Stochastic techno-economic assessment based on a Monte Carlo simulation and the Response Surface Methodology: The case of an innovative linear Fresnel CSP system

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ABSTRACT

Combining technological solutions with investment profitability is a critical aspect in designing both traditional and innovative renewable power plants. Often, the introduction of new advanced-design solutions, although technically interesting, does not generate adequate revenue to justify their utilization. In this study, an innovative methodology is developed that aims to satisfy both targets. On the one hand, considering all of the feasible plant configurations, it allows the analysis of the investment in a stochastic regime using the Monte Carlo method. On the other hand, the impact of every technical solution on the economic performance indicators can be measured by using regression meta-models built according to the theory of Response Surface Methodology. This approach enables the design of a plant configuration that generates the best economic return over the entire life cycle of the plant. This paper illustrates an application of the proposed methodology to the evaluation of design solutions using an innovative linear Fresnel Concentrated Solar Power system.

Keywords: Monte Carlo Simulation; Response Surface Methodology; Renewable Energy; Stochastic Business Plan; Investment Evaluation; Linear Fresnel Concentrated Solar Power.

List of abbreviations

Fresnel concentrated solar power (CSP)
key performance indicators (KPI)
response surface methodology (RSM)
internal rate of return (IRR)
net present value (NPV)
payback period (PBP)

discounted payback period (DPBP)
levelized cost of energy (LEC)
life cycle cost (LCC)
Monte Carlo method (MCM)
grid-connected photovoltaic system (GCPVS)
stand-alone photovoltaic system (SAPVS)
direct normal irradiance (DNI)
discounted profitability ratio (DPR)
return on investment (ROI),
return on equity (ROE)
project cover ratio (PCR)
mean square pure error (MSPE)
MSPE of the mean (MSPE MED)
MSPE of the standard deviation (MSPE STDEV)
Italian National Agency for New Technologies, Energy and Sustainable Economic Development (ENEA)
probability density function (pdf)
face-centred composite (FCC)
analysis of variance (ANOVA)
cash flows (OFCF)
interest rate (WACC).

List of nomenclature

Net Present Value (NPV): is the algebraic sum of the cash flows over several years of the analysis horizon discounted at an interest rate.
Pay Back Period (PBP): is the point of temporal equilibrium of the cash in and cash out discounted at an interest rate.
Discounted Profitability Ratio (DPR): is the ratio between the net present value and the initial investment.
Internal Rate of Return (IRR): is the interest rate at which the NPV is zero.
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.
Levelized Electricity Cost (LEC): is the price at which electricity must be generated from a specific source to break even over the lifetime of the project.
Return On Investment (ROI): measures, per period, the rate of return on invested money
Key Performance Indicators (KPI): is a business metric used to evaluate factors that are crucial to the success of an organization.
Response Surface Methodology (RSM): is a methodology that explores the relationships between several explanatory variables and one or more response variables.

1. Introduction

This study is part of the FREeSUN[1] project, which is aimed at the design, optimization and construction of an innovative linear Fresnel concentrated solar power (CSP) system.

[1]The FREeSUN project was born in 2009 under the competitive announcement "Industry 2015 – Energetic Efficiency" and financed by the Italian Ministry of Economic Development, for a total amount of 12.5 million Euros. The partnership, coordinated by Fabbrica Energie Rinnovabili (FERA), is composed of companies, universities and Italian research centers (CNR, Polytechnic of Milan, University of Genoa, University of Catania, and University of Florence).

The specific mandate for this study consists of a step-by-step economic evaluation of the technical solutions proposed by the partners at every project phase. The evaluation must be performed in terms of the investment key performance indicators (KPIs), including the stochasticity affecting some of the system variables.

To achieve this goal, the authors created a dynamic and stochastic business plan which, by using the Monte Carlo method, analyses the behaviour of the primary economic variables related to the investment while varying specific technical and performance parameters.

Moreover, using the response surface methodology (RSM) technique, different design solutions are compared, considered both individually and in combination.

Consider, for example, two plant components A and B, each one with different possible alternatives (A_1, A_2,…,A_n and B_1, B_2,..,B_k), as shown in Fig. 1.

The proposed approach, unlike typical deterministic analyses, leads to a regression model as follows:

$$\hat{y} = \varphi(A, B)$$

which is used to describe the behaviour of a single KPI varying the other components.

Therefore, the proposed approach identifies the solution A_iB_j that maximizes (or minimizes) the economic target KPI.

In this way, a techno-economic optimization of the plant is derived, in which all of the possible design decisions are made considering the economic return of the investment.

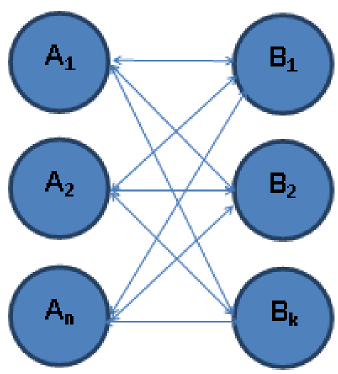

Fig. 1 Factor interaction scheme

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

1.2 Review of the Literature

To date, most techno-economic analyses applied to renewable power plants have focussed 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. They determined the yearly cash flows of the investment, considering all of the connected direct and indirect costs, and calculated the primary financial indexes, such as the internal rate of return (IRR), the net present value (NPV) and the energy production cost. Finally, their paper presented a traditional sensitivity analysis on the effect of the contribution rate on the investment profitability [1].

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 simple and discounted payback period (PBP and DPBP), and the levelized cost of energy (LEC) [2].

M. Horn et al. presented an investment evaluation, determining the NPV and the LEC of an integrated solar combined-cycle system in Egypt [3].

R. Hosseini et al. performed a comparative study of different traditional and solar power plants using the levelized electricity cost as the reference metric [4].

A comparison in terms of the LEC between linear Fresnel and parabolic trough collector power plants was performed by G. Morin et al. [5].

Comparative analyses using the LEC among different renewable electricity generation technologies have been developed by Varun et al. [6] and by S. Giuliano et al. [7].

A. Poullikkas has implemented a parametric study of different parabolic trough solar thermal technologies [8]. For this purpose, a simulation software package was used to analyse the investment in terms of the NPV, the IRR, the PBP and the 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 [9]. They considered the cash flows generated by the investment and 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 [10].

All of the studies mentioned above, while technically valid, provide evaluations that are not exhaustive given the stochasticity that characterizes many of the factors involved. The uncertainty connected to these variables has not been considered in the above-mentioned studies.

For this reason, recently, some researchers have begun to develop studies in the 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. have 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 [11].

Cun-bin et al. have 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 the IRR [12].

Guanche et al. performed an analysis of the uncertainty that influences wave energy farm financial returns. The authors performed a statistical analysis of the IRR, the NPV and the PBP by simulating the life-cycle production. The uncertainty sources considered include the climate conditions, the political environment and current legislation issues [13].

E.J. da Silva Pereira et al. presented a methodology that uses the Monte Carlo method (MCM) 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 [14].

The study presented in this paper belongs to this second research line, i.e., the implementation of the economic analysis in the stochastic regime. This approach is supported by the fact that the investment is by nature characterized by high uncertainty. However, compared to the previous studies, in the current work, a methodology is developed that supports the technical decision makers in the selection of different technological solutions in real time according to the overall economic impact.

An important difference between the previous studies and the current work is that, rather than considering a predefined and fixed structure of a plant, this approach optimizes the choice among different technological solutions to maximize the economic result.

Moreover, the cited papers that applied the Monte Carlo methodology did not use a solid scientific approach to determine the number of simulation runs to be performed (some made 1,000 runs, others 100,000 runs and others do not state the number of runs in the publication at all). There was also no evidence that they measured the experimental error in the simulation results; therefore, they were unable to estimate the tolerance and confidence intervals for the simulation output.

Finally, there was no published evidence of the application of RSM techniques to economically optimize renewable power plants.

The result of this study is a methodology that retains the original vision of the investment and estimates the economic impact of new technological solutions, both singly and combined. The methodology builds on previous studies related to both investment under uncertainty [15,16] and RSM techniques [17-21].

The case study presented in this paper includes the analysis of two specific plant components (the reflecting surface and the absorber tube), for which different solutions are proposed by technology partners during the design phase. Among all of the feasible technological solutions, the proposed approach leads to the selection of the ones that are also economically sustainable.

2. Technical features of the plant

The studied plant is composed of 16 modules. Each module comprises 160 mirrors organized in 8 rows of 20 mirrors in each row. The dimensions of each mirror are 0.6 m by 5.85 m. The features of the plant are shown in Table 1.

Table 1
Plant features.

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

The proposed technology differs from that based on linear parabolic connectors for the use of almost flat mirrors arranged in lines. The mirrors concentrate the light on a linear absorber tube located above the solar field. To compensate for the angular spread, an additional surface is placed above the absorber tube to re-concentrate the solar rays (Fig. 2). The annual efficiency of the solar collector (solar to thermal) is approximatively 42%.

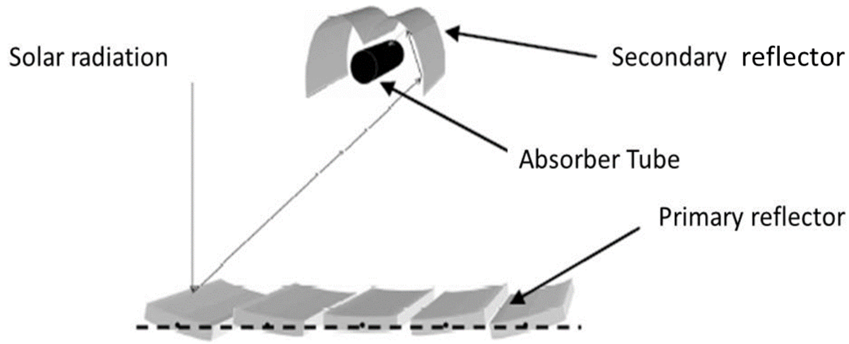

Fig. 2. Plant representation

The heat produced by the solar field is converted to electrical power using an organic Rankine cycle (ORC). A dry and spray cooler is used for the cooling part of the cycle. This cooler is equipped with fans that are usually powerful enough to ensure the heat removal. However, when the external temperature is 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 is 270°C at 55 bar (saturated steam). The thermal to electrical net efficiency at the design point is 23%, with 25°C/35°C inlet/outlet temperature of the cooling water.

The storage time is not long; there is 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 produces low pressure steam with a high conversion efficiency; therefore, the strategy is similar to the sliding pressure mode of a steam Rankine turbine, i.e., it is 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 Fig. 3.

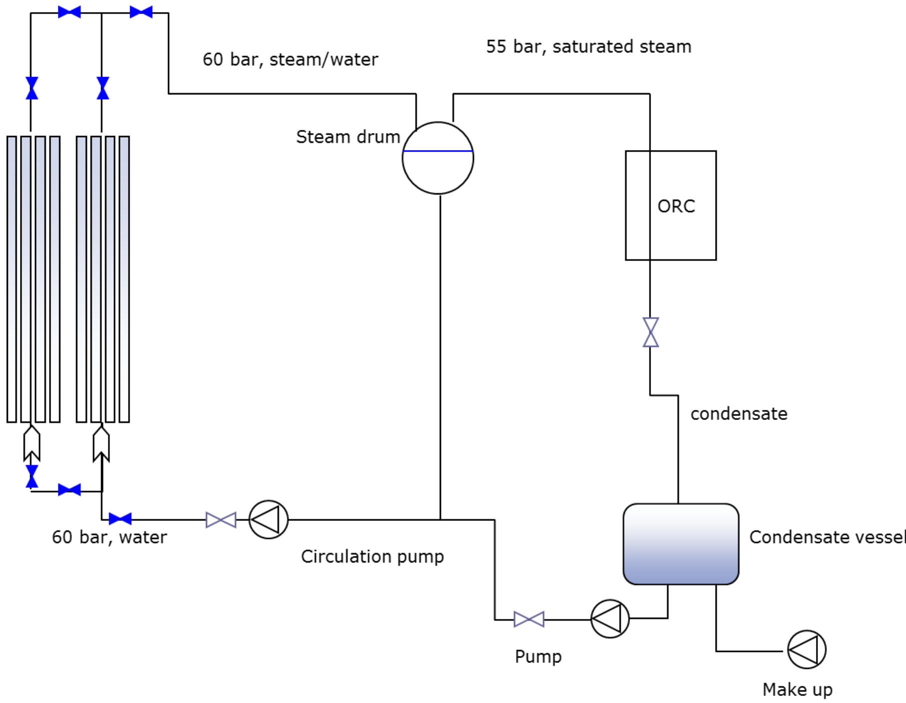

Fig. 3. Plant schematic

The use of limited temperatures allows the minimization of heat loss and a simultaneous increase in the efficiency of the collector.

Water is 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 rotate around their own axes. The support mechanism is on a continuous axis on which the heliostat rotates. It bears 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) offer reduced exposure to wind. However, if the wind strength is not in line with the mirror supports, the mirrors go to their stow position.

Because of these technological features, both investment and maintenance costs are strongly reduced compared to equivalent parabolic plants. However, the average working efficiency is 5-7 percentage points lower than that of parabolic troughs (8-10% versus 15%) [22].

Other performance improvements can 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 project focuses on:

- 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 is studied by using superficial coating and protective painting on the reflective parts and glasses;
- an 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 does not require a vacuum; and
- a tracking mechanism with high accuracy and reliability over time, even in adverse environmental conditions (in the presence of sand).

3. The proposed business plan model

The first phase of the study is the design and creation of a flexible and dynamic business plan model using MS Excel. The model is used to compare different design solutions and to identify the best economic plant configurations.

Table 2
Plant costs: Initial assumptions

	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

The model includes 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.).

The following four types of input variables are identified:

- technical variables: the installed power, the components that are employed, the features of the components, the efficiency, etc.;
- weather-environmental condition variables: the direct normal irradiance (DNI), the parameters defining the wind, etc.;
- regulatory context variables: the amount of governmental subsidies, the duration of the subsidies, etc.;
- economic-financial variables: the cost of the components, the discounted rates, the interest rates, etc. (see Tables 2 and 3);

Table 3
Economic parameters

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

After the input variables are defined in the model, the structures of the income statement, the balance sheet and the financial statement are set up to calculate the KPIs for the economic sustainability of the investment as the NPV, the PBP, the discounted profitability ratio (DPR), the IRR, the return on investment (ROI), the return on equity (ROE), the project cover ratio (PCR) and the LEC (see Appendix A).

These KPIs from the business plan model are arranged into a decisional dashboard (Fig. 4) with visual alerts to provide the decision maker with an at-a-glance summary of a specific technological choice.

Fig. 4. The decisional dashboard

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

In this study, a Monte Carlo simulation tool, @Risk Software of Palisade Inc., is integrated into the business plan model to simulate the behaviour of the input variables and to obtain simulation outputs that are more reliable than those derived from a deterministic analysis. Each output value is associated with a probability of occurrence, thus allowing the decision maker a significant improvement in the level of detail available to use in the decision process.

An important topic in the experimental phase is the response accuracy. To determine the accuracy of the responses, the mean square pure error (MS_{PE}) evaluation method was applied to each financial KPI in replicated runs [23].

Increasing the number of simulations resulted in a better fit to the statistical distributions. The MS_{PE} methodology was used to evaluate both the stabilization phase of the curve and the residual error in the results. The error was controlled by increasing the number of runs because the MS_{PE} approaches zero as the run size increases.

Using this methodology, the sample size of the simulation runs is calculated, which provides an unbiased estimation of the related population parameters, and the effect of the tolerance interval on the result is estimated. For a more detailed analysis, see Appendix B.

The analysis of the NPV index (Fig. 5) shows that after 4000 runs, the MSPE of the mean ($MS_{PE\ MED}$) and the MSPE of the standard deviation ($MS_{PE\ STDEV}$) do not change.

After the correct number of simulations for an accurate solution is identified, any scenario can be analysed using the model.

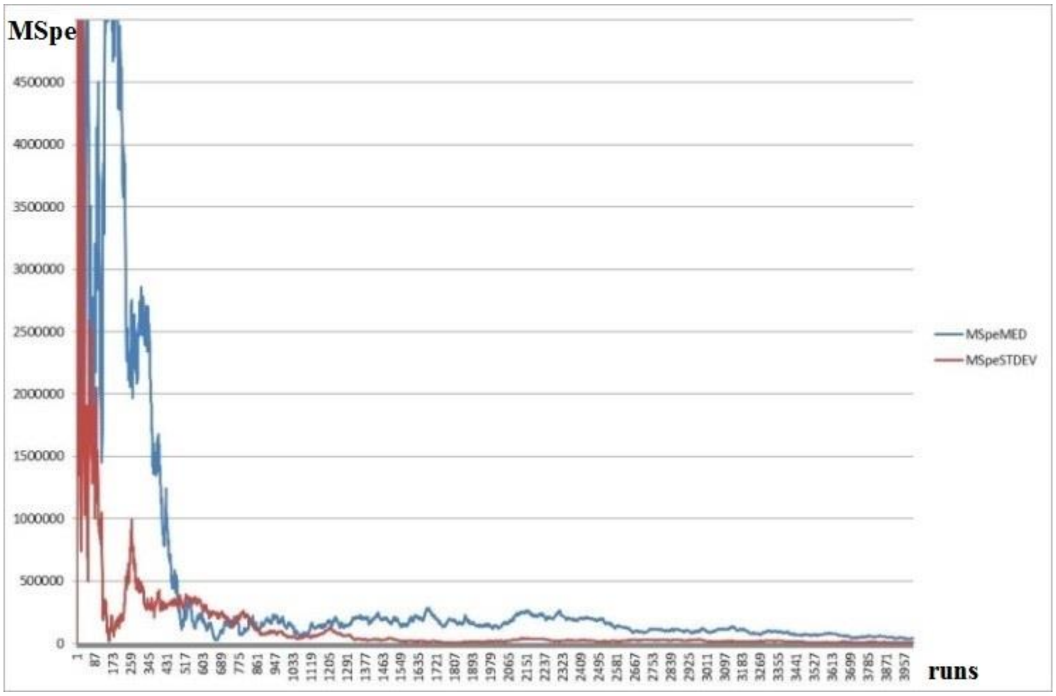

Fig. 5. MS_{PE} evolution curve of the NPV index

In particular, by request of the project leader, 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 Fig. 6, 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.

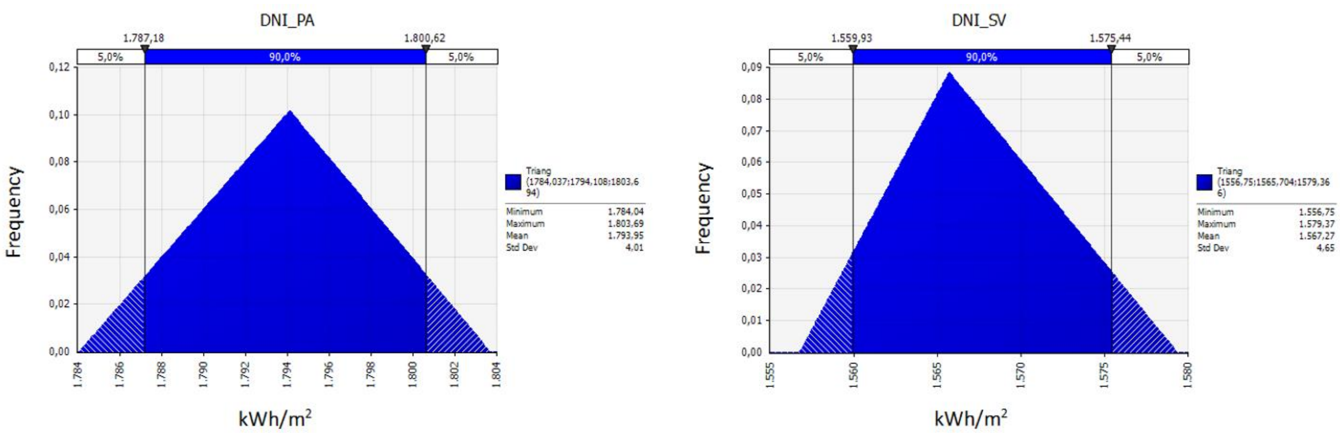

Fig. 6. DNI probability density functions (annual average)

For each site, the KPIs related to two possible technical configurations, one with a high conversion efficiency and one with a lower efficiency (see Table 4), are evaluated.

Table 4
Plant configurations.

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

5.933.183	9,1

Combining the two selected sites with the configurations of Table 2, four economic scenarios are generated as follows:

- 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 scenarios, the business plan model is used to determine the probability density function of the economic KPIs. The kWh price used in this model includes governmental subsidies provided by the third "Conto Energia".

In particular, as an example, Figs. 7-10 show the probability profiles related to the NPV and the LEC.

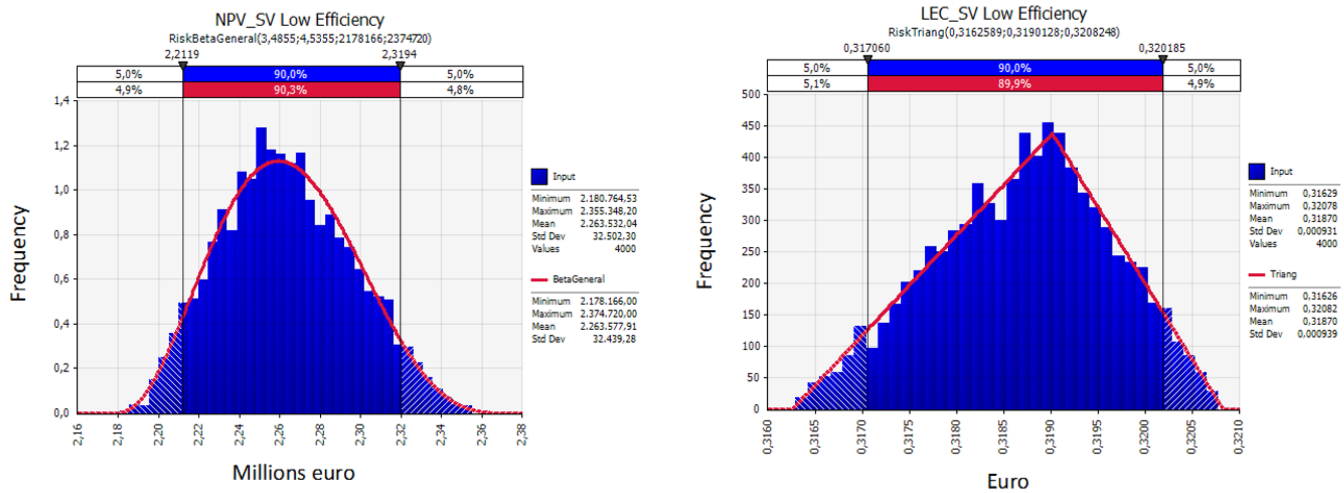

Fig. 7. NPV and LEC for Scenario 1

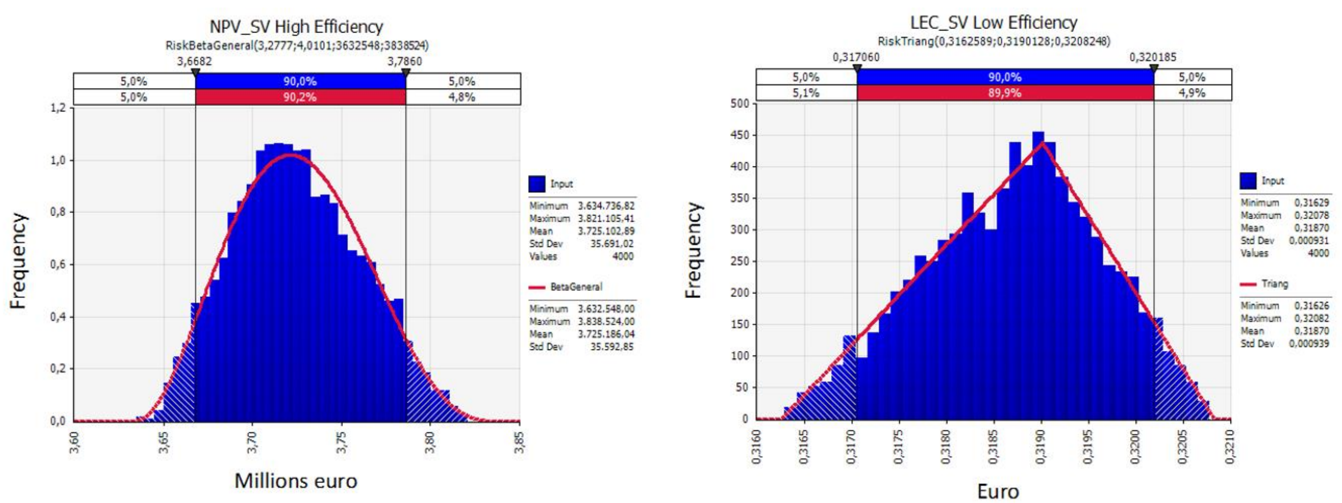

Fig. 8. NPV and LEC for Scenario 2

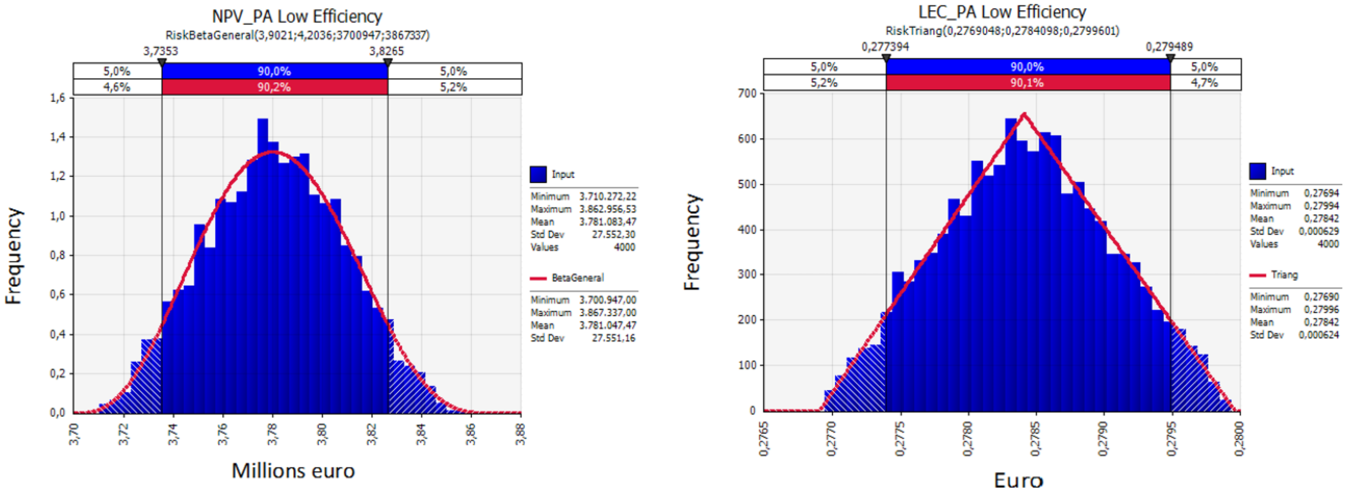

Fig. 9. NPV and LEC for Scenario 3

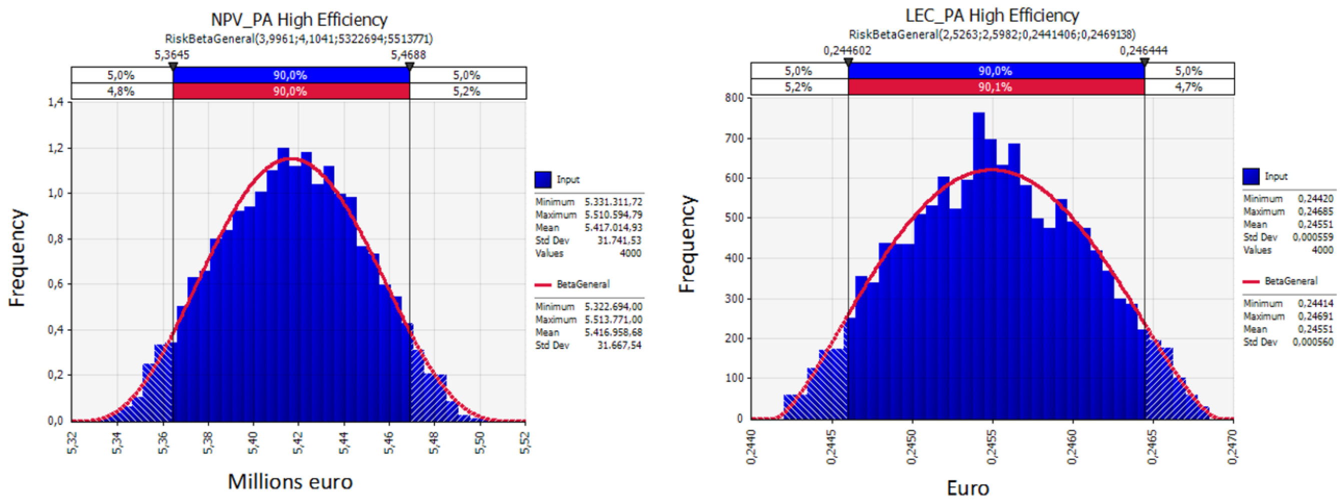

Fig. 10. NPV and LEC for Scenario 4

In Figs. 7-10, the frequency histograms are derived using the business plan model described in section 5. Then, the probability density functions (pdfs), represented by the red curves, are rebuilt. Using a statistical fitting model, the pdfs that provide the best fit are chosen from among those that pass the chi-square test.

The results of the 4 scenarios show that Scenario 4 (Palermo High Efficiency) has the highest NPV (mean value € 5,417,000 with a standard deviation € 31,741), a lower LEC (mean value 0.24551 and standard deviation 6E-4) and a higher DPR (mean value 0.9130 and standard deviation 0.0053). The location of Savona, on the contrary, is not competitive for any of the analysed KPIs. For example, the NPV in scenario 2 (high efficiency) has 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 show that Palermo is the preferred location for the 1 MW experimental plant. Therefore, the remaining analyses refer to the Sicilian site.

4. Technological solution to be analysed

After the business plan is complete and validated using the MS_{PE} technique, the response surface methodology technique is used to compare the available design alternatives.

In particular, sensitivity analyses are 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 is simulated.

4.1 Reflecting surface

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

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

The three technical alternative designs are the following:

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

The normal reflectance used during the simulation is 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 is better than for the thick glass because of a higher flexibility; the difference, however, is slight, approximately 0,5% between the different treatments.

To aid in achieving the goal of this study, which is to create a new investment choice methodology, the technologists have provided a qualitative analysis of the advantages and disadvantages of each type of reflecting surface (Table 5).

Table 5
Advantages and disadvantages of each type of reflecting surface.

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

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

4.2 Absorber tube

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

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

The solar absorbance is 96% for the evacuated pipe and 94% for the non-evacuated pipe.

In the first case (Fig. 11), the absorber tube is surrounded by air contained in the cavity formed by the coupling between the secondary reflecting surface and the horizontal glass plate.

The primary assumptions for this case are as follows:

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

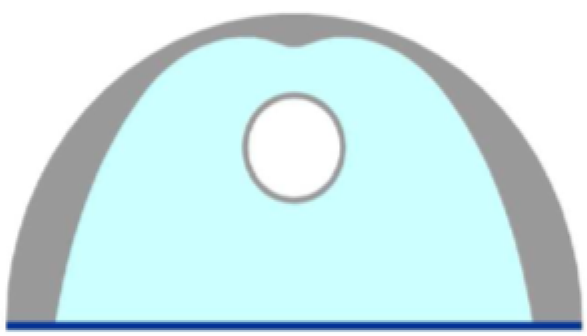

Fig. 11 Tube in air with a glass lock

In the second configuration (Fig. 12), the absorber tube is surrounded by air contained in a coaxial pipe made of glass.

The primary assumptions for this case are as follows:

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

- the absorber tube exchanges with the glass jacket by radiation;
- the boundary surface of the system (glass jacket) exchanges heat through convection and radiation with the external environment.

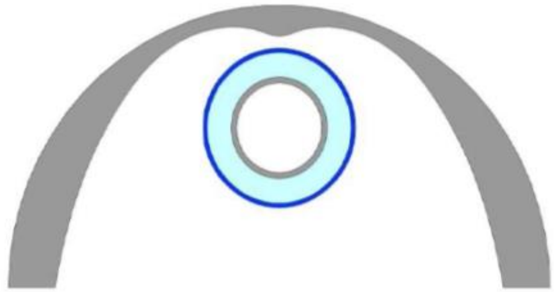

Fig. 12 Tube in air with a glass jacket

In the third case (Fig. 13), the absorber tube is contained in a coaxial pipe (jacket) made of glass and the annular cavity is maintained at a vacuum.

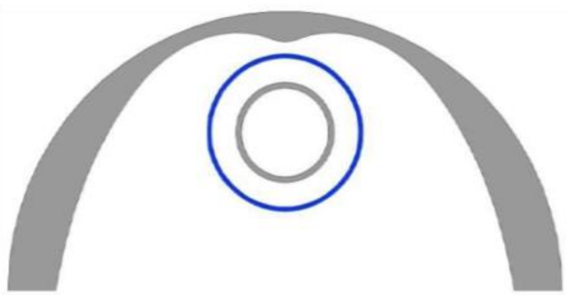

Fig. 13 Vacuum-sealed tube

The primary assumptions for this case are as follows:

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

5. Economic assessment based on RSM

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 components mentioned above.

The first step is 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. This type of design is called a 2^2 factorial design. Four extra central points are 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.) [24]. The scheme of the experimental design is shown in Fig. 14.

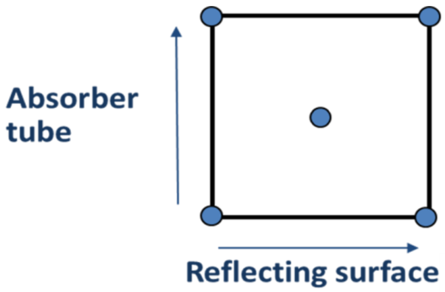

Fig. 14 Scheme of the two-level factorial design

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, are conducted (see Tables 6 and 7). Levels are then assigned based on the cost of the adopted solution. For example, in the case of the reflecting surface, the low level corresponds to the lowest cost, while the opposite is true for the absorber tube, as shown in Table 8.

Table 6
Reflecting surface: Cost assumptions and the resulting impact on efficiency.

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

Table 7
Absorber tube: Cost assumptions and the resulting impact 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 8
Factor levels.

	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

A regression model for the NPV, the LEC and the DPR was then applied.

The results from the experimental campaign conducted on the business plan model provide, for each configuration, the KPIs shown in Table 9.

Table 9
2^2 factorial design: Experimental data.

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

To find the regression model for each dependent variable, the software Design Expert, by Stat Ease, Inc., is used. The 2^2 factorial design provides a first-order meta-model, which does not describe the existing relations between the economic variables and the various technological solutions (see Appendix C).

The following step fits a second-order meta-model using a face-centred composite (FCC) design (see Table 10).

Table 10
FCC design: Experimental data.

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

The scheme of FCC design the reported in Fig.15.

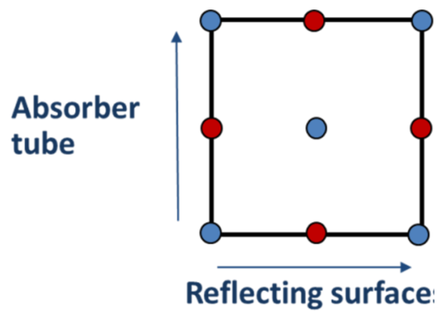

Fig. 15 Scheme of the FCC design

The FCC results for the three variables show that second-order meta-models correctly describe their behaviour. For example, in Fig. 16, the analysis of variance (ANOVA) for the NPV results show that both Fisher's regression tests pass.

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. 16 FCC design: ANOVA results for the NPV

6. Results and discussion

The second-order meta-models and the related response surfaces of the NPV (Fig. 17), the LEC (Fig. 18) and the DPR (Fig. 19) are as follows:

$$NPV= 2.966E006+7.119E005A-5.526E005B-170.69AB+1.738E006A^2+1.367E006B^2-35.73A^2B-7423.68A^2B^2 \quad (1)$$

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

$$LEC=0.30-8.40E-003A+0.013B-0.043A^2-0.033B^2-2.90E-003A^2B+8.375E-003A^2B^2 \quad (3)$$

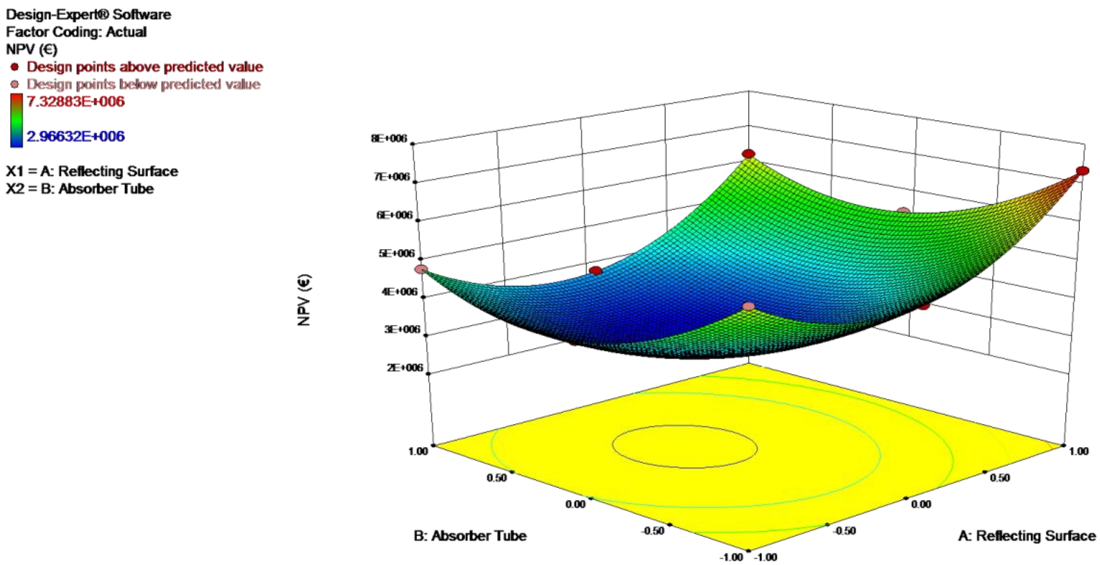

Fig. 17 Response surface of the NPV

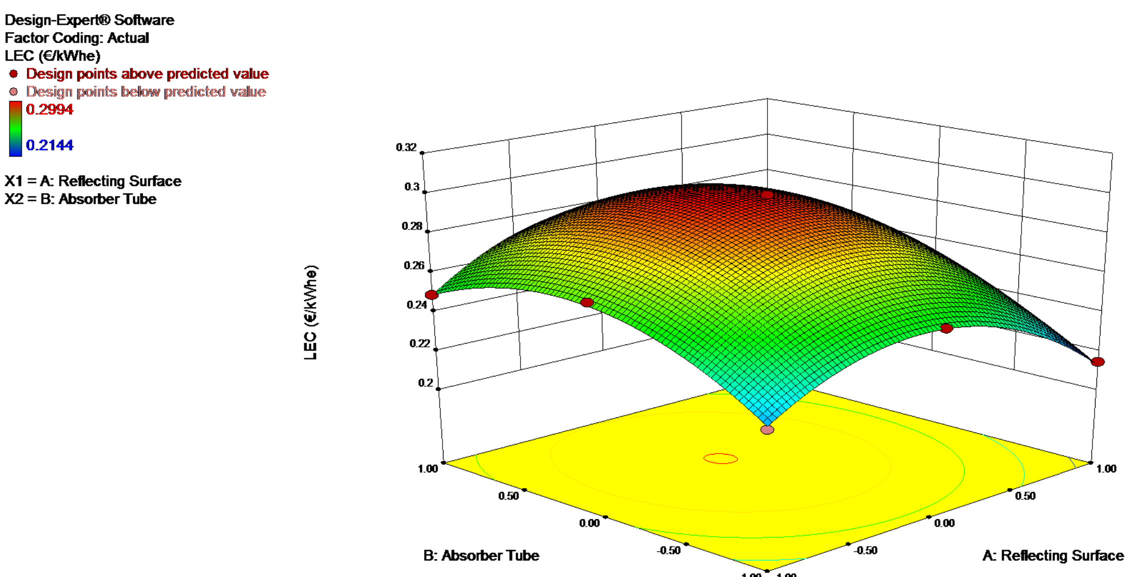

Fig. 18 Response surface of the LEC

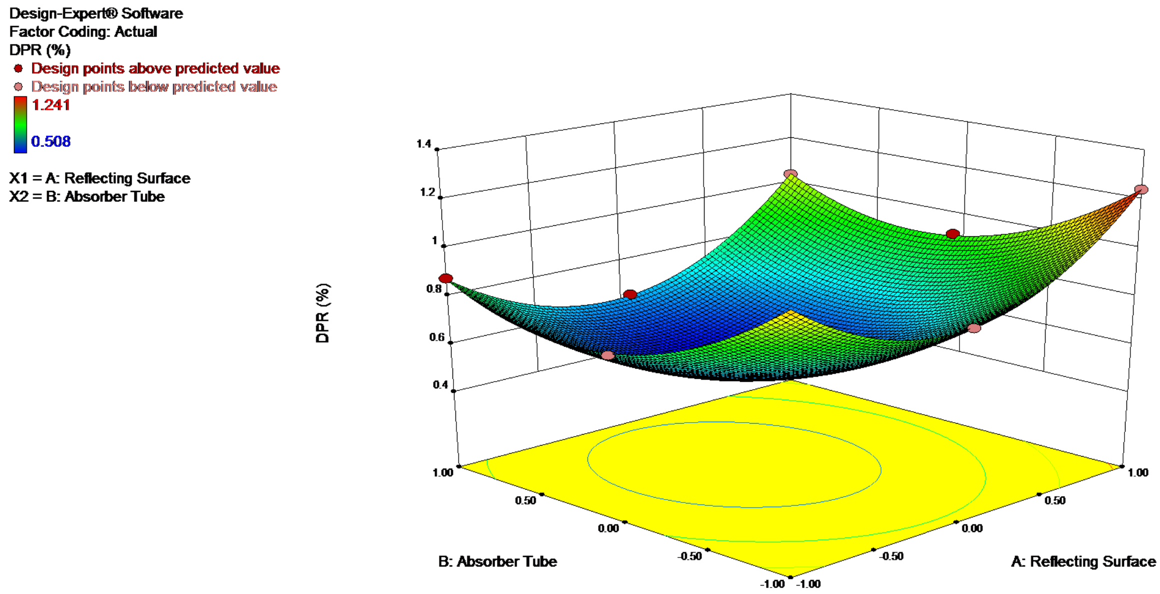

Fig. 19 Response surface of the DPR

The regression meta-model results show that, from the economic point of view, the best technological configuration is the glass reflecting surface with plastic supports and the vacuum-sealed tube. This configuration yields the highest NPV, the highest DPR and the lowest LEC.

It is the high conversion efficiency (10,4%) that most positively influences the result.

On the contrary, the less favourable configuration is 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 (see Table 12 for the related results). That particular solution is less expensive if only the cost of the components is considered. However, a lower conversion efficiency (7,4%) drastically impacts the total production, thus impacting the overall economic result.

The confidence intervals are calculated for all of the regression models (see Tables 11-13).

Table 11

NPV confidence interval 95%

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 12

LEC 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 13
DPR 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

Fig. 20 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 show that the size of the confidence interval on the average response is sufficiently stationary along the entire variability range of factor A (reflecting surface).

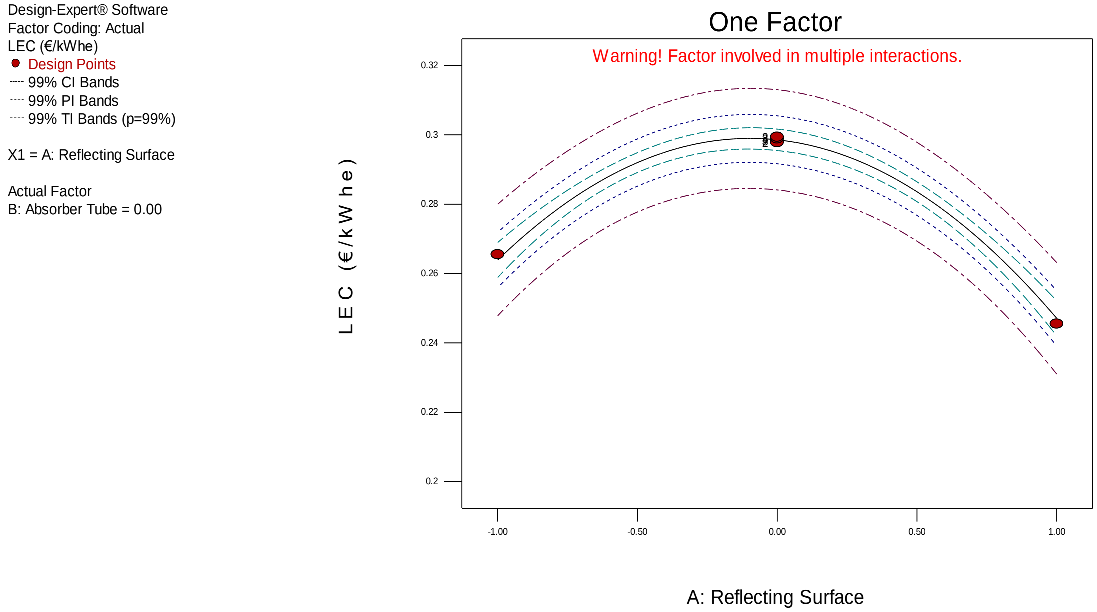

Fig. 20. Confidence intervals for the mean response of the LEC.

7. Conclusions

The paper identifies a methodology for the renewable energy investment evaluation which allows the designer to choose the plant components in accordance with the investment.

In fact the designer, trying to identify the most technologically advanced solution, often the designer is unable to take into account the consequences of the choices on the economic parameters, penalizing the investment overall results.

Consequently, disagreements between designers/construction companies and lenders arise once the plant is built.

Applying the proposed methodology, the designer can protect both himself and the investor in the certainty of achieving the best balance between the plant cost and the technical/economic result.

The Authors have realized that operating in stochastic regime the result precision level is significantly higher than in deterministic regime.

So the Monte Carlo method is used in this methodology. A probability density function and, consequently, the occurrence probability for each possible value of the variability interval, are determined for every economic and financial index. The results are efficaciously organized in a dashboard to provide to the decision makers, at a glance, a complete vision of the investment profitability.

In addition to this phase of preliminary investigation, an economic and comparative analysis of the technological alternatives is performed based on the RSM technique.

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

The case study (the linear Fresnel CSP of the new concept) validates the proposed approach and demonstrates that the technical solution identified by the technology partners would, if implemented, generate a decrease in the investment parameters.

Appendix A

Economic parameters for the evaluation of the investment

The economic parameters used in this study for the evaluation of the investment are listed and defined below. These parameters are calculated in stochastic regime using the business plan model.

Net Present Value (NPV)

The 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) as follows:

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

Pay Back Period (PBP)

The investment pay-back period is the point of temporal equilibrium of the cash in and cash out discounted at the WACC rate as follows:

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

where the PBP index must be determined.

Discounted Profitability Ratio (DPR)

The discounted profitability ratio is the ratio between the net present value and the initial investment. It provides the percentage return of the investment expenditure for the lifetime of the project as follows:

$$DPR\ (\%) = \frac{NPV}{FCFO_0} \times 100$$

Internal Rate of Return (IRR)

The internal rate of return is the interest rate at which the NPV is zero. It is determined using the following equation:

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

Project Cover Ratio (PCR)

The 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 as follows:

$$PCR_t = \frac{\sum_t^n FCFO_t}{Debt_t}$$

Levelized Electricity Cost (LEC)

The LEC 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 the project lifetime: the initial investment, operations, maintenance, cost of fuel, and capital costs.

$$LEC = \frac{Annualized\ Investment\ Expenditure + O\&M + Fuel}{\text{Annual electricity generation } (kWh_e/year)}$$

Return On Investment (ROI)

The ROI metric measures, per period, the rate of return on invested money as follows:

$$\text{ROI (\%)} = \frac{\text{Net profit}}{\text{Investment}} \times 100$$

Appendix B

Role of the mean square pure error in the definition of the correct number of runs for the Monte Carlo simulation

The "goodness" of a Monte Carlo model depends not only on the construction of the model, i.e., the system analysis, the data survey, and the logic transcription, but also on performing a complete experimental activity, which should include the measurement of the experimental error, which is generally a normal distribution (NID (0, σ^2)) (Box et al. 1987, Myers et al. 1985, Montgomery 1997).

The value of σ^2, which can be estimated using Cochran's theorem (Montgomery 1997) through the measurement of the mean square pure error (MSPE), its unbiased estimator, is an intrinsic characteristic of each model and is strictly connected to the investigated reality because it is directly dependent on the overall stochasticity of which this reality is affected. In other words, any object system displays its own level of stochasticity conditioning the behaviours of the output variables and entering in the simulation model, by producing a characteristic error which cannot be set aside. In the experimental phase, the real problem is not the background error, which cannot be eliminated because it is chromosomal in each stochastic system, but the possibility to add to it a second important error source, which, contrariwise, can be controlled and, if necessary, even eliminated. This second source is represented by a number of extractions from random variable distributions in the model inadequate to obtain, in the simulation phase, 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 of the subsequent positive consequences reliability analysis on the model output results.

On the contrary, there are object systems that cannot be managed in the experimental phase according to the MSPE evolution scheme in the simulated time.
This problem occurs each time that 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 not adequate to obtain an effective description of the above-mentioned distributions.
This class includes all of the economic-financial models such as the one described in this paper.
In this case, particular variables, characterizing any following accounting period, are assigned to the form of frequency distributions displaying an uncertainty character growing in time (costs of raw materials, personnel, and services; sale proceeds; transfers; investments; etc.) from those, in the experimental phase, it will be selected, at worst, a single value destined to characterize any specific activity.
The primary difference between this methodology and the evolution time methodology is that, in this case, both the variance of the mean response ($MSPE_{MED}$) and the variance of the standard deviation ($MSPE_{STDEV}$) must be monitored. Using these two parameters, the optimal number of runs to obtain an unbiased evaluation of the experimental error afflicting the objective function can be chosen.
Common sense indicates that a larger sample yields a better description of the population. With this methodology, it is possible to graphically illustrate the evolution of the variance of the experimental error as a function of the sample size. In this way, the experimenter will be able to choose the best ratio between experimental cost and expected results.
In conclusion, the proposed methodology identifies the number of replicated runs required to minimize the error generated by inadequate overlapping of the probability density functions of the variables, with Monte Carlo extraction, according to the needs of the experimenter.
The technique for the MSPE study in the replicated runs can be divided into the following phases:

- fix a number K>2 of simulations, performed in parallel, in which the independent model variables are maintained at the same level, modifying only the triggering seeds of the random numbers. In the case of a single replication factorial experiment or central composite design application, K is equal to the central runs used in the experimental design (recall that the variance of the pure experimental error must be constant in each point of the operability region and therefore in the centre as well as at the boundary).

- for each simulation, establish a number N >>1 of replications y_{ij} with i=1...N, j=1…K

- for each of the K runs, calculate N means $\overline{y_{ij}}$ with i=1,..n..N, where

$$\overline{y_{nj}} = \frac{\sum_{i=1}^{n} y_{ij}}{n} \quad \text{(B.1)}$$

- calculate N means of the means $\overline{Y_i}$ with i=1..n..N as follows:

$$\overline{Y_n} = \frac{\sum_{j=1}^{K} \overline{y_{nj}}}{K} \quad \text{(B.2)}$$

- calculate N values of $MSPE_{MED}$ as follows:

$$MSPE_{MED}(i) = \frac{\sum_{j=1}^{K} (\overline{y_{ij}} - \overline{Y_i})^2}{K-1} \quad \text{(B.3)}$$

where $1 \leq j \leq K$ and $1 \leq i \leq N$.

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

According to Cochran's theorem, $MSPE_{MED}$ 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 distributions of the means.

Figure B.1 shows the $MSPE_{MED}$ concept as a dependent variable dispersion measure:

for each of the K runs, given N replications, a frequency distribution is obtained with a mean $\overline{y_{Nj}}$;

the K means, $\overline{y_{Nj}}$ where $1 \leq j \leq K$, opportunely sampled, produce the mean frequency distribution with a mean of $\overline{Y_N}$ and unbiased variance estimate by $MSPE_{MED}$.

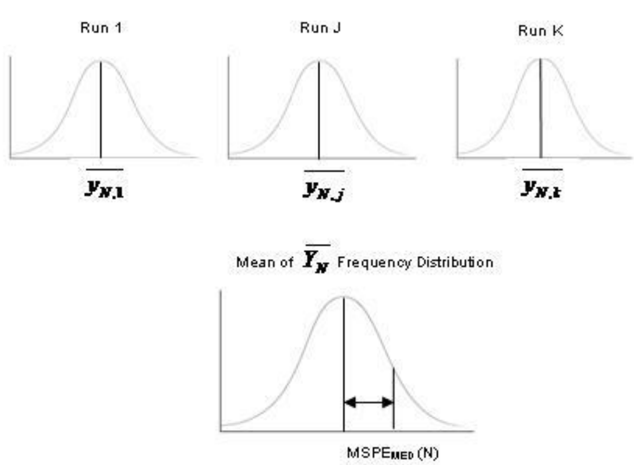

Fig. B.1 ($MSPE_{MED}$ generation display)

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:

$$\overline{stdev_n} = \frac{\sum_{j=1}^{K} stdev_{nj}}{K} \quad . \qquad \text{(B.4)}$$

Then, N $MSPE_{STDEV}$ are calculated as follows:

$$MSPE_{STDEV}(i) = \frac{\sum_{j=1}^{K}(stdev_{ij} - \overline{stdev_i})^2}{K-1} \qquad \text{(B.5)}$$

where 1 ≤ j ≤ K and 1 ≤ i ≤ N.

Each MSPE carries knowledge that yields important inferences as 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* from a single simulation lies in it.
In the time-based evolution systems, usually managing small samples (the K for parallel runs in simulation problems is seldom greater than ten), the generic expression of this interval is as follows:

$$\bar{y} - 3\sqrt{MSPE_{MED}} \le y^* \le \bar{y} + 3\sqrt{MSPE_{MED}} \qquad \text{(B.6)}$$

In the runs-based evolution systems, the following holds:

$$\bar{y} - 3\sqrt{MSPE_{MED}} - 3\sqrt{\overline{VAR} + MSPE_{STDEV}} \le y^* \le \bar{y} + 3\sqrt{MSPE_{MED}} + 3\sqrt{\overline{\mathrm{VAR}} + MSPE_{STDEV}} \qquad \text{(B.7)}$$

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

Moreover, when each of the experimental responses resulting from K parallel runs would have a sufficiently great wideness to allow an exhaustive description of the population behaviour, contrary to what happens for the temporal evolution MSPE, the two MSPE values evolving in the simulations would crash on the axis of the abscissa (MSPE = 0). In this way, the entire stochastic description of the real system, and, consequently, in the model, is represented by the experimental response variance as follows:

$\lim N \to \infty \; MSPE_{MED} = \lim N \to \infty \; MSPE_{STDEV} = 0$

for which

$$\bar{y}_{MED} - 3\sqrt{VAR} \leq y^{*\infty} \leq \bar{y}_{MED} + 3\sqrt{VAR} \qquad \text{(B.8)}$$

For the experimenter, the problem is not to obtain a theoretical MSPE = 0, but to limit the number of runs N 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 to perform in the calculation of the statistical parameters (mean, etc.) of the dependent variable and the number of R survey points of the dependent variable MSPE calculation.
With respect to the number K runs performed in parallel, the interest to choose a high K can be correct. As K increases, the sample for that operation becomes wider. Therefore, the size of K necessarily affects the accuracy of the mean of the dependent variable mean/variance distribution. In many cases, therefore, in spite of the computational power availability, it could happen that, as K increases, the MSPE calculation time rapidly becomes heavy.
To correctly evaluate both the stochastic effect on the experimental response and the characteristic error, it is important to choose N of 104 or greater. With respect to K, most importantly, when it would be impossible to reuse the collected information, for example during the central runs of a composite design, 5-6 replications seem, generally, more than sufficient for a correct estimation of the MSPE evolution and thus of the response confidence interval.

Appendix C

The primary point of the RSM philosophy is to adapt to the problem regression meta-models at an order as low as possible. For this reason, the first adaptation hypothesis is that the reality can be described with a first-order meta-model. This condition must be subsequently verified using the F-test on the regression and the lack of fit F-test. The experimental design which can provide the best-performing first-order meta-model is the 2^k factorial design. In this case, none of the three objective functions taken into account could be described with first-order models as shown, for example, in the analysis of the ANOVA table for the DPR (Fig. C.1).

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	0.061	3	0.020	0.15	0.9275	not significant
A-Reflecting S	*0.021*	*1*	*0.021*	*0.15*	*0.7143*	
B-Absorber T	*0.039*	*1*	*0.039*	*0.28*	*0.6242*	
AB	*9.025E-005*	*1*	*9.025E-005*	*6.499E-004*	*0.9809*	
Residual	0.56	4	0.14			
Lack of Fit	*0.56*	*1*	*0.56*	*37237.41*	*< 0.0001*	*significant*
Pure Error	*4.475E-005*	3	*1.492E-005*			
Cor Total	0.62	7				

Fig. C.1 First-order DPR ANOVA table

In the far right column, the terms "not significant" and "significant" indicate the failure of the F-test on regression and thus the failure of the lack of fit F-test. These data show that a first-order meta-model is not the correct model to describe the objective functions.

Therefore, it is necessary to use a second-order meta-model, formed by adding the four additional design points (the axial points).

The second-order face-centred composite design (used in chapter five) is a good adaptation for all three objectives in this study.

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