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Uncertainty and Reliability of Comparison of Energetic Scenarios

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ABSTRACT

Background: Comparison of scenarios that involve devices for conversion or production of energy needs energetic criteria. Energy Payback Time is a typical energetic parameter used to compare the performances of systems under specific scenarios. To discriminate between scenarios the difference of parameter values is considered. The significance of the difference makes the confidence on the result and the reliability of a comparison, it depends on the difference and its uncertainty. **Objective:** This paper shows and discusses how to evaluate the uncertainty of the difference of parameters, defines a target uncertainty to achieve reliable discrimination. A case study on photovoltaic scenarios is used to apply methodology, commercial modules monocrystalline Si, amorphous Si and polycrystalline Si were considered for comparison. **Results:** Scenarios were compared by their energy payback time. All uncertainty sources were quantified and discussed and energy payback time uncertainty was calculated. Confidence of comparisons was lower than 95% and a target uncertainty was calculated**. Conclusion:** The use of uncertainty approach gives a much more detailed information on comparison. Confidence is the reliability of the comparison. Uncertainty analysis identify the opportunities to reduce uncertainty and enhance confidence in comparison results.

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INTRODUCTION

The energetic sustainability of an energy productive systems and their energetic performances can be compared to choose the most convenient energy production system on the base of energetic criteria and other criteria too. One main challenge for penetration rates of alternative energy systems is the knowledge of variability and uncertainty of data, input and output exhibit variability at all timescales (from seconds to years) and the prediction of the variability itself is not accurate (Pelland *et al*., 2013). The choices based on uncertainty quantification in the sizing procedure of energy systems would get more reliable and economical results, how to quantify the uncertainty is under discussion to get the best performance in comparison and design procedures (Pratt and King, 2010; Parker, 2011; Cho and Fumo, 2012; Pelland *et al*., 2013). Several methodologies to develop a system analysis from an energetic point of view are available to predict energy device systems performance.

The Net Energy Analysis is an available “technique for evaluating energy systems which compares the quantity of energy delivered to society by an energy system with the direct and indirect energy used in the delivery process” (Cleveland, 1992). It allows to identify the sources that provide the best energy yield and to choose the best performing system for fixed source. The available energy, the return of energy, the energy invested and the time for the energy realization must be estimated to perform a Net Energy Analysis by the energetic balance of the energy producing systems on its life time (Herendeen and Bullard, 1975). The Net Energy Analysis or Energy analysis of a system, accounts for all the energy input and salable energy products, this includes the energy investment required to build the system (Shie *et al*., 2011). Energy analyses are not simply an input and output energy balance, they are more scientific, precise, and indicative of the real value and energy-producing capabilities of a system than Economical Analysis (Klass, 1998).

Many parameters can be identified to compare the performance of energy production systems.

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Energy PayBack Time (EPBT), Energy Return on Energy Invested (EROEI) and Net Energy Gain (NEG) are the typical energetic parameters used (Herendeen and Bullard, 1975). Energy payback time (EPBT) was largely used as a final result of LCA analyses (e.g., Alsema *et al*, 1999; Fthenakis *et al*., 2011) definitions are congruent but not exactly the same (Frankl at al., 1998; Alsema *et al*, 1999; Lloyd and Forest, 2010; Fthenakis *et al*., 2011) some difference and vagueness can be found leading to a variability of practical interpretation. IEA Methodology Guidelines on Life Cycle Assessment of Photovoltaic Electricity (Alsema *et al*., 2009) does not give an accurate definition of EPBT. Energy Return on Energy Invested (EROEI) or Energy Return on Investment (EROI), was proposed to compare different sources and energy plants (Murphy and Hall, 2010). EROI and its variants are sometimes called the assessment of energy surplus, energy balance, or net energy analysis (Cleveland, 1992), EROI is not an ordinary conversion efficiency (Gurzenich *et al*., 1999). EROI was initially applied and used to evaluate the energy to find and produce oil (Cleveland *et al*, 2005), it was subsequently used for harvest, and process biofuels (Yu and Tao, 2009). A standard definition is not yet available (Murphy and Hall, 2010). A positive net energy gain (NEG) is achieved by expending or wasting less energy than that coming from a source, solar energy for PV systems, and someone called it Energy Balance (Kaldellis and Sotiraki, 1999). A standard definition is not yet available (Pearce and Lau, 2002). Data coming from different literature sources are often not comparable because the lack of a standard definition makes a variability to calculated data. Furthermore the comparison of literature data fails because the boundary conditions for scenarios they must be aimed to the comparison they are used for. Battery limits, sources conditions, connectivity, geographical position, exposure to environmental conditions are the main boundary condition that must be well stated for the comparison definition.

A reliable discrimination of the values of the calculated performance parameters is strictly necessary to discriminate the scenarios under comparison, i.e., the difference of parameter values must be significant. The significance of the difference is strictly related to its uncertainty, as a simple consideration, if the uncertainty is one order of magnitude lower than the value the sign of the difference is known and it is possible to state which system shows the higher value of the parameter. A criterion of consistency for a comparison must be identified, the criterion have to account for the value and the uncertainty of the difference, statistical tests can help to set a threshold over which the difference is significant (Sprinthall, 2013). The uncertainty of the values of the energetic parameters must be quantified in order to have a reliable comparison of the scenarios.

The life cycle assessment LCA is a fundamental tool to identify and calculate the energy sources related to the system realization operation, maintenance and decommission (Fthenakis, 2010). Available life-cycle studies reported a wide range of primary energy consumption for devices (Alsema,2000; Jungbluth *et al*., 2008; Perpinan *et al*., 2009; Nishimura *et al*., 2010), they mostly stress the environmental concerns, unfortunately very few information are available about the uncertainty of the calculated values. The ISO Guide to the Expression of Uncertainty in Measurement (JCGM 100, 2008) is a useful tool to address the quantification of uncertainty. A budget of the uncertainty is a main toot to identify the most critical source of uncertainty along the calculation of the values of parameters (Sassi *et al*., 2011; Marchi *et al*., 2012).

The aim of this paper is to show a method to analyze the uncertainty of one of the cited energetic parameters for an energy converting device. A method to calculate the confidence of the comparison of energetic parameters values is here proposed. A target uncertainty was identified as the maximal uncertainty that enables to discriminate the scenarios under comparison. Commercially available photovoltaic (PV) plants were here considered, extensive quantities were referred to the unit square meter of PV module surface. As a case study typical commercial PV arrays, monocrystalline Si (mSi), amorphous Si (aSi) and polycrystalline Si (pSi) were considered for the comparison in a specific 1,000,000 people town. A simplified design procedure was used for the case study.

1. Parameter for Energy Analysis:

Definition of Parameter:

Energy Pay Back Time (EPBT) and Energy return on energy invested (EROI) were chosen as energetic parameters. To provide comprehensive and comparable results, a standard verbal definition is necessary, or, at least, an uncertainty must be associated to the lack of definition. Hereafter a precise definition and realization is used for each parameter to reduce variability. Precision reduces variability, on the contrary, over a threshold of complexity, vagueness embodies truth and enhances significance (Zadeh, 1973), in other words the reduction of variability can introduce a unpredictable bias in the results.

Energy Pay Back Time (EPBT) definition comes from the harmonization of available proposals (Frankl at al., 1998; Lloyd and Forest, 2010; Fthenakis *et al*., 2011): “EPBT is the period required for an energy converting device to generate the same amount of primary energy spent to make the device able to produce that energy and to decommission the device”.

Realization of definition of Parameters:

The realization of definition is the mathematical algorithm for calculation, it can introduce a further bias. A rigorous realization of definition of EPBT would involve the integral of instantaneous energy fluxes. Data on energy gain (E_g) are generally available for discrete time intervals (month or year) thus at least a discrete sum is performed while primary energy (E_p) is usually considered as delivered at the beginning of the lifetime. To simplify the model a yearly energy gain averaged on a reference period is considered; expected lifetime is usually considered as reference period. The duration of the reference period on which the energy gain is calculated introduce a bias in the EPBT calculation. Under this assumption the definition of EPBT was realized as:

$$EPBT = \frac{E_p}{E_{g,y}} \qquad (1)$$

Where E_p is the total primary energy demand to get the device able to give the energy gain (E_g) over the whole lifetime and to decommission the device at the end of the lifetime, $E_{g,y}$ is the yearly energy gained averaged over the whole lifetime and t_L is the expected life time. EPBT is time dimensioned it is an intensive quantity, i.e., at a first approximation it does not depend on system dimension.

Realization of component definitions:

Total primary energy demand (E_p) is the total amount of primary energy required for the manufacture, transport, construction, installation, operation, maintenance and decommissioning of the device (Lloyd and Forest, 2010; Fthenakis *et al*., 2011). It can be considered as an energy cost or an energy investment. Six primary energy demands have been identified and are generally accepted (Keoleian and Lewis, 1997; Fthenakis *et al*., 2011): 1. to produce materials comprising system ($E_{p,mat}$); 2. to manufacture system ($E_{p,manuf}$); 3. to transport materials used during the life cycle ($E_{p,trans}$); 4. to install the system ($E_{p,inst}$); 5. for end-of-life management ($E_{p,EOL}$); 6. for operation and maintenance ($E_{p,op-man}$). The PV array was modeled by three unit operations (France and Tony,1990; Klein, 1978), i.e., the photovoltaic (PV) modules, the balance of system (BOS) and the inverter (I). The PV modules convert solar energy in direct current energy. The BOS connects the modules to the inverter, energy is transferred through the BOS by direct current. The inverter converts direct current in alternate current. The contribution of grid connection, transmission and possible energy storage devices was not considered, i.e., the energy gain was calculated from the energy delivered before the grid connection. The primary energy (E_p) is here considered to come from the energy mix of the region in which is spent. Life Cycle Assessment (LCA) is the most used methodology to calculate the primary energy demand for each of the six demands (Alsema *et al*., 2009; Fthenakis *et al*., 2011). Total primary energy demand is the sum of the six portions for each unit operation. Operation and maintenance were considered as primary energy and spent at the beginning of life time.

$$E_p = E_{p,PV} + E_{p,BOS} + E_{p,I} + E_{p,op-man}$$

Energy gain is the energy delivered by the system under study, for a PV devise can be calculated from the effective solar energy (E_t) that hit the panel reduced for the efficiencies and amount of energy spent for each unit operation. Conversion efficiency of PV modules, conversion efficiency of inverters, energy spent for power conditioning and joule effect in wiring were considered, the last two accounts for the BOS. The degradation of PV modules over time is also considered (France and Tony,1990). Five efficiencies were considered to account of total reduction of energy: η_e solar-electric energy conversion in PV panels; η_{vr} CD-AD current conversion; η_{vr} power conditioning; η_w wiring; η_d panel degradation. Total efficiency is the product of all listed efficiencies.

Table 1: Primary input quantities for energetic performance parameters.

Symbol	Description	Unit	Symbol	Description	Unit
ϕ	Longitude	°	$\square_d$	Panel Degradation Efficiency	%
λ	Latitude	°	h_c	Power conditioning device losses	%
K_t	Coefficient	-	h_w	Losses by wiring	%
β	Tilt angle PV Surface	°	h_{vr}	Losses in the DC/AC inverter	%
ρ	Ground reflectivity	-	$E_{p,x}$	Primary energy demand	
E_t	Effective solar energy	MJth/m^2	$E_{p,PV}$	PhotoVoltaic panels	MJth/m^2
T_a	Ambient Temperature	°C	$E_{p,BOS}$	BOS (Balance of the system)	MJth/m^2
h_r	Reference conversion efficiency	%	$E_{p,I}$	Inverter	MJth/m^2
B	Temperature coefficient	°C^{-1}	$E_{p,op-man}$	Operation and Maintenance	MJth/m^2
NOCT	Nominal Operative Cell Temperature,	°C	t_L	Lifetime	years

The conversion efficiency (η_e) depends on operative temperature of the module (T_o). Several models are available to describe the dependency of efficiency from temperature (Skoplaki and Palyvos, 2009) the simplest model for instantaneous efficiency was used:

$$\eta_e = \eta_{e,ref}\left[1 - B_{ref}\left(\mathrm{T_a} - T_{a,r2} + \frac{\mathrm{E_t}}{\mathrm{E_{t,ref}}}\left(\mathrm{NOCT} - \mathrm{T_{a,r1}}\right)\right)\right] \qquad (3)$$

Where NOCT is the Nominal Operative Cell Temperature supplied by the panel manufacturer, $E_{t,ref}$ and $T_{a,r1}$ are the standard conditions at which NOCT is measured ($E_{t,ref}$=800 W/m^2 and $T_{a,r1}$=20°C) (IEC, 2005; 2006), E_t is the effective solar energy and T_a is ambient temperature during operation, $\eta_{e,ref}$ is the reference efficiency supplied by the panel manufacturer and measured at standard conditions (E_t=1000 W/m^2; $T_{a,r1}$=25°C) (IEC, 2008), B_{ref} is the temperature coefficient supplied by the panel manufacturer(IEC, 2008), $T_{a,r2}$ is the reference temperature at which $\eta_{e,ref}$ is measured and T_o is the operating temperature. The average hourly and daily ambient temperature T_a can be calculated by an analytical model (Klein, 1978; Kolhe *et al*., 2003) which considers the monthly average maximum and minimum temperature of the air ($T_{a,max}$, $T_{a,min}$) and the time delay t_p between the minimum and maximum temperature of the day. Historical datasets about monthly temperatures of the air are necessary. Ambient temperature can be calculated hourly from datasets of historical data from maximal and minimal temperature in the month. A monthly average value of the efficiency can be also calculated. Inverter efficiency (η_{vr}), PV power conditioning efficiency (η_c), wiring efficiency due to joule effect ((η_w) and the degradation efficiency (η_d) are supplied by plant manufacturer or the designer.

The yearly energy gain averaged over the whole lifetime can be calculated in different ways depending on the average time that is considered for each quantity, averaging time is rarely reported and can be deducted. Typically E_t, T_a, η_e and η_d are calculated on monthly (equation 4 subscript m) or yearly (equation 5 subscript y) average while η_{vr}, η_c, and η_w are time independent.

$$E_{g,y} = \frac{\eta_c \eta_{vr} \eta_w}{t_L} \sum_{y=1,t_L} \left[\sum_{m=1,12} \left(\eta_{d,m} \eta_{e,m} E_{t,m} \right) \right]$$

$$E_{g,y} = \frac{\eta_c \eta_{vr} \eta_w}{t_L} \sum_{y=1,t_L} \left(\eta_{d,y} \eta_{e,y} E_{t,y} \right)$$

Solar energy hitting the panel (E_t) depends on geographical position (mainly the inclination of sun), weather (the efficiency crossing the atmosphere), time (again the inclination that changes during the day and the year), the orientation of the panels (fixed or variable orientation on 2 axes to adapt to sun inclination), the surroundings (the ability of reflect solar energy of the surfaces around device). Several models are available (Noorian *et al*., 2008; Meteonorm, 2013) they all consider hourly total irradiation incident on a tilted surface is composed of direct, ground reflected and sky-diffuse irradiation. The difference among models is about the description of diffuse radiation. The clearness index (Kt), the tilt and rotation angles ((β, γ) of the panel surface, the latitude (λ) of the device, the Julian day of the year (jd) are the input quantities of the models. Measured data retrieved from literature (ATLAS, 2001-2013) and data calculated by the Liu Jordan model (Liu and Jordan, 1961) were used.

The life time of the whole device is a single evaluation that takes into account obsolescence, degradation, stress, funding opportunities, maintenance (Laronde *et al*., 2012). It is an expected value usually given as a conventional value generally accepted for a specific technology (IEA, 2013).

2. Uncertainty:

The uncertainty of a value could be viewed as a range in which the value is highly expected to fall; uncertainty is a value subjectively chosen on objective knowledge. Quantification and variability are source of uncertainty. Quantification can be done by measurement, estimation, evaluation, calculation or guessing, uncertainty comes from the lack of knowledge and the limit of discrimination proper of the quantification method. A list of main sources is available (JCGM 100, 2008). The uncertainty due to lack of knowledge may be reduced enhancing the information about the system under study. The uncertainty can be reduced by increasing the discrimination ability, e.g., changing the measurement method, by restricting the scenario or by a more precise definition of the system under study.

All primary input quantities, listed in Table 1, must be measured or estimated to perform calculations of EPBT. The first necessary step of any uncertainty analysis is to estimate the uncertainty of quantification of each single primary input quantity. A standard way to estimate the uncertainty of a quantification does not exist, some guidelines are available (NIST, 2000; Bell, 2001; Hässelbarth, 2006; JCGM 100, 2008; Castrup and Castrup, 2010; Ellison and Williams, 2012). All the significant sources must be considered to calculate the total uncertainty at which the value is know, the uncertainty of each primary parameter will be discussed in detail. As a general state, the chosen value of uncertainty should be a rough conservative value, rough means that the order of magnitude and the first digit are the needs of calculation, conservative means that the expected uncertainty is lower than the chosen value.

The uncertainty of a composed quantity, i.e. calculable by models from other measured or estimated quantities, may be calculated by Monte Carlo method or by locally linearly approximated models (JCGM 100, 2008). The uncertainty due to the measurand definition and realization may be reduced enhancing the modeling of the system. A budget of uncertainty may be redacted in order to identify the most critical contributions to the uncertainty. Following the ISO Guide to the Expression of Uncertainty in Measurement (JCGM 100, 2008) the uncertainty of the composed quantity can be calculated by local linear approximation of the model.

$$u^2(\mathrm{y}) = \sum_{\mathrm{i}=1,\mathrm{N}} \left[\mathrm{c}_{\mathrm{Y,i}}^2 \mathrm{u}^2(\mathrm{x_i}) \right] = \sum_{\mathrm{i}=1,\mathrm{N}} \mathrm{w}_{\mathrm{A,i}}$$

Y is the measurand (EPBT), Y=f(X_1,…,X_N) is

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the realization of measurand. Any quantity X_i contribute to the total uncertainty u(y), the contribution of the i-th quantity is a function of its uncertainty $u_i(x_i)$ and its sensitivity coefficient $c_i(x_i)$ of the composed quantity Y, i.e., the partial derivative of Y by X_i. It can be calculated by an analytical method or by a numerical method. The contribution of each quantity is its absolute weight $w_{A,I}$, a significance index $I_{S,i}$ can also be defined as indicator of the importance of the contribution:

$$I_{S,i} = \frac{w_{A,i}}{\max_{i=1,N}(w_{A,i})}$$

$I_{S,i}$=100% indicates the quantity with the most relevant contribution. $I_{S,i}$>10% indicates the quantities with relevant contribution, i.e., same order of magnitude of the most relevant contribution. $I_{S,i}$<1% indicates the quantities with negligible contribution, i.e., 2 order of magnitude less than the most relevant contribution. Relevant contribution means that the contribution must be reduced to obtain a diminution of uncertainty of 1 order of magnitude. The quantities with a relevant contribution ($I_{S,i}$>10%) are the sole opportunity to diminishing the uncertainty of Y, their uncertainty must be estimated with special care. The uncertainty of quantities with a negligible contribution ($I_{S,i}$<1%) can be simply limited under a conservative value.

The list of independent quantities with their unit, value, uncertainty, way to calculate uncertainty, sensitivity coefficient and significant index is here called "Budget of Uncertainty", it contains all the information to discuss about the value, its uncertainty and the opportunity to reduce uncertainty under the target uncertainty. The target uncertainty is the value of uncertainty that is low enough to enable the purpose of the final calculation, as an example that enable to discriminate the values under comparison. Since the complexity of the algorithm a numerical approach was used to calculate sensitivity coefficients. A sensitivity analysis of EPBT on any single input quantity was performed around the average value. The slope around the average value was calculated as sensitivity coefficients.

3. Quantity Comparison:

The comparison of EPBT values calculated for different scenarios is the aim of an energetic comparison. Two EPTB values are different if their difference is large enough, i.e., the probability that a value is greater than the other one is big enough. Uncertainty is considered as the standard deviation of a normal distribution of the measurement or estimation population (JCGM 100, 2008), statistical tests are available in literature to compare different populations of data comparing average values and standard deviations of normal distributions. The simplest method is z test (Sprinthall, 2013) for the null hypothesis, i.e., the two value are the same value. The z score can be calculated as the ratio of the difference of the mean and the standard deviation of the difference:

$$z = \frac{EPBT_1 - EPBT_2}{\sqrt{u^2(EPBT_1) - u^2(EPBT_2)}}$$

From the normal distribution table it is possible to calculate the probability that the null hypothesis is refused, i.e. the level of confidence of the hypothesis "the two values are statistically different". Generally the minimal level of confidence to refuse or accept an hypothesis is 95%, that is $|z| > |z_{95}|$ to refuse the null hypothesis, for $x_1 \neq x_2$ is $z_{95} = \pm 1.96$ (double side), for $x_1 > x_2$ is $z_{95} = 1.65$ (single side), for $x_1 < x_2$ is $z_{95} = -1.65$ (single side) (Sprinthall, 2013).

(7)

A target uncertainty can be calculated as the maximal uncertainty that enable to have a significant difference, i.e., to refuse the null hypothesis at 95% confidence. Since the quantity is the same and the value are close each the same uncertainty can be considered:

$$u_{target}\,(EPTB) = \frac{EPBT_1 - EPBT_2}{z_{95}}$$

4. Scenarios and input quantities uncertainty:

The identification of the differences under investigation is a base of the comparisons, congruent scenario definitions are necessary. The definition of scenarios mainly depends on the aim of the comparison. The reference amount of system depends on expected design specifications. If the available surface area is limited, e.g., available roof in a house quarter or city for a PV system, total surface area occupied by the plant is the reference amount and the comparison have to be done per unit installed area. If the plant is targeted to supply energy need of a specific user the produced energy is the reference amount and the comparison have to be done per unit nominal power. Rarely a scale effect is considered for comparisons, scale effect is thus embedded in the uncertainty of comparison. The actual comparison is about the performances of different panel PV materials, i.e., monocrystalline Silicium (mSi), polycrystalline Silicium (pSi), amorphous Silicium (aSi). The scenarios differ for the solar PV material only. The definition of such materials is not really precise, under the same name a multitude of materials with different performance are available, performance variability is embedded in the uncertainty of comparison.

Lifetime (t_L):

The lifetime of the device accounts for a general aging of the physical system and the obsolescence of technologies. New technologies with higher performance can influence the decision to decommission the device even if it can still work and specific component, especially electronic ones, could be not available anymore for maintenance. The expected lifetime is usually reported between 20 and 30 years, there is not yet consensus on appropriate lifetime for PV systems (Alsema *et al*., 2009); 28 years was considered as lifetime for all scenarios. The nature itself of lifetime as a quantity is highly uncertain because variability of duration, variability of technical choices and lack of knowledge. The lack of knowledge is intrinsic because data cannot be available before than the technology become obsolete. A uniform distribution between 20 and 30 years makes 2.9 years uncertainty (JCGM 100, 2008), 4 years was chosen to embed variability.

Geographical localization:

The definition of the location deals with the variability of the geographical quantities (incident solar energy and ambient temperature). Torino city in Italy was chosen as representative of a 1,000,000 people city in the temperate zone around the 45° parallel. Formally the localization was considered as a rectangular site between 45° 10' 0" North 7°31'East and 44° 57' 0" North 7°46' East. A uniform distribution on the site was considered to calculate the uncertainty (JCGM 100, 2008), i.e., the device was localized in any place inside the site. Latitude: ϕ=45°3'30''=45.06°,u(ϕ)=4'=0.07°=7,5km;
Longitude: λ=7°38'30''=7.64° u(λ)=4'=0.07°=5,2 km.

Effective solar energy (E_t):

Measurement of solar incident irradiation on a tilted surface in different conditions are available (Christensen and Barker, 2001; Noorian *et al*., 2008; Gairaa and Bakelli, 2011; ATLAS, 2001-2014). At 45° latitude, optimal fixed tilt angle and south exposure monthly data can be estimated with 9% uncertainty, the yearly mean can be estimated with 30% uncertainty from available data. Several models to calculate the diffusion energy are available (Noorian *et al*., 2008; Meteonorm, 2013), 12 of them were considered to calculate the uncertainty coming from the realization of the definition of diffusion energy (Noorian *et al*., 2008). The variability of modeling using a uniform distribution (JCGM 100, 2008) is around 4%. The uncertainty of calculation by Liu-Jordan model uncertainty is calculated from the uncertainty of clearness index (Kt), tilt angle PV Surface (β), ground reflectivity (ρ), latitude (ϕ).

Clearness index is a measure of the efficiency of light transport across the atmosphere and it is referred to the solar energy that reaches a horizontal surface at the ground level (Kalogirou, 2009). The NASA database (NASA, 2014) reports Kt monthly average values since 1983, spatial resolution of data is 1° latitude and longitude, measurement uncertainty of data is reported lower than 0.01 (NASA, 2014). K_t mean value and variability on space and time were calculated from the 9 nodes around the site. The mean values ranges in 0.42-0.50 depending on the month of the year. The variability of the monthly mean in one year was around 0.06, the variability of monthly clearness on 30 years observation was around 0.06, the variability of yearly mean was around 0.03. The spatial variability of monthly mean was between 0.04 and 0.08. Clearness uncertainty was considered to be 0.10 combining the worst variability on time and on space and the measurement uncertainty. A more accurate calculation can be done for the single months of the year.

Modules are inclined from a horizontal position by the tilt angle β, the solar energy captured is maximal when the tilt angle put the module to face the sun during the day. A fixed tilt angle was considered, its optimal value depends mainly on longitude (Sayigh and Backus, 1977, Kalogirou, 2003). The optimal value on the whole year was calculated by the Liu-Jordan model (Liu and Jordan, 1961) in the centre of the site. Spatial variability and calculation uncertainty were composed to calculate the uncertainty. Tilt angle optimized on the whole year and south orientation were β resulted 34.5° (34°30') with 0.6° (36') uncertainty.

Ground reflectivity is defined as the ratio of reflected radiation from the ground surface and the incident radiation. The ground reflectivity varies typically from 0.04 for fresh asphalt dark surfaces to 0.8-0,9 for fresh snow (Markvart and CastaŁżer, 2003; Thevenard and Haddad, 2006). Grass is around 0.25, fresh concrete is around 0.55 (Markvart and CastaŁżer, 2003), for urban zone is typically related 0.20 (IBPSA, 2011). The site may be completely considered as an urban zone. The energy reflected by the ground play a significance role for small and separated PV array (Drifa at al., 2008), in the most case for large PV arrays cover or reduce the surface that can be hit by the reflected energy. A triangular distribution between 0.1 and 0.7 with a mode value 0.2 was here considered, 0.12 was calculated as uncertainty (JCGM 100, 2008). The effective solar energy calculated by Liu Jordan model was 6450 MJ/m^{2}yr with a 3% uncertainty. The total uncertainty combines calculation and modeling variability was 5% uncertainty.

Ambient temperature (T_a):

Monthly average maximum and minimum temperature data were retrieved by the last 30 years historical data in Caselle Airport (Turin) (SMAM, 2000). The instantaneous ambient temperature was calculated by a sinusoidal model between a maximal and a minimal daily value (Kolhe *et al*., 2003). For each decade (10 days), a maximal and a minimal temperature are reported as a mean of the maximum or minimal daily temperature measurement in the decade. For each decade of the year the air temperature mean and variability were calculated for minimal and maximal daily values, a uniform distribution in the range measured for that decade along 30 years has been considered. Temperature variability resulted to be in the range 0.4-1.4°C. Single point measurement uncertainty was calculated to be 0.1°C. The total uncertainty for maximal and minimal daily temperature value was considered lower than 1.5°C.

Reference conversion efficiency (B_{ref}) and Temperature coefficient (B_{ref}):

$\eta_{e,ref}$ is the efficiency of a solar cell at the reference condition (IEC, 2008), it depends on the material and process to make the PV cell, the value of the efficiency is usually measured and given by manufacturers (Skoplaki and Palyvos, 2009). The values for PV module efficiency under standard conditions were retrieved from different sources: from manufacturer declarations easily available from internet (Kyocera Solar, China Solar, Anji Technology, Redarc, Sanyo, Solarmax, Sharp, SunEdison, SolarWorld, Sharp, ZED Fabric, Mitsubishi Electric), from literature as typical values for commercial PV (Lloyd and Forest,2010), highest value (Green *et al*., 2012) and technological target (IEA, 2010), they are reported in Table 2. A measurement uncertainty 0.003 to 0.006 was retrieved from literature (Green *et al*., 2012) for standard measurement (IEC, 2008).

Table 2: Reference conversion efficiency ηe,ref available values.

Cell Technology	Manufacturers		Typical	Highest	Technological target		
	Min	Max			2015	2020	2030
mSi	0.133	0.172	0.153	0.250	0.21	0.23	0.25
pSi	0.124	0.166	0.144	0.204	0.17	0.19	0.21
aSi	0.021	0.067	0.065	0.100	-	-	-

mSi = mono-crystalline; pSi = poly-crystalline; aSi = amorphous

Highest values and technological target are far from the manufacturer declarations that agree with typical values. Mean value and variability were calculated considering both a uniform distribution between the maximal and minimal values (any module has the same probability of being chosen) and a normal distribution (the mean is the value of the most probable module in a casual choice). Only the aSi shows a mean really different due to distribution, i.e., difference was around 20%, variability does not show big differences, i.e., same order of magnitude. The normal distribution was chosen, variability and measurement uncertainty were composed to calculate total uncertainty. Table 3 reports the calculated values with the number of manufacturer and module.

Table 3: Reference conversion efficiency ηe,ref: Mean and Uncertainty.

	Manufact.	Module	Mean		Variability		Relative Variability		Uncertainty
			Uniform	Normal	Uniform	Normal	Uniform	Normal	
mSi	6	26	0.153	0.157	0.011	0.008	7%	5%	0.009
pSi	3	61	0.145	0.149	0.012	0.010	8%	7%	0.011
aSi	4	35	0.044	0.036	0.013	0.012	30%	34%	0.013

mSi = mono-crystalline; pSi = poly-crystalline; aSi = amorphous

Table 4: Temperature coefficient Bref (K-1).

	Literature	Manufacturer	Mean	Variability	Relative Variability
mSi	-0.0030 -0.0052	-0.0037 -0.00485	-0.00441	0.00082	19%
pSi	-0.0037 -0.0052	-0.0043 -0.00485	-0.00445	0.00043	10%
aSi	-0.0010 -0.0029	-0.002	-0.00195	0.00055	28%

mSi = mono-crystalline; pSi = poly-crystalline; aSi = amorphous

The temperature coefficient B_{ref} of a solar cell is the relative change of conversion efficiency of the cell when the temperature is changed by 1 K. Its value is related to the ordinary value for commercial PV module and it is given in the module data sheet. The value of B_{ref} depends on the type of material of the cell (del Cueto and von Roedern, 1999; Skoplaki and Palyvos, 2009). The ranges of B_{ref} values found in literature (Skoplaki and Palyvos, 2009) and in the manufacturer declarations as reported in Table 4, data are congruent. Variability has been calculated considering a uniform distribution between maximum and minimum values, since no information is available about other uncertainty sources variability was considered as total uncertainty.

Nominal Operative Cell Temperature (NOCT):

NOCT is the working temperature of the module at reference standard conditions. Standard methods are available to measure the NOCT for crystalline silicon module (IEC, 2005) and for thin film (IEC, 2006). From the detailed analysis of NOCT measurement and calculation (Muller, 2010), a 1.3°C uncertainty can be deducted for NOCT punctual measurement, since a correction of biases is considered it accounts also for variability due to wind and ambient temperature (Muller, 2010). Variability of module absorptivity and glass emissivity by 5% each makes 1.5 °C and 0.5 °C C variation of NOCT respectively (Muller, 2010). Since the heat transport depends on the way in which the modulus is mounted, , the uncertainty due to the bias for installation can be calculated to be around 7°C if no detailed choice on installation is reported (Pellegrino *et al*. 2009). The electric output variability is not considered at all by the model but it plays a very important role in determining the operating temperature of the module (Mutombo and Inambao, 2012). The PVCDROM of the Photovoltaic Education Network (Honsberg and Bowden, 2014) reports that “the best module operated at a NOCT of 33°C, the worst at 58°C and the typical module at 48°C respectively”, it agree with literature data (Pellegrino *et al*., 2009; Sabuncuoglu *et al*., 2012) and manufacturers declarations. Due to the large uncertainty, no significant difference was found between the NOCT value for the three materials under comparison. To account for the unknown sources, measurand definition and measurand realization, 10°C was calculated as combined NOCT uncertainty and 48°C was chosen as average value.

Panel Degradation Efficiency (η_d):

$\eta_d$has been defined in standards (IEC 2005; 2006), it accounts for the PV performance evolution over time because the degradation of the material. Panel efficiency sharply decreases of about 0.02-0.04 in the very first days of exposure (Dunlop *et al*.,2003). After the first week efficiency decrease at 0.003-0.009 per year (Skoczek *et al*. 2009; De Lia *et al*. 2003). Average initial decrease was calculated to be 0.026 with a variability of 0.013 (Dunlop *et al*., 2003). The average value on the life time is 0.893 with 0.03 uncertainty. Uncertainty can be sensibly reduced using data retrieved for the specific module (Skoczek *et al*. 2009).

Losses in power conditioning (η_c) wiring (η_w) and DC/AC inverter (η_{vr}):

η_c is the derate factor for the Mismatch, the Diode and the connections (NREL, 2013), the derate factor for PV module mismatch accounts for manufacturing tolerances. Slight differences yield in current-voltage characteristics of the module which do not operate at its peak efficiency a derate factor between 0.97 and 0.995 was considered (NREL, 2013).The derate factor for losses from voltage drops across diodes and from Joule effect in electrical connections is in the range 0.990 to 0.997, with an average value 0.995 (NREL, 2013). Uniform distribution was considered for all the derates, the average values were multiplied and the variability was composed to calculate the total losses 0.976 and its uncertainty 0.009. η_w accounts for resistive losses in module to module connection and module to inverter connection, it range between 0.97 and 0.99 (NREL, 2013). The derate factor for AC wiring due to resistive registered energy losses, ranges between 0.980 to 0.993 (NREL, 2013). Uniform distribution was considered for all the derates, the average values were multiplied and the variability was composed to calculate the total losses 0.967and its uncertainty0.009. A list of inverters approved by the California Energy Commission (CEC, 2014) was considered to be representative of the available inverters. A normal distribution of efficiency values was considered, a mean value 0.955 with 0.014 uncertainty was calculated. Efficiency accounts for the combined efficiencies of inverter and transformer.

Total amount of primary energy requirement (E_p)

To calculate the total amount of primary energy requirement a LCA (Life Cycle Assessment) may be performed (ISO, 1998; 2006a; 2006b). Following the IEA PVPS guidelines (Alsema *et al*., 2009), a complete Life Cycle Analysis for the energy inputs of the PV system devices under study was performed. Primary energy requirement was calculated from data varying into a reasonable range to account for the vagueness of the scenarios definition and intrinsic variability. The energy mix composition strongly affects the results (IEA, 2013) a vague geographical definition of the site may lead to a very high uncertainty, here a few km wide site was considered.

PV modules ($E_{p,PV}$):

The amount of primary energy requirement for a single module has been largely investigated and reviewed in the last years (Jungbluth *et al*., 2008; Alsema and de Wild-Scholten, 2006; Fthenakis *et al*., 2009; Alsema and de Wild-Scholten 2007; Perpinan *et al*. 2009; Lloyd and Forest, 2010; van der Meulen and Alsema, 2011). Results show a high variability as reported in Table 5. The choices on silicon technology used to produce PV modules and on the fraction of waste materials not accepted for electronic grade, strongly affect the amount of primary energy requirement for mSi and pSi (Alsema 2000, Lloyd and Forest, 2010), this variability and trend are a relevant part of uncertainty (Alsema and de Wild-Scholten 2007). A further relevant source of uncertainty for mSi and pSi come from wafer thickness and wafering losses (Alsema, 1999). Sensitivity analysis confirmed that silicon purification and crystallization processes give the most relevant contribution to the variability for both mSi and pSi modules (Alsema, 2000).

Table 5. Energy requirement for a single module

$E_{i,PV}$	Literature					Calculated for the scenarios				
MJth/m^2	Min	Max	Average	Variability		Min	Max	Average	Variability	
mSi	3300	16500	9900	3811	38%	3450	4120	3785	193	5,1%
pSi	1800	4000	2900	635	22%	2500	3230	2865	211	7,4%
aSi	710	2000	1355	372	27%	970	1250	1110	81	7,3%

mSi = mono-crystalline; pSi = poly-crystalline; aSi = amorphous

The main source of uncertainty for aSi is coming from variability of substrates and encapsulation materials. A minimal uncertainty of 40% is reported in literature for mSi (Perpinan *et al*. 2009). Based on sensitivity analysis and the qualitative information 40% was chosen as relative uncertainty for mSi while 30% was chosen for aSi and pSi when hypotheses on production technology and recycling are not available. When information on production technology and recycling fraction are available the relative uncertainty was considered to be 10%.

Balance Of System ($E_{p,BOS}$):

Little attention has been paid to the LCA studies of the balance of system (BOS), and so inventory data are scarce (Fthenakis *et al*., 2011). Life cycle inventory datasets established six types of photovoltaic mounting systems in compliance with the ecoinvent quality guidelines (Fthenakis *et al*., 2011). The range 500-2000 is reported for a generic BOS (Lloyd and Forest, 2010). A different range is reported for rooftop mounted panels, i.e., 200-1400 (Frankl *et al*., 1998; Jungbluth *et al*.,2008). For ground mounted panels a range 500-1800 is reported (Frankl *et al*., 1998). Uncertainty is then around 30-40%, a uniform distribution was considered. BOS primary energy depends also on the possibility to change the panel orientation and angle. 1100 MJth/m^2 for fixed panels, 2340 MJth/m^2 for two axis and 1400 MJth/m^2 for one axis tracking are reported (Perpinan *et al*., 2009). A variability of 20% have to be considered if the choice is not specified. In the present comparison the same BOS energy requirement can be considered for the different panels since variability is high and the technical solution for different panel material are quite similar. A fixed panel is here considered, 1200 MJth/m^2 were considered as an average value for BOS energy requirement with 30% uncertainty.

Inverter ($E_{p,I}$):

Inverter primary energy demand is reported lower than 1% of the total energy demand (Perpinan *et al*., 2009), i.e., less than 50 MJth/m^2, since the variability of the energy requirement for PV modules and BOS the energy for inverter can be neglected in the sum and the value is takes as uncertainty.

Maintenance and operation ($E_{p.op-man}$):

Primary energy demand for maintenance and operation is widely considered in the LCA assessment of PV systems in different ways as a theoretical approach (Keoleian and Lewis, 1997; Fthenakis *et al*., 2011), however data are not available from literature. Operation energy is zero for many PV installations but some energy is consumed during operation in the case of arrays that have tracking systems (Keoleian and Lewis, 1997). The energy invested in the maintenance and operation was considered as zero in grid connected PV system (Bernal-Agustìn and Dufo-Lòpez, 2006). "This approximation, due to the lack of information about the subject, has been considered to do not alter the results of the EPBT calculations, as the specific energy necessary in the fabrication stage of the components is much greater than that invested in the other" (Bernal-Agustìn and Dufo-Lòpez, 2006). Scheduled Maintenance/Cleaning, Unscheduled Maintenance, Inverter Replacement Reserve are considered to calculate the maintenance costs (Enbar and Key, 2010). Inverter Replacement takes the 50% of the total maintenance cost that is 1-5% of the invested cost (Enbar and Key, 2010) while Inverter take the 7% of the installed cost (Key and Peterson, 2009), it means that the 10 to 40% of inverters are replaced during the lifetime of the whole device. It agree with a 10% replacement every 10 years (Mason *et al*. 2006). Other replacements can happen because unexpected failures or external events, 4 % of maintenance cost accounts for BOS and another 4% accounts for modules (Enbar and Key, 2010) while they account for 7 and 50% of installed cost respectively (Key and Peterson, 2009). It means that 0.5-3% of BOS and 0.1-0.4% of modules are expected to be replaced on the device lifetime. Taking into account the rate of failure and the primary energy for the installed module, BOS and inverter a total maintenance can be calculated, it resulted around 40 MJth/m2 with a 30% uncertainty.

RESULTS AND DISCUSSION

Energy payback time (EPBT) was calculated for the three scenarios, the uncertainty was calculated as combination of the uncertainty sources previously described and associated to the value. A difference can be calculate as a comparison between scenarios, the fastest payback was calculated for poly crystalline while amorphous has the slowest. Uncertainty was calculated around 30-40% mainly due to variability of material definitions.

Table 6: Average value and uncertainty of EPBT of scenarios.

Quantity	Units	mSi	pSi	aSi
mean	yr	2,7	2,2	3,5
u	yr	0,9	0,9	1,2
u_{rel}		33%	41%	34%

mSi = mono-crystalline; pSi = poly-crystalline; aSi = amorphous

Table 7: Probability and target uncertainty of comparison.

Comparison	z	Confidence	Target (yr)
pSi<mSi	0,393	66%	0,30
pSi<aSi	0,867	81%	0,79
mSi<aSi	0,533	70%	0,48

mSi = mono-crystalline; pSi = poly-crystalline; aSi = amorphous.

z score of each comparison was calculated by equation (8) and confidence was retrieved from normal distribution tables, results are reported in table 7. The confidence can be considered as the probability that the EPBT of a specific realization of the device is lower with the selected materials. The target uncertainty is the maximum acceptable value of EPBT uncertainty to have at least 95% confidence. In order to discriminate in all comparison uncertainty have to be reduced at one third of the actual one. An opportunity to reduce the level of uncertainty comes from the most relevant contributions to EPBT uncertainty. Reference conversion efficiency, temperature coefficient and NOCT had the highest values of significance index defined in equation (7). It means that their uncertainties give the most relevant contribution to the EPBT uncertainty.

Enhancing the precision of description of the material the variability of the material performances would be reduced and total uncertainty would decrease. Comparing the best materials of each class the variability of reference conversion efficiency is dramatically reduced, under these scenarios uncertainty would be at around 20% and the confidence for comparison of pSi vs. aSi would be almost 95%.

6. Conclusions:

Uncertainty approach was used to investigate the confidence in a scenarios comparison. Uncertainty indicates the spread of performance for possible devises realization. The confidence express the reliability of the result that is the probability that the higher performance is associate to the scenario that won the comparison. Similar results of comparison may have different degrees of significance due to the different precision of the description of the scenarios. The analysis of the sources of uncertainty helps in the identification of the most relevant sources of uncertainty. The reduction of the relevant contributions is an effective reduction of the EPBT uncertainty. The target uncertainty explicit the goal for the reduction of the uncertainty contributions in order to reach a good confidence in the result of the comparison.

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