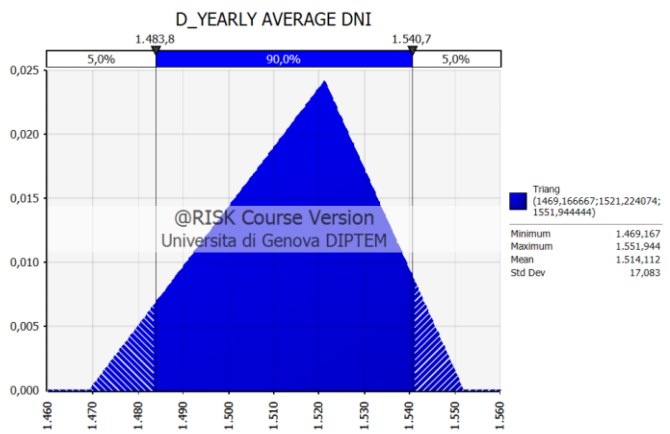

Fig 5.4: yearly average DNI profile for Foggia

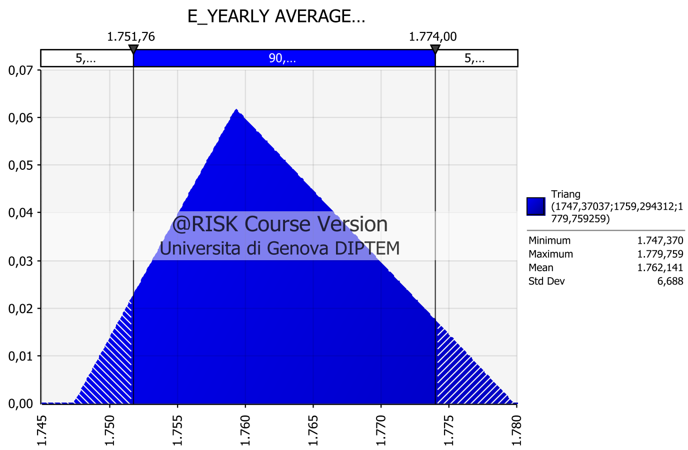

Fig. 5.5: yearly average DNI profile for Reggio Calabria

The amount of the experimental error affecting the results in the form of MSPE played a fundamental role.

As shown in Chapter 2, the MSPE methodology in replicated runs, using the business plan output, allows determining the magnitude of the experimental error in accordance with the number of runs.

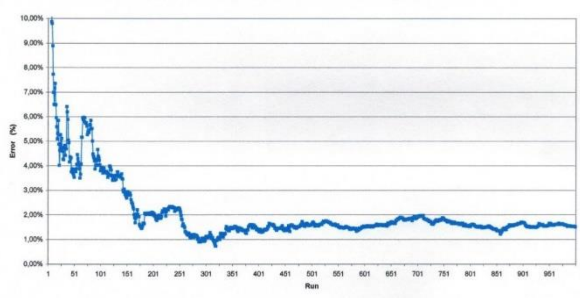

Fig. 5.6: percentage error in relation to the number of runs

Figure 5.6 shows how, after 1000 replicated runs, the error affecting the estimate of the average value of the objective function was approximately 1%. In the initial analysis phase, this approximation could be deemed acceptable in order to limit computational time, although the possibility remained to reduce it further in the future.

5.3.2 Step 2: domain reduction

It was now possible to evaluate the capacity of the decision variables to significantly affect the objective function. Obviously, this was not in the absolute sense but fell within the assigned ranges of variability.

In particular, a 2^5 factorial design replicated 3 times was selected. The results showed that the importance of B and C factors was marginal compared to that of the A, D and E. Therefore, it was possible to set B and C at every value of their ranges. The first choice was to set B and C equal to zero (no investment in those locations). However, having a forgivable loan of 15M€ in both sites, the minimum investment in Locations B and C was rationally 15M€ so, in the following analysis, they were set equal to 15M€.

A new 2^3 factorial design was launched (replicated 3 times with 5 central tests), the effects analysis was performed and the regression meta-model was obtained.

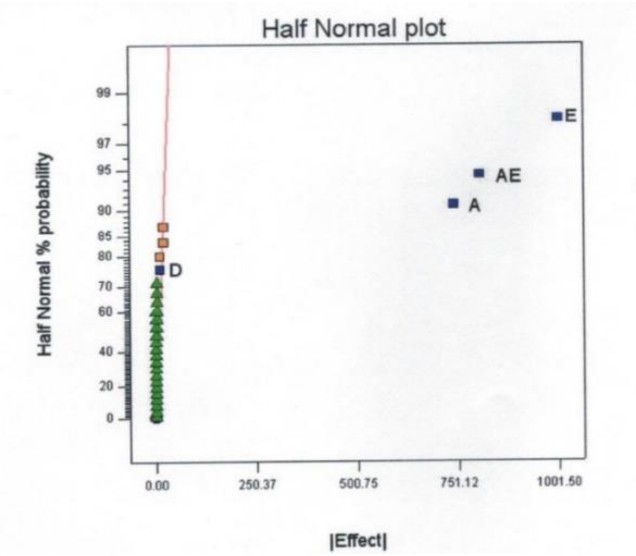

Fig. 5.7: 2^3 factorial design “effects”

The effects analysis’ results, shown in Figure 5.7, indicated that factor D was not significant. Factor A, factor E, and their interaction (AE) were the only factors that significantly influenced the objective function.

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	Remarks
Model	13.229.722	4	3.307.431	11.916	< 0.0001	significant
A	*3.303.516*	*1*	*3.303.516*	*11.902*	*< 0.0001*	
D	*811*	*1*	*811*	*3*	*0,10*	***not significant***
E	*6.018.007*	*1*	*6.018.007*	*21.681*	*< 0.0001*	
AE	*3.907.389*	*1*	*3.907.389*	*14.077*	*< 0.0001*	
Curvature	855.042	1	855.042	3.080	< 0.0001	significant
Residual	6.384	23	278			
Lack of Fit	*5.886*	*3*	*1.962*	*79*	*< 0.0001*	*significant*
Pure Error	*498*	*20*	*25*			
Cor Total	14.091.148	28				

Fig. 5.8: 2^3 factorial design ANOVA

The subsequent ANOVA, represented in Figure 5.8, confirmed the irrelevance of factor D on the objective function. Therefore, it could be set to any value in the variability range without affecting the response. Thus, having neither constraints nor advantages on the investment in this location, it was decided to renounce investment in Location D.

5.3.3 Step 3: optimal zone identification

A problem that initially involved 5 independent variables was now reduced to the research of the investment values in Locations A and E, which maximized the NPV= f (A, E). The RSM researchers developed "methods for approaching the optimal zone in wide domains" by adapting certain algorithms originally used by mathematicians as optimization methods. These included mixed-type designs that combined simultaneous designs (2^k factorial designs) and sequential designs (traditionally the Steepest Ascent Method). In the test case a mixed-type design was applied, combining a 2^2 factorial design with the Steepest Ascent Method.

When applying this methodology to investment contexts a significant problem arose. It was caused by the previously mentioned influence of the MSPE on the test results. The approach proposed in the following Paragraphs neutralized this negative effect, making the obtained results reliable.

5.3.3.1 The simultaneous/sequential approach

Initially, a first order meta-model was considered an adequate approximation of the actual (unknown) area around the domain point from which the investigation started.

Then it was necessary to apply a new procedure to sequentially move along the so-called “path of Steepest Ascent”, meaning the direction in which the maximum increase of the response was noted. This direction was identified by the gradient, which, in the case of two generic variables, takes the form:

$$\nabla f(x_1, x_2) = \left[\frac{df(x_1, x_2)}{dx_1}, \frac{df(x_1, x_2)}{dx_2} \right] \tag{5.1}$$

This was done by selecting the subsequent design points in the direction of the maximum increase (Figure 5.9).

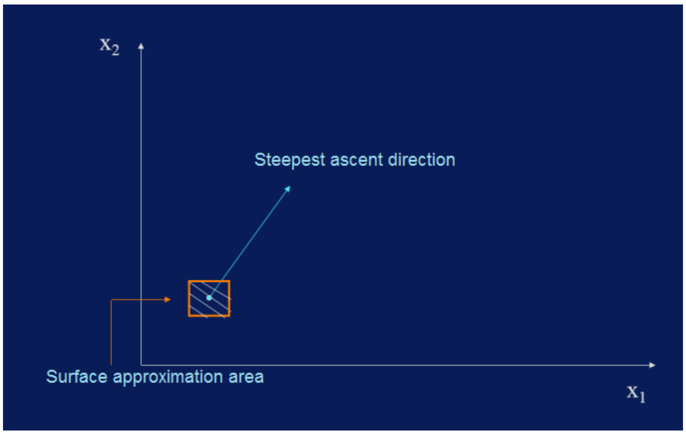

Fig. 5.9: 2^2 design combined with Steepest Ascent

The experimenter continued in this direction until the value of the objective function decreased compared to the previous measurement.

At this point, a new exploration of the surfaces around this point had to be performed. Therefore, a new first order model was adopted, centred on this point, and the procedure continued by determining the new path of Steepest Ascent and conducting new tests on this path. After a certain number of cycles, the proximity of a stationary point (optimal, suboptimal, saddle) was reached. This was indicated by the lack of fit of the first order model.

To avoid the danger of identifying a relative optimal point instead of an absolute point, the methodology required the procedure to be reset starting from other field points in order to compare the results obtained.

So the methodology was replicated 4 times, starting from the 4 different domain vertexes and defining the following 4 paths:

- pathway 1: starting from point (A=0, E=0)
- pathway 2: starting from point (A=100, E=60)
- pathway 3: starting from point (A=0, E=60)
- pathway 4: starting from point (A=100, E=0).

<u>Pathway 1</u>: starting from the launch of the 2^2 factorial design in point (A=0, E=0), the algorithm moved towards the opposite end of Location A. The optimal point was therefore directly identified

(A=100, E=0). The corresponding NPV value was equal to 2,756*10^2 M€.

<u>Pathway 2</u>: starting from the launch of the 2^2 factorial design in point (A=100, E=60) the path of Steepest Ascent headed towards the opposite end of Location E. With E corresponding to 12M€, a sharp decrease was noted in the objective function, which dropped to 2,688*10^2 M€ (green rectangle in Figure 5.10). As a maximum point was identified in the previous pathway (A=100, E=0), it was considered it logical to expect, to the contrary, a linear increase of the NPV up to the previous value of 2,756 * 10^2 M€. For this reason it was decided to relaunch the Steepest Ascent at the point immediately below (A=100; E=10), and it was noted that the response increased and converged once again with point (A=100, E=0).

Because of these analyses it was decided to conduct an investigation targeting the zone demarcated by the values 80-100 for Factor A and 10-18 for Factor E because it was of particular practical interest (see Paragraphs 5.3.3.2 and 5.3.3.3). In fact the previously identified maximum point was not feasible from a political point of view because it was not possible to focus the investment on a single location.

Pathway 3: starting from the launch of the 2^2 factorial design in point (A=0, E=60), the algorithm led to point (A=80, E=28), with three changes in direction.

Pathway 4: given the results of the previous pathways, which identified the NPV maximum point as (A=100, E=0), it was unnecessary to launch a simultaneous design in this zone.

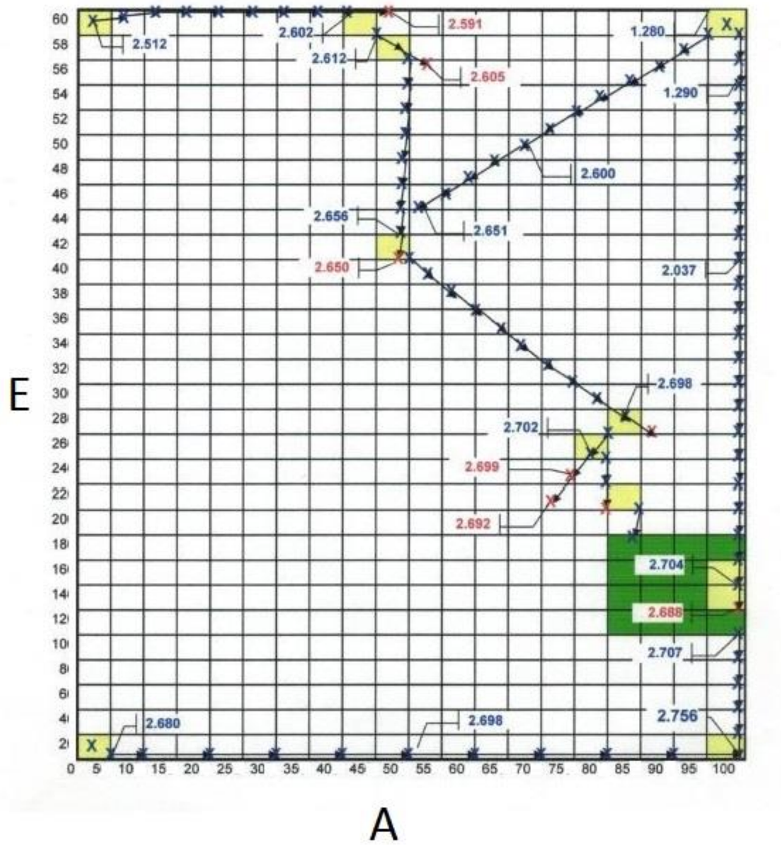

Fig. 5.10: representation of the Steepest Ascent model four pathways

Figure 5.10 shows the 4 pathways and certain values of the objective function measured along the ascent. The areas in which the 2^2 designs were launched are shown in yellow, while the zone in which the methodology identified a sub-optimal level is shown in green.

5.3.3.2 First phase of the sub-optimal zone investigation

The first investigation conducted in the suboptimal zone included the entire green area of Figure 5.10 ($80 \leq A \leq 100$; $10 \leq E \leq 18$). However, given the small variations between one point and the next in the field, an error of 1%, which up to now was deemed acceptable, was now unacceptable as it could lead to a point error interval of about 2,7 M€. Therefore, it was necessary to reduce the MSPE that affected the average response. This could be achieved, according to MSPE theory, by increasing the number of replicated runs. Through subsequent attempts, an MSPE of 0.0021 m€^{2} was achieved, which corresponded to 25,000 runs and drastically reduced the percentage error affecting the result from 1% to 10E-6. At the same time the variance decreased to 0.1 M€.

At this point, it was possible to launch an RSM design to identify the trend of the objective function (response surface).

After an initial attempt to launch a CCD on the range ($80 \leq A \leq 100$; $10 \leq E \leq 18$), which failed due to the lack of fit of the regression meta-model, it was decided to restrict the range ($85 \le A \le 95$; $12 \le E \le 16$).

A CCD with 5 central tests was launched on this range.

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	Remarks
Model	56,98	5	11,40	28,02	0.0002	significant
A	*0,81*	*1*	*0,81*	*2,00*	*0.2001*	
E	*8,52*	*1*	*8,52*	*20,95*	*0.0026*	
A^2	*9,82*	*1*	*9,82*	*24,15*	*0.0017*	
E^2	*9,62*	*1*	*9,62*	*23,64*	*0.0018*	
AE	*16,24*	*1*	*16,24*	*39,93*	*0.0004*	
Residual	2,85	7	0,41			
Lack of Fit	*1,36*	*3*	*0,45*	*1,21*	*0.4129*	***not significant***
Pure Error	*1,49*	*4*	*0,37*			
Cor Total	59,82	12				

Fig. 5.11: CCD ANOVA

Figure 5.11 shows that the adaptive regression meta-model was a second order model in A, E, AE, A^2 and E^2.

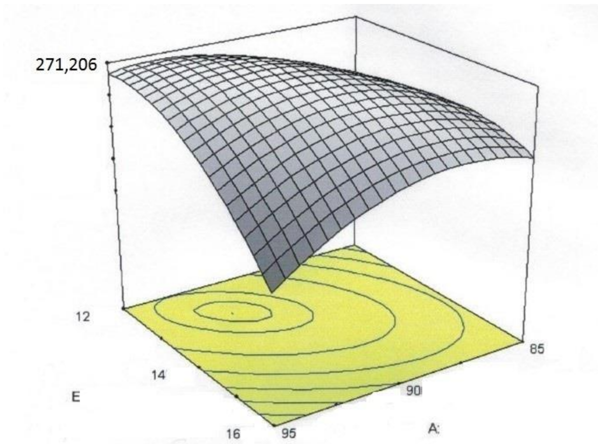

Fig. 5.12: response surface

From Figure 5.12, the optimal point of the suboptimal surface is clear (A=92,5, E= 13) with a NPV equal to 271,206 M€.

5.3.3.3 Second phase of the sub-optimal zone investigation

To obtain an additional confirmation of the suboptimal zone existence, it was decided to apply a sequential technique called Simplex Method algorithm (Figure 5.13).

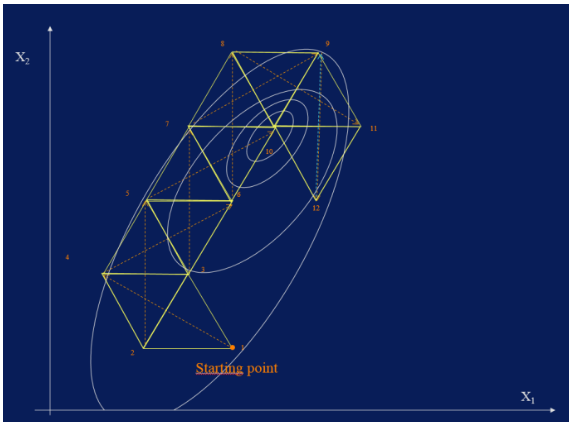

Fig. 5.13: Simplex Algorithm

This algorithm, in fact, is particularly appropriate for Monte Carlo simulation applications, in which the objective functions are not known.

This is because, by exploring the unknown surface in a two-dimensional space, the underlying basis of the algorithm is less sensitive to the surface shape.

The Simplex Method was launched at the same four starting points as the Steepest Ascent and, at the end, it identified the same optimal point and suboptimal zone.

For the sake of brevity, not all of the pathways are reported. Only those launched at the point (A=100, E=60) are shown, as they identified the sub-optimal zone (Figure 5.14).

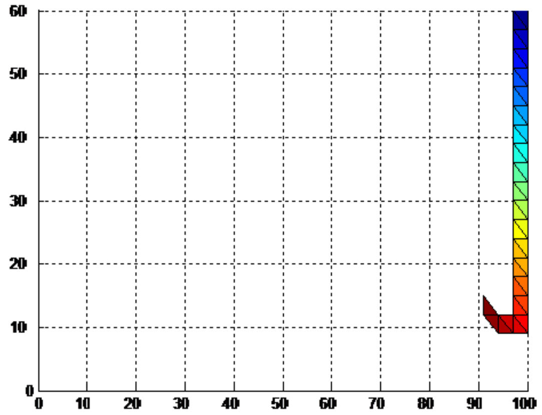

Fig. 5.14: pathway originating at point (A=100, E=60)

5.3.4 Step 4: optimum value identification

It was, then, decided to extend the investigation to the zone including both the optimal and suboptimal points to obtain an integrated view of the problem.

Therefore it was decided to investigate a rectangular field with 74,5 ≤ A ≤ 100 and 0 ≤ E ≤ 15,6. In this field, a FC CDD was applied using the Design Expert tool of Stat-Ease.

The final surface model used was a fourth-order meta-model (the first passing the two Fisher's tests), for which the actual factors equation is (5.2).

$$PV = 3132.1397 - 0.9837 * A - 10.0285 * E + 0.02181 * AE + \\ +5.9163e-004 * A^2 + 4.1336e-003 * E^2 - 1.2493e-005 * A^2 E + \\ -1.31749e-009 * A^2 E^2 \qquad (5.2)$$

Finally, Figure 5.15 shows the corresponding response surface.

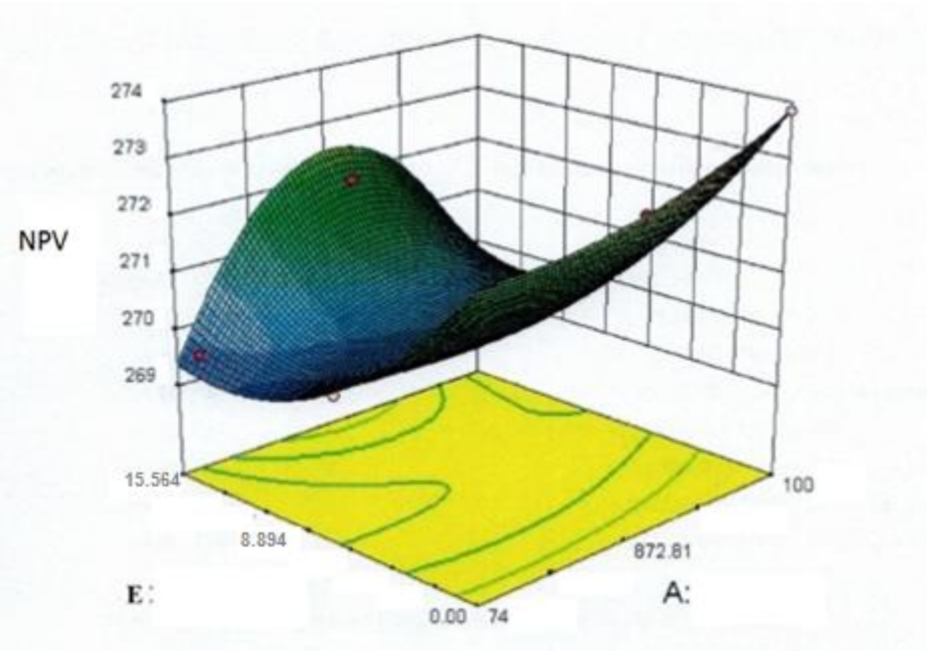

Fig. 5.15: response surface

An analysis of Figure 5.15 revealed 3 key considerations:

- the theoretical optimal point was set at (A=100, E=0), as determined both by the Steepest Ascent Method and the Simplex Method;
- there were both a suboptimal zone and a suboptimal point;
- from a comparison between the coordinates of the optimal point and those of the suboptimal zone, it was clear that there was no significant difference in terms of NPV.

However, an investment focused on a single location, as identified by the theoretical optimal point, was politically infeasible. On the contrary, the possible combinations of the suboptimal area were identified as being of particular interest.

Figure 5.16 shows a resume of the approach steps in a schematic way.

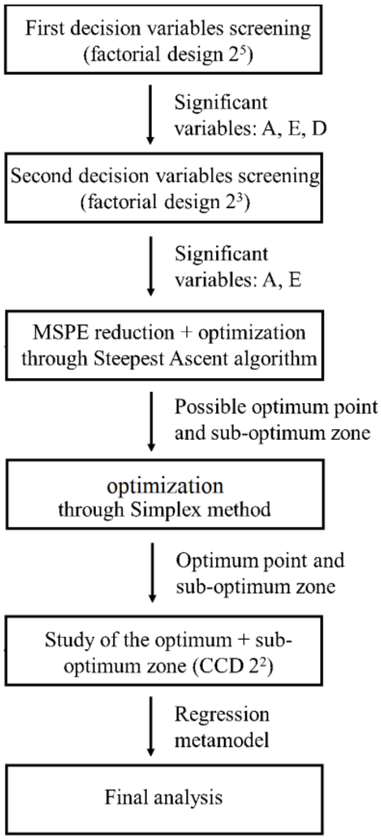

Fig. 5.16: approach steps scheme

5.3.5 Results' analysis

As a result of the performed work, two different investment combinations were identified as capable of bringing the NPV to satisfactory values. The first combination was:

- Location A: 100 M€
- Location B: 15 M€
- Location C: 15 M€
- Location D: 0 M€

- Location E: 0 M€

with an average NPV value equal to 2,756 * 10^2 M€. With this solution 57.20tons/h of CO_2 were saved.

The sub-optimal combination was:

- Location A: 87,2 M€
- Location B: 15 M€
- Location C: 15 M€
- Location D: 0 M€
- Location E: 14,5 M€

with an average NPV value equal to 2,720 * 10^2 M€. With this solution 57.95tons/h of CO_2 were saved.

For the optimal solution the DPR was 212% (10,6%/year) while for the suboptimal solution it was equal to 206% (10,3%/year). The results are summarized in Table 5.1.

	INVESTMENT IN EACH LOCATION (M€)					NPV (M€)	DPR	DPR/year	CO2 REDUCTION (tons/h)
	A	B	C	D	E				
OPTIMAL SOLUTION	100	15	15	0	0	275,6	212%	10,6%	57,2
SUB-OPTIMAL SOLUTION	87,2	15	15	0	14,5	272	206%	10,3%	57,95

Table 5.1: optimal and sub-optimal results

From these considerations, it could be noticed that the choice of the suboptimal solution (the politically feasible one) was nearly equivalent to the optimal (unfeasible) solution in terms of investment evaluation. In both cases, the remaining disposable income, compared to the budget made available by the investing company, was even greater than 100 M€. For this reason, alternative solutions that, for the same NPV, increased the amount of energy produced, were identified. This to reduce even more the amount of CO_2 released into the atmosphere from other fossil fuel plants present on the territory. All this, of course, while keeping the DPR within acceptable values for the investor (6-10% per annum). As already stated, sites B and C could generate, for the same NPV, an increase of an additional 30MW in energy production with an additional investment of €30 M.

This would increase the investment to €161.7M, keeping the same NPV, and, consequently, determining a lower DPR (about 168% over twenty years, equal to 8.4% per annum). However, this investment could increase the CO_2 reduction of about 13.2 tons/h and, for this reason; it was deemed more than economically acceptable and was chosen as best solution as it combined the economical optimization (primary request of the methodology) with the environmental impact. Table 5.2 shows the results of the chosen solution.

INVESTMENT IN EACH LOCATION (M€)					NPV (M€)	DPR	DPR/year	CO2 REDUCTION (tons/h)
A	B	C	D	E				
87,2	30	30	0	14,5	272	168%	8,4%	71,15

Table 5.2: results of the chosen solution

5.4 Discussion

The problem of maximizing the economical results of a multi-site investment for the production of electricity from photovoltaic systems was considered. At the end of the optimization, the results were analysed and compared considering another important aspect: the reduction of CO_2 emissions. The PV plants could be installed in different geographical areas (characterised by different DNIs) and could be of different sizes. A stochastic approach was developed based on a number of methodologies that came, in part, from the literature (RSM, DOE, Simplex Method, Steepest Ascent) and, in part, specially structured.

The rigorous application of the proposed approach, which can be applied also to other cases, led to:

- the identification of both sites and sizes of higher performance in terms of NPV, based on the economic availability for each site;
- the identification of a sub-optimal solution that, compared with a minimum reduction in the NPV (1.3%), was, in reality, the most "politically" viable one compared to the optimal one;
- the attainment of the other classical analysis parameters for an investment, indispensable for an overall assessment of the technical-economic choices viability;
- an estimate of the CO_2 amount which was not released into the atmosphere due to the replacement of fossil fuel plants with photovoltaic systems.

Chapter 6

Energy Resources Intelligent Management using on line real-time simulation: a decision support tool for sustainable manufacturing

At a historic time when the eco-sustainability of industrial manufacturing is considered one of the cornerstones of relations between people and environment, the use of energy from Renewable Energy Sources (RES) has become a fundamental element of this new vision. After years of vain attempts to hammer out an agreement to significantly reduce CO_2 emissions produced by the burning of fossil fuels, a binding global accord was finally reached (Paris, December 2015; New York, April 2016).

However, some of the most commonly-used RES, such as solar or wind, present the problem of discontinuity in energy production due to the variability of weather and climatic conditions. For this reason, in this Chapter, a new methodology is presented with the aim of combining industrial users' instantaneous energy needs with the RES production capacity, supplemented, when necessary, by energy created through self-production and/or acquired from third-party suppliers. All of this minimizing CO_2 emissions and energy costs.

Given the massive presence of stochastic, and sometimes aleatory elements, for the proposed model, both the Monte Carlo simulation and Discrete Event Simulation (DES) were used, as well as the appropriate predictive algorithms (both online and online real-time).

The obtained results were of interest both economically and with regard to the CO_2 emissions reduction, as clearly shown by the test conducted on a tannery located in southern Italy, equipped with a 700 KWp photovoltaic installation. In fact, in one year, the methodology application allowed to save several hundreds of thousands euros in energy costs and to reduce CO_2 emissions by hundreds of thousands tons. Its systematic use, starting from the industrial sector, which included tanneries, and gradually expanded to other industries, could result in very consistent benefits for the entire system.

These studies and results have also been published in [44].

6.1 State of the art

Since the early 2000s, the concept of Sustainable Manufacturing has had an increasing presence in the industrial field. To summarize extremely briefly, the principal objective is to establish a relationship between manufacturing and the environment, with greater attention to protecting the latter.

The idea of sustainability applies and extends to each phase of the industrial manufacturing cycle:

- in product design: possibly making use of recyclable and non-polluting materials
- in manufacturing: seeking to minimize manufacturing waste and the use of energy from traditional sources, with the consequent CO_2 emissions
- in distribution: reducing as much as possible ground transportation and product's carbon footprint.

The correct energy management, particularly electric power, makes a significant contribution for sustainability. The term "sustainable", when applied to the energy use, is evoked, on the one hand, in the search for less consumption per unit produced, and on the other hand, in the growing use of self-production through RES. However, there is a significant problem caused by randomness in the volumes of production generated by most RES, whose behavior is predictable only with uncertainty margins. This makes their use problematic in cases where there are continuous consumption demands according to pre-set schedules, as with industrial applications. It is, then, necessary to supplement discontinuous RES sources (sun and wind, for example) with traditional sources to ensure continuity in energy supply during the hours in which RES production is absent. A focus on sustainability, therefore, requires the identification of an integrated management model that privileges, where possible, the self-production of RES. To obtain an effective and efficient RES management, predictive models for both industrial energy demand RES production capacity in relation to the predicted weather and climactic patterns, are required. The objective of the proposed study was to provide a tool that allowed the optimization of the energy production obtained as the mix of RES self-production, traditional sources and purchasing on the electricity market. Through this approach both the economic budget, in terms of energy procurement costs, and the ecological budget, expressed in terms of reduction of CO_2 emissions, could be significantly reduced. This was in full accord both with the Sustainable Manufacturing philosophy and with the new trends regarding the ecosystem.

In the scientific literature, some authors approach the problem only from the perspective of predicting energy consumption [45-46] while many others only from the perspective of predicting energy availability from RES sources [47-50]. With regard to the use of DES for the purpose of energy savings and optimization of consumption, there are some interesting contributions. Ghani et al. [51] use DES for the real-time evaluation of energy demand in the automotive industry in the redesigning phase of the manufacturing process in order to optimize the sizing of the production line, with a view toward energy savings.

Kouki et al. [52] developed a framework called ERDES (Energy-Related Discrete Event Simulation), which again uses DES for predicting future energy consumption at various times of the day in order to test different scheduling scenarios for manufacturing activities and, consequently, minimizing energy costs.

Both contributions, though offering interesting insights, approach the problem only from the perspective of consumption optimization and not from the point of view of RES production.

6.2 Methodology

In dealing with the problem of the supplemented and optimal use of energy produced by RES in manufacturing, a modelling approach based on two steps was considered. It was based on two models, one logically following the other, called ERIM-P (Energy Resources Intelligent Management-Predictor) and ERIM-RT (Energy Resources Intelligent Management-Real Time).

The purpose of ERIM-P was to develop, 24 hours in advance, two types of predictions:

- the hourly electrical energy requirement of a manufacturing plant based on a production plan created for the following day, but keeping in mind the system stochastic events (breakdowns, stoppages, missed appointments, materials unavailability, variability of processing and set up times, etc.)
- the quantity of possible RES self-production, based on weather predictions for the following day.

By comparing the two hourly profiles (consumption and RES self-production) it was be possible to determine, as a consequence, the quantity of electrical energy to be self-produced through traditional sources (i.e. micro-turbines) or to be purchased from the grid. This model, which will be described in detail in Paragraph 6.2.1, acted under stochastic conditions through a DES simulator of the manufacturing plant. Its objective was to optimize the use of available energy sources by knowing, one day in advance, the lack/surplus of the hourly requirement compared to the quantity of producible energy, from both economic and environmental standpoints, attempting as much as possible to make use of renewable sources.

The second model, ERIM-RT, placed logically after ERIM-P, acted on the current day, using an online real-time DES simulator. It took into account what was happening real-time (with projections repeated for each remaining hour of the day) and the real instantaneous production of RES energy, due to weather conditions. The use of a special predictive algorithm [53] provided, every 30 minutes, starting from the real weather situation, an update of the available RES energy production prediction for subsequent times of the day. ERIM-RT, correcting the projections made through ERIM-P, helped establishing if and when to activate self-production from traditional sources and/or to access the electricity market in the subsequent hours of the day.

6.2.1 ERIM-P Model

The Energy Resources Intelligent Management-Predictor model was conceived with the objective of planning the use of the available RES and traditional sources, with the goal of protecting economic values and minimizing environmental impact. To identify the hourly energy production expected for the following day, special weather prediction sites were used, which provided conditions for RES sources availability for each hour of the day. The ERIM-P model translated the RES hourly producibility into a probability distribution and combined them using Monte Carlo simulation. The model's output provided the hourly availability of RES energy to supply the manufacturing plant. To obtain this result, it created a sub-model within ERIM-P called Internal Energetic Source Predictor (IESP), whose task was, as previously noted, to obtain an hourly availability profile of RES electrical energy.

A second sub-model in ERIM-P consisted of a DES simulator that reproduced the manufacturing plant. This simulator was kept online with the plant, and its purpose, at the end of each working day (starting from the current status of the plant and from the production plan for the following day), was to provide a consumption profile for each hour/half hour of the following day. The two energy profiles supplied by the IESP model and the DES model fed the ERIM-P model, which developed the hourly energy plan for the following day (Figure 6.1).

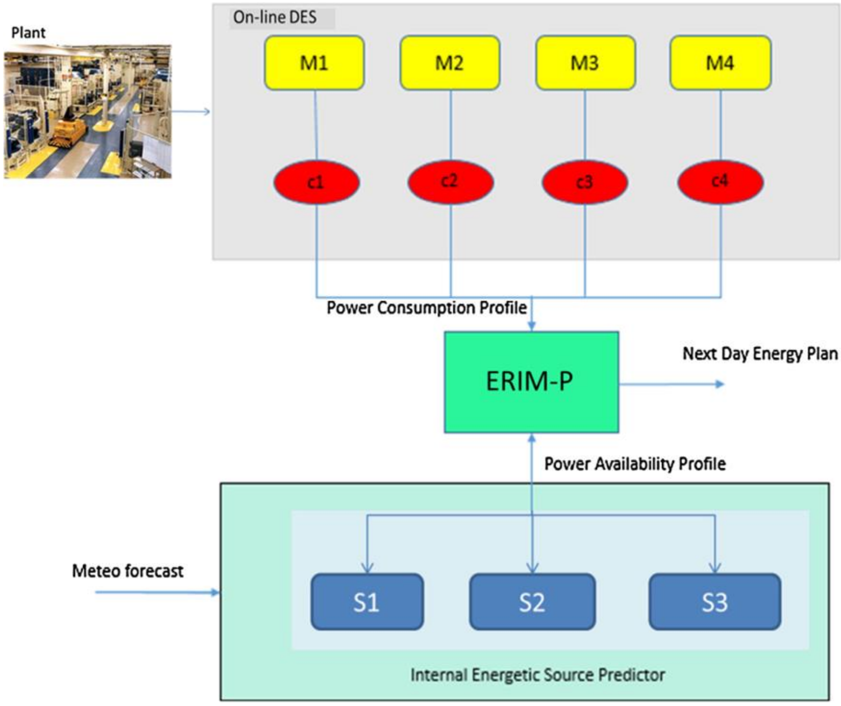

Fig. 6.1: ERIM-P framework.

In the event that the RES were not able to meet the entire energy requirement, ERIM-P gave the following outputs, for every half-hour of the next day:

- X - consumption of energy (KWh) required by the plant
- Y - electrical energy self-produced by RES
- Y' - energy self-produced with other sources
- Y' max - maximum availability of self-production
- Y" - energy that needed to be purchased on the electrical market.

These data were, then, used to plan the supplemented use of non-renewable sources or the purchase on the market for the following day.

As already emphasized, knowing one day in advance the presumed behavior of the system as a whole allowed to optimize, as much as possible, decisions regarding self-production and purchase.

6.2.1.1 Limits of ERIM-P

The use of a stochastic predictive approach using online DES and Monte Carlo simulators provided clear benefits in the capability to describe the behavior of complex systems, leading to results that were absolutely consistent with the real system. However, unpredictable events and/or extemporaneous decisions made by production management could create significant deviations between the consumption predicted by the simulator the previous day and the reality of the following day.

In addition, the IESP model was based on hourly weather predictions, which was also subject to randomness. These considerations did not compromise the methodology results, but, under certain conditions, they became a limit to the benefit of the proposed model. This was because the single or combined action of the two influences (production and/or weather variations) could generate differences that also affected the economic results of energy management.

For this reason, the ERIM-RT model was created to be used as a supplement to the previous one.

6.2.2 ERIM-RT Model

This model was put in sequence to ERIM-P with the aim of overcoming its limitations. The core elements of ERIM-RT were: a DES simulator working online real-time with the plant and a predictive update algorithm for RES production, which was also an online real-time agent with weather conditions (Figure 6.2).

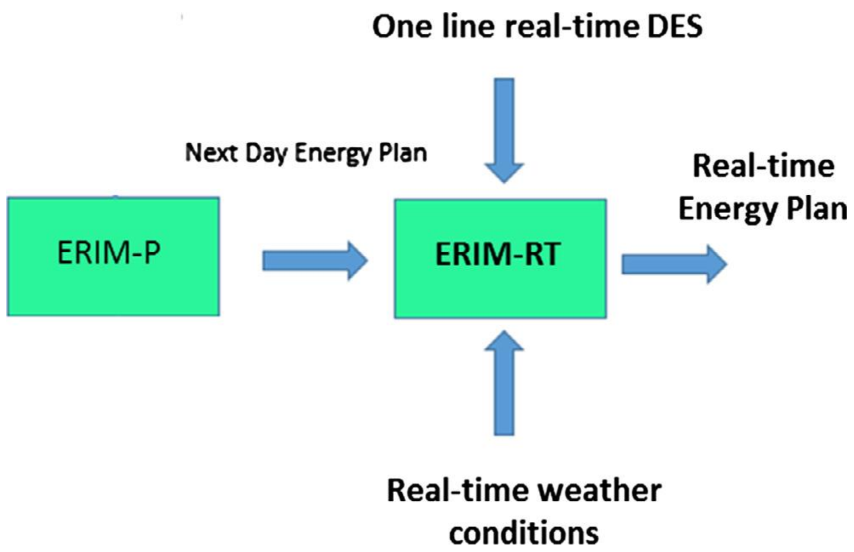

Fig. 6.2: Input/Output schematization of ERIM-RT.

Starting from the zero moment of the morning shift, the simulator, every 30 minutes, received the data for the current status of the plant (machine occupation and operators, breakdowns, production plans, changes thereof, etc.) and projected them along the entire arc of the production day. In this way, the hourly demand profiles, individual and total, calculated by ERIM-P the previous day, were updated every 30 minutes based on actual operations and until the end of the working day. The actual hourly quantity of energy that had to be made available to the manufacturing plant for that day was, then, calculated.

The predictive update algorithm for RES energy production recalculated, every 30 minutes, based on the actual weather conditions, the quantity of RES energy that it could produce from that moment until the end of the day. The additive algorithm was formulated as follows:

$$F(k+i\,|\,k) = \min\left\{F(k+i\,|\,k-1) + M(k) - F(k\,|\,k-1), P_p\right\} \tag{6.1}$$

where:

- F(k+i|k) was the prediction of power production made at the moment k for all the remaining hours of the current day
- M(k) was the quantity of power actually produced by RES at moment k
- F(k|k-1) was the prediction of power production made at moment k-1 for the moment k and, obviously, it could not, in any case, exceed the peak power of the RES plant (P_p)
- F(k+i|k-1) was the prediction of the quantity of power produced at the moment k-1 for the hours from k to the end of the current day.

Following this logic, ERIM-RT was able to notably improve the performance of ERIM-P. The benefit derived from the fact that, even if the ERIM-P predictions for the following day power demand were completely erroneous (due to changing in operating and/or weather conditions), ERIM-RT was able to redefine these predictions. Obviously, the more energy-intensive the manufacturing processes were and/or the higher their stochasticity was, the more using ERIM-RT yielded significant economic results in terms of lower costs for energy used.

From now on, the use of ERIM-RT in sequence to ERIM-P will be called ERIM-GM (Energy Resources Intelligent Management-General Model).

6.3 Test case

The plant taken into consideration for testing the proposed approach was a medium-sized manufacturing tannery, located in southern Italy in the tannery district of Solofra. Its annual production was on the order of 9,000 tons of hides treated, and the peak power used was on the order of 500 kW (in sizes of 55/65 kW for the major machines). The duration of individual processing cycles ranged from a few minutes per piece to approximately 20 hours for calcination and unhairing. The annual consumption of electric power was approximately 3 million kWh, while thermal energy consumption was approximately 2,500,000 kWh.

The sum of the two amounts of consumption exceeded 5 GWh/year, and therefore this particular tannery could be considered for all intents and purposes an “Energy Intensive” industrial process.

The tannery’s capacity for self-production of electric power was provided by:

- a photovoltaic panel installation for a total of 700 kWp. The average DNI of the site was 1,750 kWh/M^2
- 2 co-generative micro-turbines, supplied by natural gas, with a nominal electric power of 200 kW (with 33% efficiency) and thermal (water at 60-70°C) equal to 285 kW, for a total efficiency major than 80%.

To manage the self-production of electric power, it was decided to adopt eco-sustainability as a general rule. As a consequence, the aim was to produce, as much as possible, only the energy strictly required for tannery operation, or to keep the difference between electric power consumed and electric power produced (ΔkWh) as close to zero as possible.

From this perspective, given that photovoltaic production was connected to exogenous factors, the way to minimize CO_2 emissions was to optimize the two micro-turbines management.

For this tannery, the “cost of eco-sustainability” for the kWh produced, once the cost of investment in energy production plants were amortized, could be framed as follows:

- for the photovoltaic installation: maintenance costs (cleaning of panels and possible replacement of inverters at a rate of one/two in 20 years)
- for the micro-turbines: costs for gas and maintenance which were, overall, lower than costs for purchasing from the electric market.

Considering that, in Italy, excess power to the electrical grid was sold at a price per kWh that was markedly lower than the price of purchasing from the same market, the tannery needed to use the co-generating micro-turbines to produce only what the tannery could use.

6.3.1 Modelling the tannery process through DES

The plant received raw and salted hides and produced batches of wet blue leather (hides that have completed the entire tanning process). This process is shown in Figure 6.3.

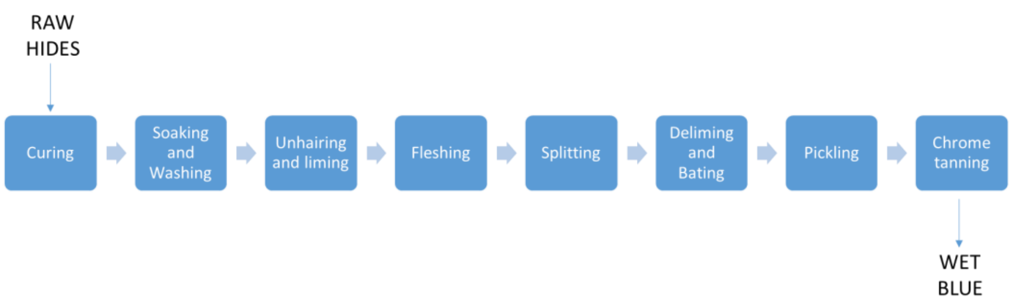

Fig. 6.3: tanning process

Production took place in three 8-hour shifts/day, six days a week. Using the Simul 8 software, a DES simulation model was developed for the entire hide processing cycle. Thus, it was possible to evaluate the daily energy demand for the various machines. Stochasticity was included in the model through suitable probability density functions, deduced from data gathered on field, such as: duration of individual processing, breakdowns, ordinary maintenance, employees availability, etc.
Since the DES simulation model was an essential component of both ERIM-P and ERIM-RT, its capability to accurately reproduce the operating of the actual system was an indispensable element for obtaining real benefits from the proposed methodology. For this reason, in addition to statistical validation tests on the magnitude of the experimental error, it was considered also a further verification test based on the congruency between the quantity of energy actually consumed by the tannery in a standard year and the quantity obtained from the simulator. The difference was on the order of 3%; that is, approximately 2,925,000 kWh simulated compared to 3,000,000 kWh consumed by the actual plant. It was, therefore, possible to conclude that the DES model was fully capable of providing reliable data on the quantity of energy consumed by the tannery every 30-60 minutes. It could, then, be used as a predictive tool, both for the “following day” demand (in off-line mode in the ERIM-

P model) and for the "current day" demand (in real-time mode in the ERIM-RT model).

6.3.2 Implementation of ERIM-P and ERIM-RT

The use of ERIM-P, compared to traditional management of the energy consumed by the tannery, could lead to significant benefits, both economically and environmentally (reduction of CO_2 emissions).

In fact, the model allowed, the day before, an initial optimization of the energy to be self-produced and/or purchased, acting on a behavior prediction that was very consistent with the reality of the tannery.

On the other hand, ERIM-RT acted on the current day, basing on ERIM-P predictions, and correcting them online real-time, basing on the instantaneous operations of the tannery.

The advantages created by the use of ERIM-GM versus the single use of ERIM-P are illustrated in Paragraph 6.3.3, through an analysis of some typical days.

To facilitate comparison between the performance of the two models in economic and environmental terms, an appropriate KPI, called ΔkWh, was introduced to measure the prediction error.

This represented the difference between the kWh actually consumed by the plant and the energy requirement predicted by the model.

There were three possible cases:

- ΔkWh = 0, that is, the model predicted, with no error margin, both plant demand and RES production, such that the energy produced was the only energy consumed. This represented the ideal condition of maximum eco-sustainability;
- ΔkWh < 0, the model overestimated energy production compared to actual demand. The excess energy produced could be sold on the electricity market (at level price which did not make it convenient the production with the aim of selling the energy overproduction);
- ΔkWh > 0, the model underestimated the energy demand. This situation required the production of a greater quantity of energy than the predicted amount. This could occur through the use of the two 200 kWh micro-turbines and, if more energy was needed, through purchasing on the electricity market.

In all cases where ΔkWh was other than 0, the tannery could have an excess of CO_2 emissions, certainly in the second case (ΔkWh > 0), and possibly in the first case (ΔkWh < 0).

To estimate the benefits in economic terms, the following cost and revenue parameters were taken into consideration:

- cost of micro-turbine energy production equal to an average value of 0.11 €/kWh, with this value varying +/-2 cents in relation to the cost of fuel purchase
- cost of photovoltaic production equal to zero, since the installation was already amortized and the impact of cleaning

costs for panels per individual Kwh produced was a few cents at most

- cost of purchasing energy from the grid equal to 0.25 €/kWh, as the average cost of sale charged by the Italian national agency for electrical energy

In terms of environmental impact, the analysis was conducted basing on Kg of CO_2 released into the atmosphere for every kWh of electrical energy produced:

- 0.45 kg/kWh for micro-turbines and conventional power plants supplied by fossil fuels
- no contribution from the photovoltaic installation.

6.3.3 Scenario analysis

To determine the economic benefits obtainable through use of the proposed methodology, 3 possible scenarios were taken into consideration:

- Scenario 1: the energy demand for the tannery, estimated the day before, was in line with the actual consumption, while the hourly production from photovoltaic sources, estimated the previous day, was not in line with the actual availability for the day
- Scenario 2: the energy demand for the tannery, estimated the day before, was not in line with the actual consumption, while the hourly production from photovoltaic sources, estimated the previous day, was in line with the actual availability for the day

- Scenario 3: both the energy demand for the tannery and the production from photovoltaic source estimated the day before were in line with actual consumption/production.

The 3 scenarios were compared in terms of results obtained through the use of ERIM-P model versus ERIM-GM model.

6.3.3.1 Scenario 1

In Figure 6.4, the energy demand predicted by ERIM-P DES is compared with the actual demand for the day.

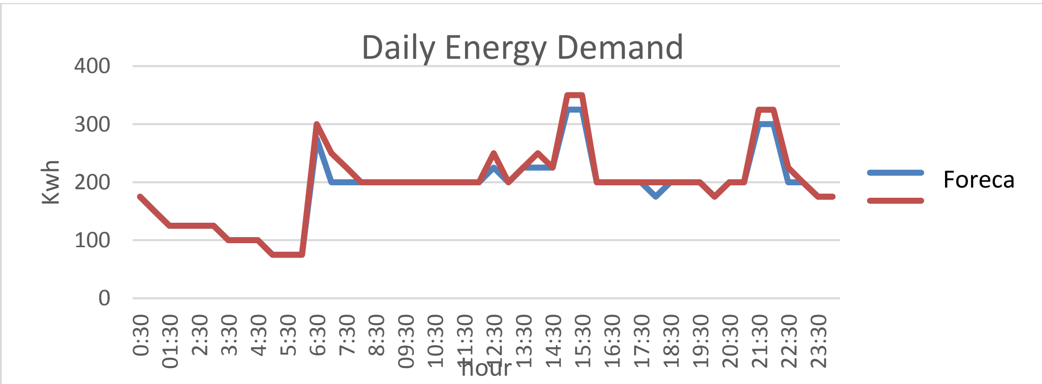

Fig. 6.4: Daily energy demand for Scenario 1

The analysis in Figure 6.4 shows that in the absence of particular random elements disrupting production, the off-line DES simulator succeeded in faithfully reproducing, one day in advance, the operations of the tannery and the consequent energy demand over the various hours of the day.

Figure 6.5 shows the deviation between the production of photovoltaic energy estimated by the IESP sub-model of the ERIM-P and the energy actually produced the following day.

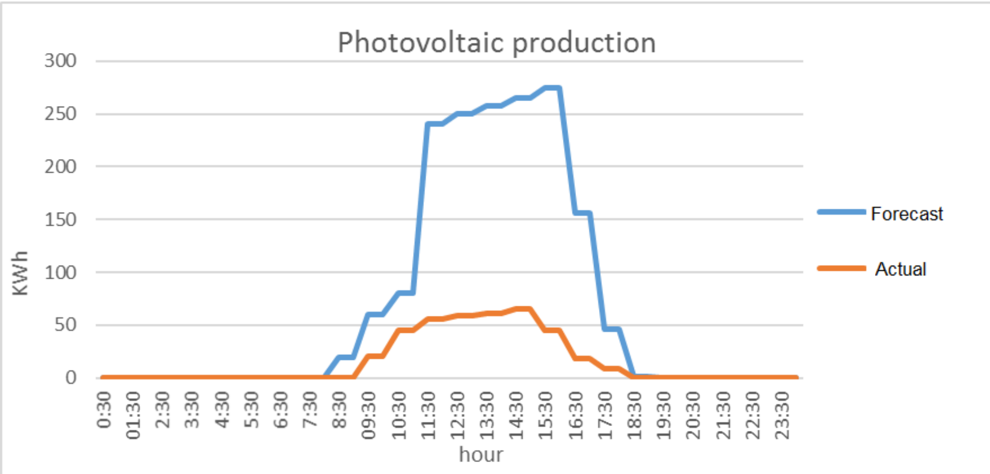

Fig. 6.5: Photovoltaic production for Scenario 1

In Figures 6.6 and 6.7, the different behaviors of ERIM-P and ERIM-GM in the situation described in this scenario are shown. The application of ERIM-P (Figure 6.6) generated an underproduction, in particular during the central hours of the day, caused by incorrect planning for operation of the micro-turbines. To cover this instantaneous demand, it was necessary to use the electrical power market or the unplanned operation of the turbines. On the other hand, the ERIM-GM model (Figure 6.7), through the predictive update algorithm, planned a more correct use for the micro-turbines, whose kWh production cost was lower than purchasing from the grid.

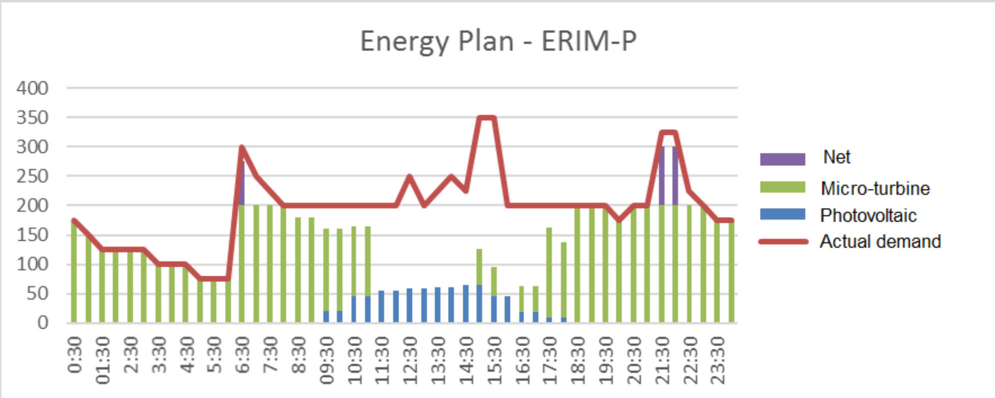

Fig. 6.6: ERIM-P output for Scenario 1

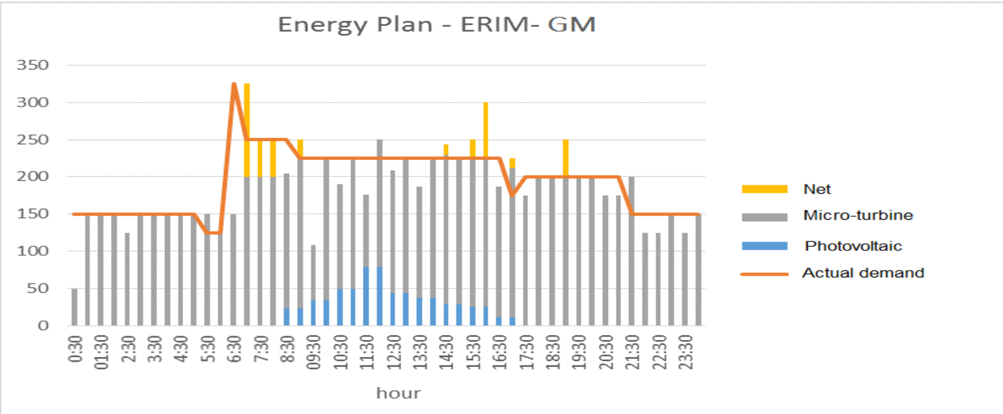

Fig. 6.7: ERIM-GM output for Scenario 1

By comparing the results obtained with the two models, it was possible to calculate the prediction errors committed by both models and to compare them:

- ERIM-P generated a negative ΔkWh equal to 2,328 kWh during daylight hours and equal to 2,503 kWh throughout the entire day (24h)

- ERIM-GM generated a negative ΔkWh of 426 kWh during daylight hours and equal to 501 kWh throughout the entire day (24h).

Considering the costs previously indicated for the energy produced by the micro-turbines and for energy purchased from the market, a saving of approximately 300 € (in a day) was obtained by using ERIM-GM.

Considering the opposite situation, in which the weather prediction made the day before underestimated the production of photovoltaic energy, with ERIM-GM could be obtained a lower cost of approximately 30 € but, most important, lower CO_2 emissions, equal to more than 815 kg (in a day).

6.3.3.2 Scenario 2

A day was taken into consideration where the energy demand for the current day was greater than what was predicted the day before due to the extemporaneous insertion of further requests for the production.

The hourly weather conditions for the current day were, on the other hand, in line with the predictions of the previous day.

Figures 6.8 and 6.9 show the difference, ex post, of the two models behavior, which was accentuated by the unpredictable exogenous interference, which became significant for the current day. The comparison also showed a greater coverage with self-production from micro-turbines, in non-daylight hours, by ERIM-

GM, while the single model ERIM-P forced purchases on the electrical power market to handle the instantaneous, unpredicted demand.

The predictive error in production, attributable to the change of operating conditions in the following day, generated an increase in the tannery's energy consumption of more than 3,200 kWh.

ERIM-GM responsiveness to exogenous events decreased this value by more than 2,500 kWh, and so to only 700 kWh.

As a consequence, the costs of the predictive error were practically doubled from 0.12 €/kWh to 0.25 €/kWh.

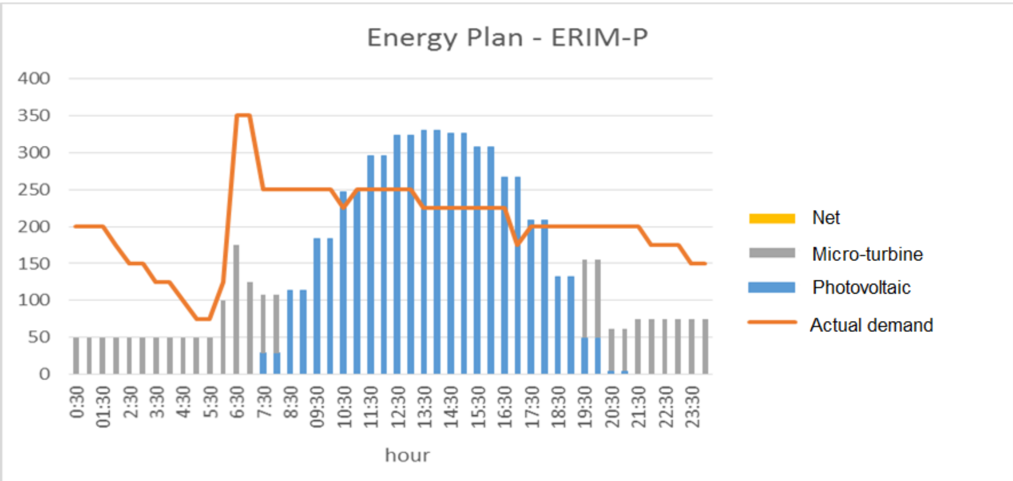

Fig. 6.8: ERIM-P output for Scenario 2

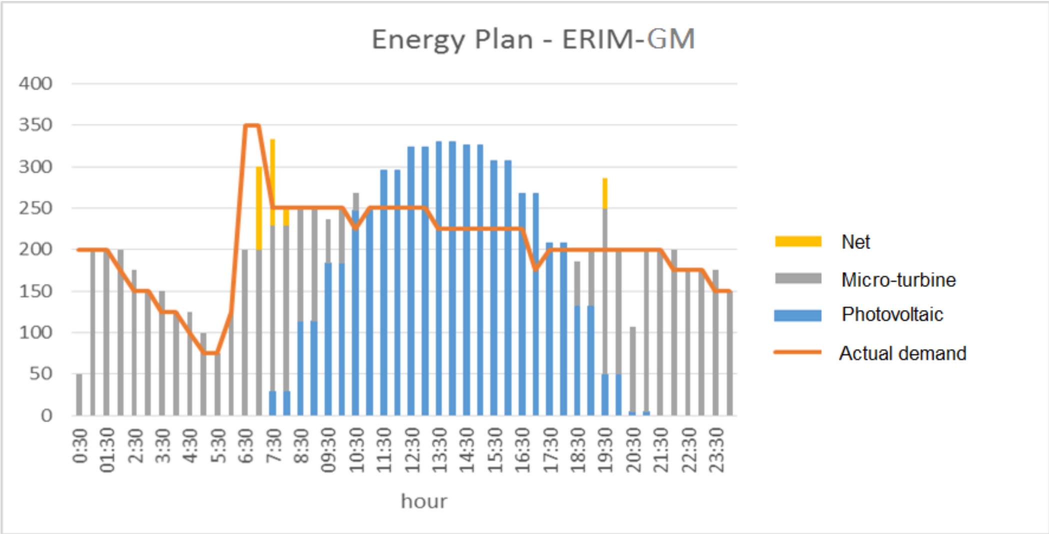

Fig. 6.9: ERIM-GM output for Scenario 2

Economically, the advantage created by ERIM-GM, derived from the sale of photovoltaic power, was quantifiable at approximately 360 € (in a day). As in Scenario 1, analyzing the opposite case where the energy demand was markedly lower compared to the predictions of the previous day, ERIM-GM helped reducing the cost of ΔkWh by 10% and halved (-52%) CO_2 emissions.

6.3.3.3 Scenario 3

A day was taken into consideration where there were significant deviations in terms of both consumption and RES production. Under these conditions, ERIM-GM increased its performance possibilities compared to ERIM-P model.

Depending on whether the deviations between the actual situation and the prediction (in terms of both demand and RES production) were positive or negative, 4 sub-scenarios could be identified:

- DLPH (Demand Lower Production Higher): predicted demand lower than actual demand and predicted RES production higher than actual RES production
- DLPL (Demand Lower Production Lower): predicted demand lower than actual demand and predicted RES production lower than actual RES production
- DHPH (Demand Higher Production Lower): predicted demand higher than actual demand and predicted RES production higher than actual RES production
- DHPL (Demand Higher Production Lower): predicted demand higher than actual demand and predicted RES production lower than actual RES production

Scenario DLPH: under these conditions, ERIM-P generated a ΔkWh of approximately 7,000 kWh, while ERIM-GM generated an error of only 900 kWh.

ERIM-P, predicting less energy consumption than the actual, undersized the use of the micro-turbines, with the related penalties in terms of costs (having to go onto the electrical market for the missing quantity). This phenomenon is shown in Figures 6.10 and 6.11.

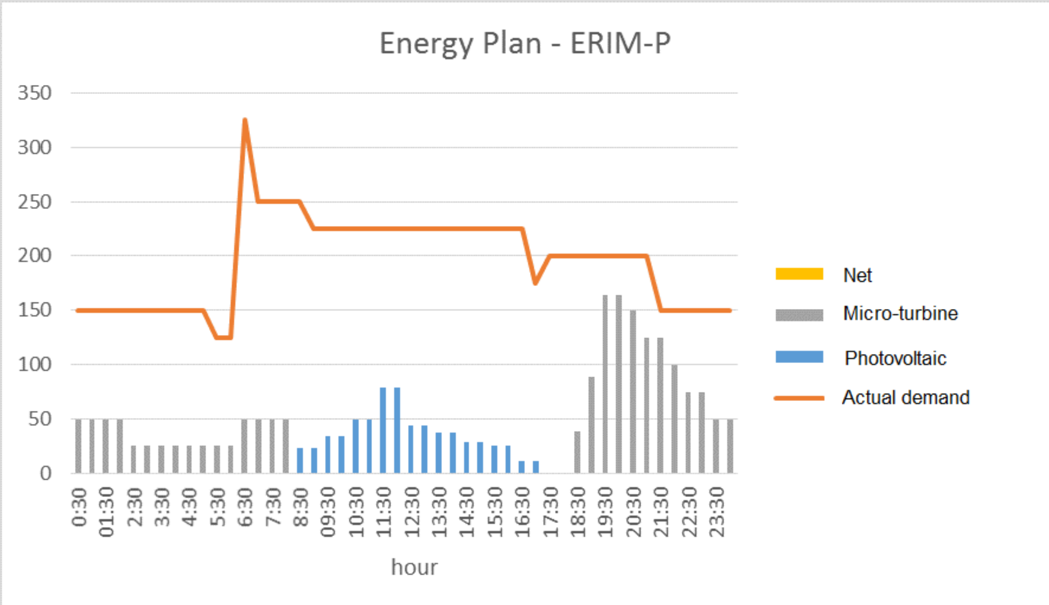

Fig. 6.10: ERIM-P output for Scenario DLPH

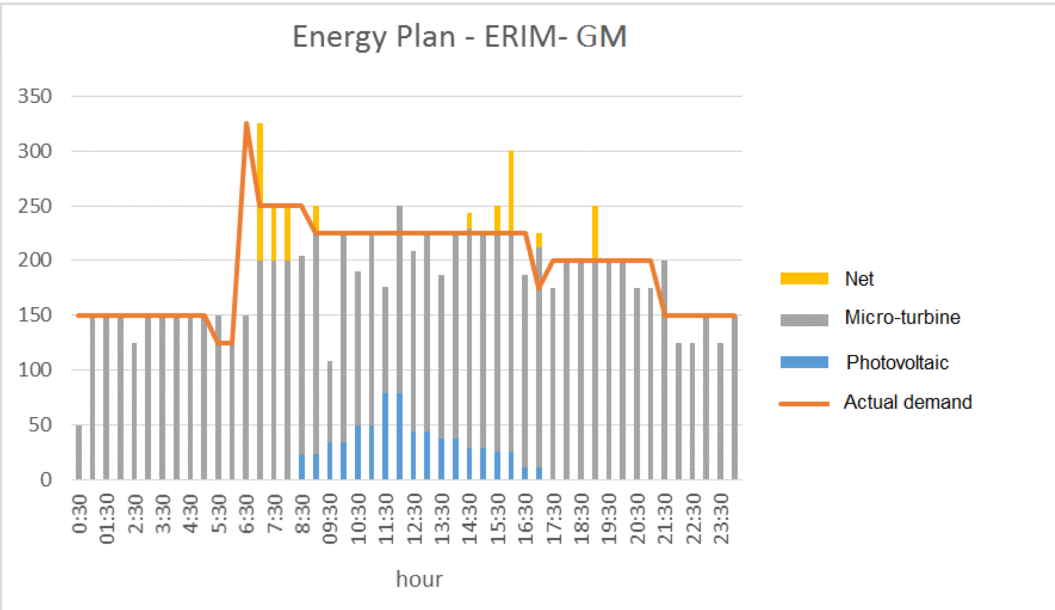

Fig. 6.11: ERIM-GM output for Scenario DLPH

However, ERIM-GM recognized, thanks to online real time update mechanisms, the changed conditions of energy demand

and production, allowing a savings of approximately 900 € (in a day), equal to 45% of the cost developed by ERIM-P.

Scenario DLPL: under these conditions, ERIM-P generated a ΔkWh of approximately -4,270 kWh, while ERIM-GM generated an error of -925 kWh (approximately one fifth less than ERIM-P). This phenomenon is shown in Figures 6.12 and 6.13.

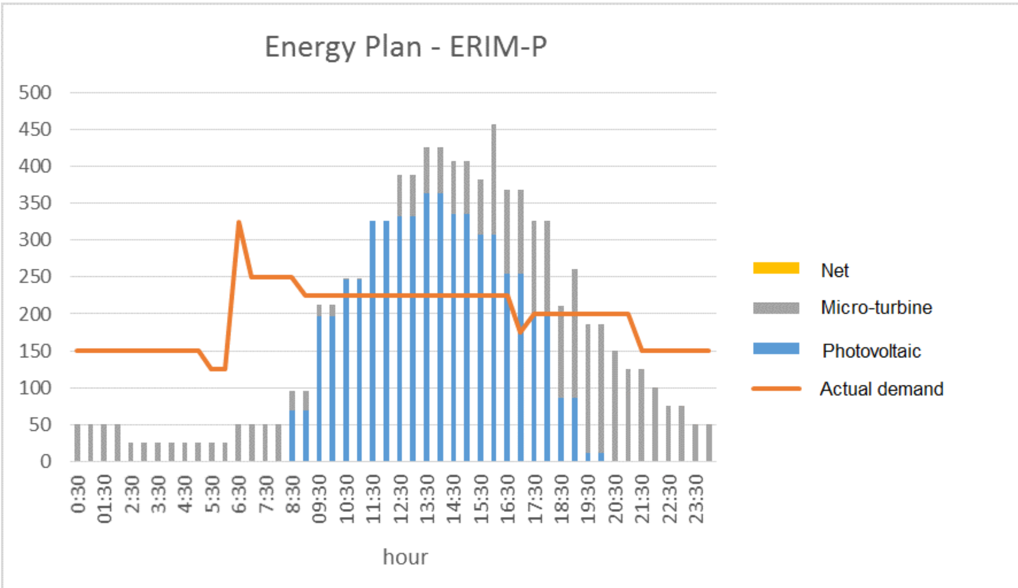

Fig 6.12: ERIM-P output for Scenario DLPL

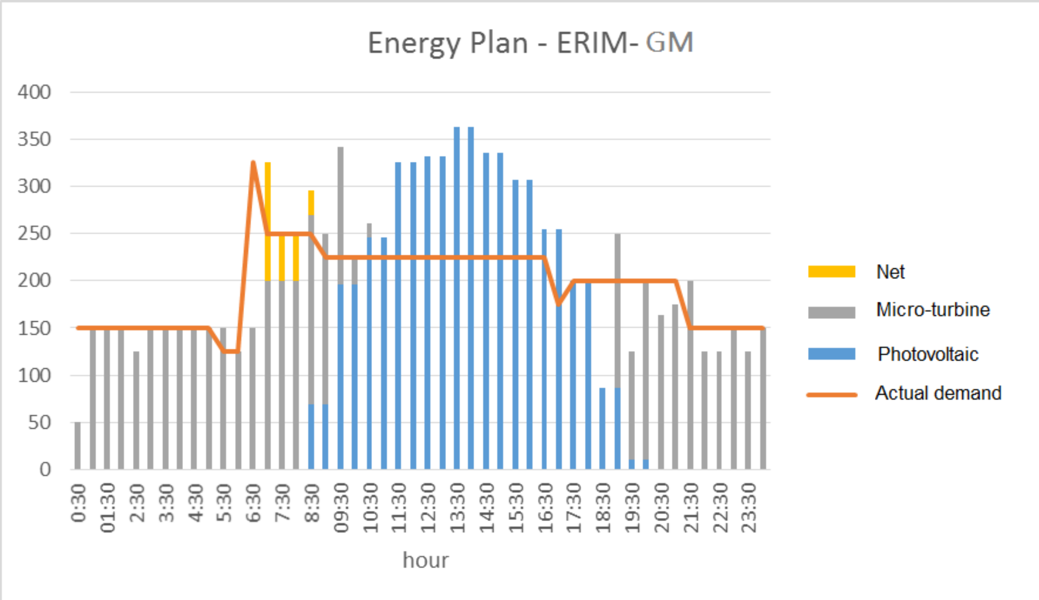

Fig. 6.13: ERIM-GM output for Scenario DLPL

This occurred because the reduced need for energy predicted by ERIM-P caused less planning for the use of the micro-turbine, with the consequent need to instantaneously buy from the electrical energy market, with the consequent increase in costs. Under these conditions, ERIM-GM brought savings in terms of energy costs of about 35% (equal to 355 €/day) compared to ERIM-P.

The benefits to the ecosystem, under these conditions, generated by the use of ERIM-GM consisted in CO_2 emissions reduced by approximately 390 Kg.

Scenario DHPH: in this case as well, the integrated ERIM-GM model was clearly more reliable, since it reduced to one-quarter the predictive error for electrical energy (approximately 1,000

kWh compared to 4,000 kWh predicted by ERIM-P), with an economic benefit of approximately 230 € over 24 hours.
With regard to CO_2 emissions, ERIM-P would involve the production of 2,703 Kg in 24 hours, compared to 1,665 kg for ERIM-RT.

Scenario DHPL: in this case, the utility of ERIM-GM was even greater. This was because with a ΔkWh of 6,600 kWh for ERIM-P, the ΔkWh of ERIM-GM was only 700 kWh. In terms of CO_2, with ERIM-P the emissions were equal to 3,800 kg, while ERIM-GM allowed a reduction of 1,000 kg.

6.4 Results' analysis

With reference to the test cases conducted on the tannery, the results illustrated showed that, in the application phase, ERIM-GM allowed obtaining significant improvements in real time estimates, for both daily energy demand schedule and actual photovoltaic production (with consequently more efficient planning of self-production with micro-turbines and/or purchasing from suppliers). In demonstration of this, in the four combined high-variability scenarios examined for Scenario 3 (DLPL, DLPH, DHPL, DHPH), a clear improvement in energy performance in terms of error reduction, CO_2 emissions and energy costs was obtained.

The higher the deviations between the prediction made the previous day and the actual profiles were, the more effective ERIM-GM was. This was because the tannery, like any other manufacturing system, was characterized not only by stochasticity, reasonably predictable by probability density functions, but also by randomness. For this reason, the more the behavior of the tannery was affected by randomness (in terms of demand versus energy production), the more the use of ERIM-GM became essential. This was also demonstrated by the two sub-scenarios DLPL and DHPL. In fact, in these cases, ERIM-GM led to improvements in predictive performance respectively 7.3 and 7 times greater than the ones obtained with ERIM-P model.

6.5 Discussion

In this Chapter a supporting tool for energy managers in manufacturing sector is presented. It used a DES model (online and online real time), Monte Carlo simulation and a special predictive algorithm. The major target was the optimization of the energy supplying mix (self-production from renewable and not renewable sources and/or purchase on the electricity market) to minimize CO_2 emissions and total costs.

The major contribution of the proposed approach was the methodology. It used the ERIM-P data prediction and combined it with a ERIM-RT real time data of manufacture plant and weather conditions, using special predictive algorithm to correct the projection of the data required.

The real application presented, related to an Italian tannery, demonstrated that the proposed approach, thanks to the integrated and optimized management of RES and non-RES production sources, could provide consistent benefits for energy savings and consequently environmental emissions.

Chapter 7

Conclusions

Renewable Energy Sources are becoming increasingly important all around the world. Different themes and research areas are developing in this field because of the large amount of opportunities connected to RES exploitation.

These opportunities are also linked to several criticalities (like the difficulty in financing due to the uncertainty of the economic-financial performance) from which different challenges arise. Creative strategies are, then, necessary to support the development of this sector.

In this thesis, some critical aspects have been considered: the investments' economic evaluations focused on the peculiarities of this sector; the economic analysis used as a support during the construction phase of renewable energy installations; the location identification for new plants maximizing the economic investment and the definition of co-existence logics between traditional and renewable energies.

Economic sustainability analysis allows to understand the real plants' sustainability and to identify the factors that have the main roles in their development.

The proposed use of RSM to reach this aim has shown that it is possible to identify which parameters are really able to impact on the results and to find out the regression meta-models that describe the behavior of the financial result.
This approach allows obtaining a dynamic investment analysis that can be applied to different systems.

The economic analysis methodology supporting the construction phase is based on a renewable energy investment evaluation approach that allows choosing the plant components in accordance with the investment objectives.
The proposed methodology, based on Monte Carlo methodology combined with RSM, enables the design of a plant configuration that generates the best economic return over the plant entire life cycle.

The problem of maximizing the economical results and of defining the plant locations for a multi-site investment is addressed through a stochastic approach based on a number of methodologies that come, in part, from literature (RSM, DOE, Simplex Method, Steepest Ascent) and, in part, specially structured.
The proposed approach leads to the identification of both sites and sizes of higher performance, based on the economic

availability, and to the estimation of the CO_2 release reduction in terms of environmental viability.

The definition of co-existence logics between traditional and renewable energies is based on a DES model (online and online real time), Monte Carlo simulation and on a special predictive algorithm. The logic combines industrial users' instantaneous energy needs with the RES production capacity, supplemented, when necessary, by self-production and/or acquisition from third-party suppliers.
In this way it is possible to obtain the optimization of the energy supplying mix (self-production from renewable and not renewable sources and/or purchase on the electricity market) to minimize CO_2 emissions and total costs.

All these themes have been approached by defining the problem aspects, by identifying the methodology steps and methods and, then, by applying the methodology to a significant test case in order to evaluate its capability to lead to significant results.

Thanks

The PhD is one of the most demanding courses, not only for its extension over time or for the constant effort it requires, but especially because it is a course in which you choose to put yourself personally in play. In this experience, professional growth is an important challenge but it is also necessary to develop soft skills to deal with reality and situations, both academic and non-academic, which are changing and uncertain.

At the end of these three PhD years, I would like to thank all the people who, in various ways, have supported me in this experience and without which this thesis would not have been possible.

First of all, I want to thank Prof. Roberto Mosca for having always been available to offer me his precious theoretical and methodological contribution, during all the steps of my research work, and for having always worked to propose me constructive experiences useful to my growth as a research doctor.

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I thank all my Italian and international friends on whom I have always been able to rely every day.

Last but not least a sincere thanks to my parents who have supported the most important personal and professional choices of my life and who have always pushed me forward on my way.

References

[1] Box G.E.P., Draper N.R., Empirical Model- Building and Response Surfaces, *John Wiley and Sons, Inc,* 1987.

[2] Myers R.H., Montgomery D.C., Response Surface Methodology, *John Wiley and Sons, Inc*, 1985.

[3] Montgomery D.C., Design and Analysis of Experiments, *John Wiley and Sons, Inc*, 1997.

[4] Myers R.H., Montgomery D.C., Response Surface Methodology, Process and Product Optimization Using Designed Experiments, *Wiley-Interscience*, 1995.

[5] Montgomery D.C, Design and Analysis of Experiments, *Wiley*, 2005.

[6] Bendato I., Cassettari L., Mosca M., Mosca R., A Design of Experiments/Response Surface Methodology Approach to Study the Economic Sustainability of a 1 MWe Photovoltaic Plant, *Renewable and Sustainable Energy Reviews*, 51, 2015, pp. 1664-1679.

[7] Cicea C., Marinescu C., Popa I., Dobrin C., Environmental efficiency of investments in renewable energy: Comparative analysis at macroeconomic level. *Renewable and Sustainable Energy Reviews*, 30, 2014, pp. 555-564.

[8] Cucchiella F., D'Adamo I., Estimation of the energetic and environmental impacts of a roof-mounted building-integrated photovoltaic systems, *Renewable and Sustainable Energy Reviews,* 16, 2012, pp. 5245-5259.

[9] Cucchiella F., D'Adamo I., Koh L.S.C., Environmental and economic analysis of building integrated photovoltaic systems in Italian regions, *Journal of Cleaner Production*, 98, 2015, pp. 241-252.

[10] Paudel A.M., Sarper H., Economic analysis of a grid-connected commercial photovoltaic system at Colorado State University-Pueblo, *Energy*, 52, 2013, pp. 289-296.

[11] Peerapong P., Limmeechokchai B., Investment incentive of grid connected solar photovoltaic power plant under proposed feed-in tariffs framework in Thailand, *Energy Procedia*, 52, 2014, pp. 179-189.

[12] Spertino F., Di Leo P., Cocina V., Economic analysis of investment in the roof top photovoltaic systems: A long-term research in the two main markets, *Renewable and Sustainable Energy Reviews*, 28, 2013, pp. 531-540.

[13] Stevanovic S., Pucar M., Investment appraisal of a small, grid-connected photovoltaic plant under the Serbian feed-in tariff framework, *Renewable and Sustainable Energy Reviews*, 16, 2012, pp. 1673-1682.

[14] Mahesh A., Jasmin K.S.S., Role of renewable energy investment in India: An alternative to CO_2 mitigation, *Renewable and Sustainable Energy Reviews*, 26, 2013, pp. 414-424.

[15] Dusonchet L., Telaretti E., Comparative economic analysis of support policies for solar PV in the most representative EU countries, *Renewable and Sustainable Energy Reviews*, 42, 2015, pp. 986-998.

[16] Talavera D.L., Munoz-Ceron E., de la Casa J., Ortega M.J., Almonacid G., Energy and economic analysis for large-scale integration of small photovoltaic systems in buildings: The case of a public location in Southern Spain, *Renewable and Sustainable Energy Reviews*, 15, 2011, pp. 4310-4319.

[17] Ren H., Gao W., Ruan Y., Economic optimization and sensitivity analysis of photovoltaic system in residential buildings, *Renewable Energy*, 34, 2009, pp. 883-889.

[18] http://www.qualenergia.it/articoli/20140625-taglia-bollette-con-spalma-incentivi-il-testo-pubblicato-gazzetta-ufficiale

[19] Bendato I., Cassettari L., Rolando F., Mosca M., Mosca R., Stochastic techno-economic assessment based on a Monte Carlo simulation and the response surface methodology: The case of an innovative linear Fresnel CSP system, *Energy*, 101, 2016, pp. 309-324.

[20] Bakos G.C., Parsa D., Techno economic assessment of an integrated solar combined cycle power plant in Greece using line-focus parabolic trough collectors, *Renewable Energy*, 60, 2013, pp. 598-603.

[21] Chandel M., Agrawal G.D., Mathur S., Mathur A., Techno-economic analysis of solar photovoltaic power plant for garment zone of Jaipur city, *Case Studies in Thermal Engineering*, 2, 2014, pp. 1-7.

[22] Horn M., Fuhring H., Rheinlander J., Economic analysis of integrated solar combined cycle power plants. A sample case: The economic feasibility of an ISCCS power plant in Egypt, *Energy*, 29, 2004, pp. 935-945.

[23] Hosseini R., Soltani M., Valizadeh G., Technical and economic assessment of the integrated solar combined cycle power plants in Iran, *Renewable Energy*, 30, 2005, pp. 1541-1555.

[24] Morin G., Derschb J., Platzer W., Eckd M., Häberlee A., Comparison of Linear Fresnel and Parabolic Trough Collector power plants, *Solar Energy*, 86, 2012, pp. 1-12.

[25] Varun, Bhat I.K., Prakash R., Energy, Economics and environmental impacts of renewable energy systems, *Renewable and Sustainable Energy Reviews*, 13, 2009, pp. 2716-2721.

[26] Giuliano S., Buck R., Eguiguren S., Analysis of Solar-Thermal

Power Plants With Thermal Energy Storage and Solar-Hybrid Operation Strategy, *Journal of Solar Energy Engineering*, 133, 2011.

[27] Poullikkas A., Economic analysis of power generation from parabolic trough solar thermal plants for the Mediterranean region—A case study for the island of Cyprus, *Renewable and Sustainable Energy Reviews*, 13, 2009, pp. 2474-2484.

[28] Chong W.T., Naghavi M.S., Poh S.C., Mahlia T.M.I., Pan K.C., Techno-economic analysis of a wind–solar hybrid renewable energy system with rainwater collection feature for urban high-rise application, *Applied Energy*, 88, 2011, pp. 4067-4077.

[29] Falconett I., Nagasaka K., Comparative analysis of support mechanisms for renewable energy technologies using probability distributions, *Renewable Energy*, 35, 2010, pp. 1135-1144.

[30] Cun-bin L., Gong-shu L., Si W., The investment risk analysis of wind power project in ChinaOriginal, *Renewable Energy*, 50, 2013, pp. 481-487.

[31] Guanche R., de Andrés A.D., Simal P.D., Vidal C., Losada I.J., Uncertainty analysis of wave energy farms financial indicators, *Renewable Energy*, 68, 2014, pp. 570-580.

[32] da Silva Pereira E.J., Tavares Pinho J., Barros Galhardo M.A., Negrão Macêdo W., Methodology of risk analysis by Monte Carlo Method applied to power generation with renewable energy, *Renewable Energy*, 69, 2014, pp. 347-355.

[33] Cassettari L., Mosca R., Revetria R., Monte Carlo Simulation Models Evolving in Replicated Runs: A Methodology to Choose the Optimal Experimental Sample Size. *Mathematical Problems In Engineering*, 2012, 2012.

[34] Bendato I., Cassettari L., Mosca M., Mosca R., Williams E., A stochastic methodology to evaluate the optimal multi-site

investment solution for photovoltaic plants, *Journal of cleaner production*, 151, 2017, pp. 526-536.

[35] Cai M., Zou T., Luo P., Li J., Evaluation of simulation uncertainty in accident reconstruction via combining Response Surface Methodology and Monte Carlo Method, *Transportation Research Part C*, 48, 2014, pp. 241-255.

[36] Mangili I., Lasagni M., Huang K., Asayev A. I., Modelling and optimization of ultrasonic devulcanization using the response surface methodology based on central composite face-centered design, *Chemometrics and Intelligent Laboratory Systems*, 144, 2015, pp. 1-10.

[37] Saravanakumar D., Mohan B., Muthuramalingam T., Application of response surface methodology on finding influencing parameters in servo pneumatic system, *Measurement*, 54, 2014, pp. 40-50.

[38] Kadaganchi R., Gankidi M.R., Gokhale H., Optimization of process parameters of aluminum alloy AA 2014-T6 friction stir welds by response surface methodology, *Defence Technology*, 11, 2015, pp. 209-219.

[39] Steihaug T., The Conjugate Gradient Method and Trust Regions in Large Scale Optimization, *SIAM Journal on Numerical Analysis*, 20, 1983, pp. 626-637.

[40] Fletcher R., Practical Methods of Optimization, *John Wiley and Sons*, 1987.

[41] Rykov A., Simplex methods of direct search, *Engineering Cybernetics*, 18, 1980.

[42] Walters F. H., Parker L. R., Morgan S. L., Deming S. N., Sequential Simplex Optimization, *CRC Press*, 1991.

[43] Barton R.R., Ivey J. S., Modifications of the Nelder-Mead Simplex Method for stochastic simulation response optimization,

Proceedings of the Winter simulation conference, 1991, pp. 945-953.

[44] Bendato I., Cassettari L., Mosca M., Mosca R., Energy Resources Intelligent Management using on line real-time simulation: A decision support tool for sustainable manufacturing, *Applied Energy*, 190, 2017, 841-851.

[45] Paolucci M., Anghinolfi D., Tonelli F., Facing energy-aware scheduling: a multi-objective extension of a scheduling support system for improving energy efficiency in a moulding industry , *Soft computing*, 2016, pp. 1-12.

[46] Taticchi P., Garengo P., Nudurpati S. S., Tonelli F, Pasqualino R., A review of decision-support tools and performance measurement and sustainable supply chain management, *International Journal of Production Research*, 53, 2015.

[47] Masa-Bote D., Castillo-Cagigal M., Matallanas E., Caamaño-Martín E., Gutiérrez A., Monasterio-Huelín F., Jiménez-Leube J., Improving photovoltaics grid integration through short time forecasting and self-consumption, *Applied Energy*, 125, 2014, pp. 103-113.

[48] Amrouche B., Le Pivert ., Artificial neural network based daily local forecasting for global solar radiation, *Applied Energy*, 130, 2014, pp. 333-341.

[49] Coelho V.N., Coelho I.M., Coelho B.N., Reis A.J.R., Enayatifar R., Souza M.J.F., Guimarães F.G., A self-adaptive evolutionary fuzzy model for load forecasting problems on smart grid environment, *Applied Energy*, 169, 2016, pp. 567-584.

[50] Pascual J., Barricarte J., Sanchis P., Marroyo L., Energy management strategy for a renewable-based residential microgrid with generation and demand forecasting, *Applied Energy*, 158, 2015, pp. 12-25.

[51] Ghani U., Monfared R., Harrison R., Real Time Energy Consumption Analysis for Manufacturing Systems Using Integrative Virtual and Discrete Event Simulation, *International Journal of Energy Engineering*, 2, 2012, pp. 69-73.

[52] Kouki M., Castagna P., Cardin O., Cornardeau C., An energy-related discrete event simulation approach, *11° congres international de genie industriel*, 2015.

[53] Bendato I., Bonfiglio A., Brignone M., Delfino F., Pampararo F., Procopio R., Definition and on-field validation of a microgrid energy managementsystem to manage load and renewables uncertainties and systemoperator requirements, *Electric Power Systems Research*, 2017, 146, pp. 349-361.