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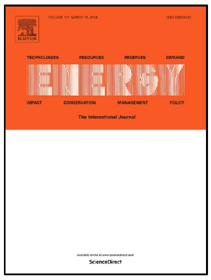

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ON THE USE OF DYNAMIC RELIABILITY FOR AN ACCURATE MODELLING OF RENEWABLE POWER PLANTS

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ABSTRACT

Renewable energies are a key element of the modern sustainable development. They play a key role in contributing to the reduction of the impact of fossil sources and to the energy supply in remote areas where the electrical grid cannot be reached.

Due to the intermittent nature of the primary renewable resource, the feasibility assessment, the performance evaluation and the lifecycle management of a renewable power plant are very complex activities. In order to achieve a more accurate system modelling, improve the productivity prediction and better plan the lifecycle management activities, the modelling of a renewable plant may consider not only the physical process of energy transformation, but also the stochastic variability of the primary resource and the degradation mechanisms that affect the aging of the plant components resulting, eventually, in the failure of the system.

This paper presents a modelling approach which integrates both the deterministic and the stochastic nature of renewable power plants using a novel methodology inspired from reliability engineering: the Stochastic Hybrid Fault Tree Automaton. The main steps for the design of a renewable power plant are discussed and implemented to estimate the energy production of a real photovoltaic power plant by means of a Monte Carlo simulation process. The proposed approach, modelling the failure behavior of the system, helps also with the evaluation of other key performance indicators like the power plant and the service availability.

Keywords: Renewable Energy, Stochastic Hybrid Automaton, Availability, Photovoltaic Power Plant, Service Availability

Nomenclature

Generic Acronyms

GHI	Global horizontal irradiation
IPER	Italian Producer Electrical Regulation
DFT	Dynamic Fault Tree
KPI	Key Performance Indicator
RDFT	Repairable Dynamic Fault Tree
SHyFTA	Stochastic Hybrid Fault Tree Automaton

Photovoltaic Power Plant

ACB	Alternate current circuit breaker
ACD	Alternate current disconnector
ACS	Alternate current section
BAT	Battery
DCB	Differential circuit breaker
DCD	Direct current disconnector
DCS	Direct current section
GCC	Grid connect coupling section
GPR	Grid protection
INV	Inverter
PVM	Photovoltaic module section
PVG	Photovoltaic generator
PVS	Photovoltaic string
SDP	Surge protection (AC section)
SPD	Surge protection (DC section)
SPR	String protection
STB	String box
TRA	Transformer
TRK	Tracker

SHyFTA Parameters

β	Shape factor (Weibull function)
γ	Scale parameter (Weibull function)
λ	Failure rate
μ	Repair rate

BE	Basic event
HBE	Hybrid basic event
Ss^k_i	i^{th} stochastic state of k^{th} basic event: S_k^1: k^{th} basic event working (good); S_k^2: k^{th} basic event broken (bad)
X_i	i^{th} real time variable:
X_{AGING_INVi}	Aging i^{th} inverter
X_{ACGi}	AC Power i^{th} generator
X_{ACS}	Total AC Power generated
X_{CONS}	Power consumed by utilities
X_{DCGi}	DC Power i^{th} generator
X_{TA}	Ambient temperature
X_{GRID}	Power output to the grid
X_{IRR}	Solar irradiance
X_{PVSi}	Power i^{th} photovoltaic string

Physical Process

α	Elevation angle
β	Tilt angle
η	Efficiency
η_m	Solar panel efficiency
η_{first}	Efficiency (first year)
$\eta_{inverter}$	Inverter efficiency
η_n	Efficiency (n^{th} year)
η_{std}	Efficiency (standard condition)
ρ	Power coefficient
A	Photovoltaic panel area
D_r	Degradation rate
E	Energy
G	Global solar irradiance
Irr	Incident solar irradiance
L	Aging
P_k	Power (k^{th} section of power plant)
P_{AC}	Alternate current power
P_{DC}	Direct current power
P_{loss}	Power loss
T_a	Ambient temperature
T_c	Solar module temperature
$T_{c,std}$	Solar module temperature (standard condition)

Stochastic Process

A	Availability
A_{ser}	Service availability
SSA	Steady state availability
U	Unavailability
pdf	Probability density function
P(E)	Probability i^{th} event

1 INTRODUCTION

In the last decades, the renewable energy industry has grown unceasingly and is expected to increase up to 2.7 times between 2010 and 2035 [1]. Renewable energies play a key role in the sustainable development of distributed generation because they contribute substantially to the reduction of the impact of fossil sources, and they are the major alternative for the provision of energy in remote locations where the electrical grid cannot be reached [2], or in agricultural cultivation where their utilization is preferred [3, 4] to diesel generation for irrigation.

Renewable technologies are usually considered to be less efficient than traditional energy conversion systems owing to their intermittency and energy storage difficulties. These properties limit the ability of renewable power plants to fully supply peak-load and base-load [5]. For these reasons, the installation of a renewable power plant can require a complex feasibility study [6] including the following activities: (i) a preliminary evaluation of the installation site so as to determine the availability of the primary resource, (ii) the design and the availability assessment of the power plant, (iii) the estimation of productivity and the policies for the dispatch/storage and (iv) the optimization strategies, including the maintenance plans. While the measurement of the primary resource availability can be performed experimentally with the use of meteorological stations, satellites or other types of instrumentation, the other activities for the design and management (ii)-(iv) are mainly realized using engineering tools based on mathematical models.

An exhaustive feasibility assessment and performance evaluation of a renewable power plant should model the physical process of the energy conversion, account for the variability of the primary resource and its effects on the system availability, model the performance deterioration caused by the fault of the system components, and allow flexible re-design and application of the model so as to estimate the plant performance within a recognized tolerance. Traditional mathematical models for the performance evaluation and feasibility assessment of a renewable power plant do not satisfy all these properties. In fact, they do not consider the performance deterioration occurring during the system lifetime and they do not account for the variability of the primary resource and its effects on the power plant availability. These properties affect the quality of the system from the design stage [7] and influence costs and performance predictions during the life cycle [8-10]. In renewable power plants, this is even more critical because the operating conditions are continuously influenced by the randomness of the renewable resource therefore the production plans and the maintenance strategies must be optimized in order to increase the continuity of service [11].

In this context, there is room to improve the accuracy of the state-of-the-art models. This paper proposes the adoption of dynamic reliability concepts [12] to overcome the limitations of traditional deterministic models and achieve a more realistic description of the process of energy conversions realized by renewable power plants. Dynamic reliability is a well-known modelling paradigm of reliability engineering and it is mainly used to perform the evaluation of the dependability attributes of an engineering system [13] that operates in non-static working conditions.

Dynamic reliability based approaches study the behaviour of complex systems by adopting a model-based approach. This implies dealing with the thermodynamic equations to specify physical processes that affect the health of system components. This methodology requires the definition of the stochastic differential equations of the process and it enables forecasting performances and failures while boundary conditions and independent variables can vary. The main hypothesis of dynamic reliability models is that non-static working conditions affect the operation modes of the system under study and its failure behaviour, e.g. the failure rates may increase or decrease under certain conditions. Traditional mathematical models are not able to capture this dynamic behaviour, therefore the application of dynamic reliability for the feasibility assessment and the performance evaluation of a renewable power plant can provide a valuable benefit.

Among the possible modelling techniques of dynamic reliability, Stochastic Hybrid Fault Tree Automaton (SHyFTA) [14] is well-suited for renewable power plants as it allows an extensible modelling, and a simple definition of reward functions [15] for the performance evaluation and feasibility assessment of a system, spreading from the dependability attributes like reliability or availability to the most important design-related key performance indexes such as the service availability and the productivity of a system. Moreover, a SHyFTA model can be coded and simulated with a general-purpose programming language (like Python, Java, C, etc.) or implemented with a high-level programming language like Matlab.

In this paper a structured approach to design a SHyFTA model for a renewable power plant is presented. The proposed approach is discussed with the aid of a case of study of a real photovoltaic power plant. The model of the power plant is built upon a previous work [16], valid only for non-repairable components and limited to the system reliability evaluation. This works extends [16] by modelling and analyzing repairable components. Additional key performance indexes of repairable systems are computed such as the power plant availability and other design-related metrics like the energy production and the service availability. In order to test the accuracy of the proposed methodology, the results of the SHyFTA and of the deterministic model have been compared with the real data of energy production, collected by the SCADA system of the photovoltaic plant

The rest of this paper is organized as follows. Section 2 gives a brief overview of the state-of-the-art approaches. Section 3 introduces the theoretical background of the SHyFTA modelling approach. Section 4 describes a real case study of a photovoltaic power plant and Section 5 shows and discusses the results of the application of SHyFTA to model other renewable power plants. Finally, Section 6 summarizes conclusions and discusses future work.

2 RELATED WORKS

To the best of the authors' knowledge, previous literature has not yet proposed any modeling formalism which is able to combine in a unified model the deterministic and the stochastic processes that affect the performance of a power plant. However, it is possible to find several works that address the modelling of deterministic and stochastic processes independently. For instance, the design and the study of renewable power plants with deterministic approaches are object of several academic courses and handbooks [17, 18].

The analysis of the effect of the stochastic behavior of the primary resource (e.g., wind, solar, hydro) onto a power plant has been recently addressed [19]. Principle component analysis has been used in [20] to evaluate the wind power generation with respect to the geographic properties of the installation site. In [21] it is stated that the optimization procedures of hydroelectric power plants require the use of techniques able to account for the non-linear behavior of these systems, such as statistical inference methods [22], evolutionary computing algorithms [23] or machine learning techniques [24]. All these approaches are based on data-driven statistical learning methods and they do not model the underlying physical process, i.e. they are purely statistical methods. Moreover, all these works are mainly focused on the randomness of the primary resource and they overlook that the performance of a system will be affected by operational conditions, components failures and, more generally by the system availability that can vary continuously. In fact, availability is an important characteristic of a system because it determines whether or not a system is available and if it is able to perform its tasks. For this reason, this property should not be excluded when evaluating the system performance.

The availability of a system is defined as the probability of a system to operate satisfactorily at a given point in time under stated operation conditions [25]. Availability can be computed for any type of industrial system comprised of different components through quantitative stochastic modelling methods. In [26], Borges reviewed the most important renewable energies (wind, photovoltaic, hydroelectric and biomass) proposing simplified versions of availability models made up of a small set of operational states. In this work, the analysis is limited to the evaluation of the dependability attributes only [25], such as reliability, availability, safety and maintainability. Moreover, it is assumed a constant failure behavior and operation conditions of the system components. This last assumption is common in other works [16], [27-29] in which the mean time to failure of the power plant components are a fixed and independent from the rest of the system parameters.

There have been proposed several modelling methods which can be divided into three groups as shown in Table 1, static, dynamic and hybrid-dynamic models [14, 30].

Table 1: Main characteristics of the models used for dependability assessment.

Static or Boolean models are the simplest models as they are based on combinatorial logic. These models are not computationally demanding because the system structure function can be obtained applying direct Boolean algebra that is not time-dependent [31]. Most of the reliability and risk assessment reports, including many examples of renewable power plants [16], [27-29], [32-35], are still based on static models.

Dynamic models have been introduced to handle temporal dependencies among the system components. In these models, the working conditions are static but the temporal dimension affects the way how the stochastic process evolves. For this reason, the resolution of dynamic models is more computationally demanding than static models and is generally achieved exploiting through analytical and simulation approaches [36]. The application of an analytical method depends on the complexity of the model. In fact, when the system interactions can be described using only the exponential distribution function, the model can be transformed into Continuous Time Markov Chains and solved analytically. Unfortunately, the computational cost in terms of memory usage and time of computation can increase exponentially with the number of components (i.e., state space explosion). In this context simulation-based methods are used so as to model large systems with a variety of probability distribution functions. Simulation-based models avoid the state-space explosion at the cost of increased simulation time.

As displayed in Table 1, both static and dynamic reliability modes are based on the hypothesis that working conditions are fixed so that components can operate into their nominal state of operation (single-state) and can be characterized with a fixed function of failure probability. This is an ideal assumption because environmental factors and operation conditions may change, affecting the performance of the system. In renewable power plants this is even more critical because the operating conditions (and thus the failure characteristics) are continuously influenced by the randomness of the renewable resource.

Hybrid-dynamic models implemented through Dynamic Reliability concepts [12], have been conceived to address the previous limitations and allow the modelling of non-constant failure rates and dynamic operation conditions. In fact, dynamic reliability enables the link between the system operation conditions and the components' failure specification by combining the system's physics-of-operation with the stochastic failure behavior of its components. These models are characterized by two concurrent processes evolving and interacting in time. Therefore simulation is the most suitable approach of resolution for dynamic reliability model. In these models, the computational cost for the specification and analysis of two processes evolving parallel in time can be very high and time consuming.

The main advantage of dynamic reliability is the possibility to address the evaluation of a system both in terms of dependability attributes (reliability, availability and maintenance) and performance (production and other relevant key performance indicators, like the service availability). Several contributions in industrial [37] and nuclear applications have already shown the improved accuracy of this modelling paradigm [14, 38], supported also by other works [39-43] addressing the evaluation of the failure rates with respect to the system working conditions. Unfortunately, the failure behavior of a system component with respect to the system operating conditions is not always known [44, 45] and this represents the most important limitation for the use of dynamic reliability approaches.

To the best of authors' knowledge, dynamic reliability has not been used to model renewable power plant systems. With the application of the SHyFTA, this paper covers this gap and shows the potentiality of dynamic reliability applications.

3 HYBRID-PAIR MODELLING OF RENEWABLE POWER PLANTS: CONCEPT AND IMPLEMENTATION OF A STOCHASTIC HYBRID FAULT TREE AUTOMATON

This section presents the theoretical concepts of hybrid-pair modelling [46] and Stochastic Hybrid Fault Tree Automaton (SHyFTA) [14], with the aim to provide the knowledge-base for designing a dynamic reliability model of a renewable power plant.

Dynamic reliability defines a mathematical framework which is able to combine deterministic (e.g., process of energy transformation) and stochastic (e.g., process of failure of a system) models [12]. Dynamic reliability makes use of non-linear functions to adapt the system failure probability according to the system operation conditions. This leads to more accurate reliability modelling able to account for environmental and operational changes of the working conditions. Moreover, recent works have shown its potential as a tool for the dimensioning of a system [46] and the understanding of other aspects of the life cycle of a system that characterizes the regime operations, like availability and maintenance.

The hybrid-pair approach was conceived to simplify the modelling effort of complex systems and solve dynamic reliability problems. The main assumption of this paradigm is to break the system down into two interdependent processes (deterministic and stochastic), which can interact by means of shared variables. In this way, a change of the deterministic model triggers the stochastic model and vice versa. One of the strengths of the hybrid-pair modelling approach is the ability to combine a dependability assessment of a system with its performance evaluation.

When implementing the hybrid-pair model for renewable power plants, the process of energy transformation operated by the power plant must be broken into two parts as shown in Figure 1: the deterministic block defines the physical equations of the energy transformation whereas the stochastic block models the system failure logic.

A hybrid-pair model can be designed with different software tools like PyCATSHOO [47], DyRelA [48] or coded with high-level software languages (e.g., C, Python or Java). In this paper, the Stochastic Hybrid Fault Tree Automaton formalism is adopted and coded using the Matlab-Simulink environment. The main reason for the adoption of the SHyFTA is that the stochastic model can be described with a repairable dynamic fault tree (RDFT) [49] for an easy implementation and evaluation of the failure model of the system [50].

In the evaluation of renewable power plants, the SHyFTA can improve the accuracy with respect to traditional deterministic approaches because it integrates a stochastic model of the system that accounts for the dynamic evolution of the system, its variables (including the randomness of the primary resource) and the fault and performance degradation states. The benefits of this technique are twofold: system health state tracking and a more realistic estimation of the power plant activities. In the next sections, the SHyFTA formalism is recalled and the steps for the design of a renewable power plant system are pointed out.

Figure 1: Mutual dependency between the deterministic and the stochastic model.

3.1 *Stochastic hybrid fault tree automaton (SHyFTA)*

The formal mathematical formulation of SHyFTA is presented in [14]. In this subsection minimal necessary concepts will be introduced. Interested readers can refer to [14] for more details.

The SHyFTA is a 13-uplet (S, Ɛ, X, Υ, δ, H, G, F, P, GA, BE, T, C), where:

- S is a finite set of discrete states $\{S_D, S_S\}$. S_D is the subset of deterministic states and S_S is the subset of stochastic states.
- Ɛ is a finite set of events $\{Ɛ_D, Ɛ_S\}$, where $Ɛ_D$ is the subset of deterministic events and $Ɛ_S$ is the subset of stochastic events.
- X is a finite set of real variables evolving in time $\{x_1, \ldots, x_n\}$.
- ϒ is a finite set of arcs of the form (s, ε_j, G_k, s') where s and s' are, respectively, the origin and the destination states of the arc k, ε_j is the event associated with this arc, G_k is the guard condition on the real variableXin state s.
- δ: $S \times X \rightarrow (\mathbb{R}^{n+} \rightarrow \mathbb{R})$ is a function of activities, describing the evolution of real variables in each discrete state.
- H is a finite set of clocks on ℝ that identify the firing of a deterministic or a stochastic event.
- F: $H \times S \times X \rightarrow (\mathbb{R}^{n+} \rightarrow [0, 1])$ is a set of applications that associate a distribution function to the stochastic events ƐS, according to the clock H, the system evolution X and the discrete state S.
- P is the instantaneous probability to be in $s_i \in S_S$;
- GA is the finite set of gates of the fault tree model.
- BE is the finite set of basic events of the fault tree model. The set BE contains a subset called Hybrid Basic Events (HBE) whose failure distribution depends on the evolution of the system and varies continuously in time. This type of basic event accounts for the multi-state nature of a component, namely those systems whose failure characteristics are not static in time but vary dynamically according to the operational conditions that, in turn, affect reliability and performance. These events are characterized by a non-static pdf through a set of functions$f_i \in F$, f_i:$H \times S \times X \rightarrow (\mathbb{R}^{n+} \rightarrow [0, 1])$.
- TE is the top event of the fault tree and corresponds with the output of the main gate.
- C is the set of connections between gates and basic events.

To design a fault tree model the designer needs to identify a top-event T, representing an undesired operational condition of the system and its elementary causes. These causes are combined through temporal and logic gates (AND, OR, VOTING k/N, PAND, SPARE, FDEP, SEQ) [49] to define the occurrence of the top-event.

Aging [51] is an important feature of dynamic reliability models and characterizes the wearing-out of complex electro-mechanical equipment, whose performance degrades in time during the lifetime. Traditional reliability models assume an exponential decay [52] that results in a non-realistic description of the degradation process (i.e. components wear out as they are always in operation without any interruption but faults). In order to account for the operation times, aging can be modelled with a Weibull probability density function (pdf), using a shape factor β> 1 (i.e., the failure rate is increasing with respect to time) [53] and the scale parameter γ that definesthe non-constant failure rate, λ(t):

$$\lambda(t) = \beta/\gamma \cdot (t/\gamma)^{\beta-1} \qquad \text{(Eq. 1)}$$

Moreover, the non-linear relationship with the mission time can be described by a piecewise deterministic Markov process, using the following ordinary differential equation:

$$\frac{dL}{dt} = i_{on} \qquad i_{on} = \begin{cases} 1, \text{if the component is switched on} \\ 0, \text{if the component is switched off} \end{cases} \qquad \text{(Eq. 2)}$$

Integrating Eq. (2) and substituting L(t) into Eq. (1) it is possible to rewrite the Weibull distribution with the non-linear aging L(t):

$$\lambda(L) = \beta/\gamma \cdot (L/\gamma)^{\beta-1} \qquad \text{(Eq. 3)}$$

The Weibull probability density function in Eq. (3) can be generalized when the scaling factor γ (L,X,S) is a function of the evolution $X=\{x_1, \ldots, x_n\}$ and state $S=\{S_D, S_S\}$ of the system. In other words, the scaling factor changes with respect to the status and working conditions of the component.

Current hesitancy in the use of dynamic reliability models is mainly caused by the unavailability of exact models of $\gamma(L,X,S)$ which account for all the possible variations of the working conditions [44, 45]. Recently, with the advance of condition-based monitoring techniques, reliability estimations are being improved with up-to-date degradation and operation information [39-43]. In the definition of a fault tree, the SHyFTA model supports both traditional and hybrid basic events. Therefore the application of a variable probability failure distribution function can be limited only to those components for which this information is available. In all the other cases, it is still suggested to use the failure rate provided by the component manufacturer.

3.2 *Design of a SHyFTA model for a renewable power plant*

The main steps for the design of a SHyFTA model are shown in Figure 2. The first activity consists in the study of the power plant and the identification of the discrete components that, with their interaction, realize the process of energy conversion. The complexity of the deterministic process can vary and depends on the amount of detail and interactions modelled. The mathematical equations should describe the contribution of each component at different working regimes. Generally, this representation assumes the form of a balance equation expressed in terms of a set of algebraic, ordinary or partial differential equations.

Figure 2: Steps for the construction of a SHyFTA model.

The main input of the deterministic process is the time-series of the primary renewable resource and of the variables that can affect the process of energy transformation. Table 2 displays the main physical inputs for different renewable technologies.

Table 2: Main physical inputs for different renewable technologies

For the fault tree model, it is important to identify a top-event, representing an undesired operational condition of the system and its elementary causes, the so-called basic events. Basic events must be combined together by the use of temporal and logic gates (AND, OR, VOTING k/N, PAND, SPARE, FDEP, SEQ) and they can be repeated (i.e., they appear two or more times in the fault tree as inputs of two or more different gates) although they represent a unique event within the real system. The discrete components identified in the renewable power plant take place in the stochastic fault tree model. In fact, the failure behaviour of a system component is used to define the probability density functions (pdf) of the time to fail of the basic event in the fault tree. Therefore, the main stochastic inputs of a SHyFTA model are the pdf of the basic events. When the relationships between the system working conditions and the failure behaviour of the corresponding basic event are known, it is possible to characterize the basic event with a dynamic probability density function and, in this case, the basic event is referred as hybrid. Otherwise, the basic event must be characterized with the pdf provided by the component manufacturer that is generally static.

The formulation of the SHyFTA is completed when the stochastic and the deterministic models are coupled through shared variables. Namely, the physical variables that affect the operating conditions of a component (modifying the pdf of a hybrid basic event) are synchronized in the fault tree model. On the other hand, the events occurring in the stochastic model, like the failure of a component are transferred to the deterministic model. In this way the contribution of the failed component is nullified in the physical process of the deterministic model (e.g., an inverter that fails will no longer output AC power).

Although the complete shutdown of a renewable power plant constituted by several generating units is very unlikely, the modelling of this scenario as the Top Event of the fault tree allows the evaluation of several performance indicators. Among them, the instantaneous active and reactive power, the energy production within a time-period and the service availability, A_{ser} that corresponds with the probability of the renewable power plant to produce a base power and guarantee the continuity of service [11, 54] for a well-defined demand curve. These key performance indicators (KPI) can provide important indications for suitable dimensioning of the power plant and the life cycle activities like production plans and the maintenance schedule.

4 CASE STUDY: A PHOTOVOLTAIC POWER PLANT

There have been proposed different fault tree models of renewable power plants that can be used as reference models to build up a SHyFTA [16, 32-35]. In this paper, the case study of a photovoltaic power plant is presented. The analyzed power plant is a grid-connected photovoltaic power plant with no trackers implemented by a private company in 2011, located in Sicily close to Syracuse (see Figure 3 and Table 3).

Table 3: PV system characteristics.

The power plant is characterized by a peak power, P_{peak} = 419,5 kW and by two identical DC/AC inverters of 220 kW_p. There are 4 string boxes for each inverter: 3 accommodate 17 strings and 1 accommodates 18 strings. The strings are connected in parallel while the modules are in series (Figures 4 and 5). Tables 4-5 summarize the main characteristics of the system.

Table 4: PV module main characteristics.

Table 5: Inverter main characteristics.

To be compliant with the Italian Producer Electrical Regulation (IPER) of 2011 (Terzo Conto Energia [55]), the power plant is connected to the national grid. The IPER states that the power plant must stop in case of disconnection from the national grid and forbids the use of energy storage systems. There is a strong economic advantage for adhering to the IPER of 2011. In fact, for the first 20 years of life of the power plant, there is a fixed economic subsidy for all the energy produced. Moreover, the energy not instantaneously consumed by the producer is tracked and sold with a price dictated by the energy market. Therefore, the power plant contributes to the company activities by supplying the internal consumption and providing a profit due to the economic incentive (subsidy) and the sale of the energy not consumed. Table 6 shows the value of the Subsidy (it is fixed by the IPER [53]) and the corresponding price of buy/sell per one kWh of energy. This latter is a rough value of the energy price in the energy market (2011). The column Total is the sum of the previous contributes and it is used to estimate the payback generated by the energy produced by the power plant.

Table 6: IPER 2011 Subsidy. Price* is based on an average value of the energy price in the energy market (2011) [43].

Figure 4 shows the Global Horizontal Irradiation (GHI) in Italy. It suggests the average annual productivity expressed in kWh that one meter square of photovoltaic panels can generate. It is possible to notice that in the area of Syracuse, the GHI is higher than in the rest of the country. In this context, the application of a model that includes possible downtimes and performance degradation can help to better estimate the payback generated throughout the life time of the power plant.

Figure 4: Global horizontal irradiation in Italy.

With reference to Figures5, 6 and 7, it is possible to identify the main components of the photovoltaic power plant.

Figure 5: Map of the power plant and its sections.

Figure 6: Power Inverter configuration.

The components of the photovoltaic power plant can be grouped into the following functional blocks (Figure 7):

1) **PV Module (PVM)**,constitutes the PV module strings of the power plants (PVS);
2) **Direct Current Section (DCS)**, made up of string protection diodes (SPR), DC disconnectors (DCD) and surge protection devices (SPD);
3) **Alternating Current Section (ACS)**,made up of inverters (INV), surge protection devices (SDP) and AC circuit breakers (ACB);
4) **Grid Connector Coupling (GCC)**, made up of grid protection (GPR), an AC disconnector (ACD), a differential circuit breaker (DCB) and a transformer (TRA).

Figure 7: Schematic decomposition of the PV system

Next, we apply the steps discussed in Section 2 to build up the SHyFTA model under the following assumptions:
1- The physical variables, input of the model, are the ambient temperature and sun irradiance;
2- The hourly aggregated samples of the physical variables are extracted by the SCADA of the PV power plant;
3- The randomness of the physical variables is achieved by applying a random seasonal variation component at each iteration of the simulation;
4- It is assumed that the inverter switches on when the output power at the PVM stage is greater than zero (during the daily time). This affects the aging of the inverter.
5- In the deterministic model, performance degradations occur only for the photovoltaic panels and for the inverters.
6- In the stochastic model, the components of the photovoltaic power plant can be only in two possible states (S1: good or working, S2: bad or failed).
7- Failure rates of all the components except inverters are constant [16];
8- The inverter failure rate is not constant and is subjected only to an aging process;
9- Repair rates of all the components are constant;
10- Restoration of a component brings the component back to as-good-as-new state.

4.1 *Definition of the Deterministic Process*

The photovoltaic conversion starts in the PVM stage where PV modules capture the solar irradiance that is converted into a DC power. They are organized in electrical strings connected in series and parallel to constitute a panel. In the same manner, several panels are connected to form arrays of generators and sum up to a higher direct current (DC) power.

As a first approximation, the electrical power generated with a simple configuration of a photovoltaic string of panels can be defined as follows:

$$P = \eta Irr \sin(\alpha + \beta) A \quad \text{(Eq. 4)}$$

As shown in Figure, Irr is the incident solar irradiance [W/m^2]; α is the elevation angle and β is the tilt angle of the module/string measured from the horizontal. Finally,A is the area of the module [m^2] and η is the system efficiency that is always less than 1.

Figure 8: Solar Irradiation, elevation angle α and tilt angle β

The total efficiency can be expressed as:

$$\eta = \prod_{i=0}^{n} \eta_i \quad \text{(Eq. 5)}$$

where ηis the number of loss effects considered at each ith stage of the power plant.

At the PVM stage, meteorological factors (e.g., wind speed, cloud transients in PV units, incident irradiance or ambient temperature) or yearly deterioration can reduce the efficiency of the photovoltaic modules. Using Eq. (6) we can compute the efficiency of the module, η_m, by considering the variation of the temperature [54]:

$$\begin{cases} \eta_m = \eta_{std}\{1 - \rho(T_c - T_{c,std})\} \\ \frac{T_c - T_a}{G} = \text{constant} \end{cases} \quad \text{(Eq. 6)}$$

Where η_{std} and $T_{c,std}$ are respectively the efficiency and the module temperature at standard conditions, ρ is the power coefficient (percentage variation of power for 1°C), T_c and T_a are the module and ambient temperatures and G is the global irradiance on the module.

To account for the degradation rate, Dr, corresponding with the percentage of efficiency lost every year [57, 58], it is possible to use a linear equation model [56]:

$$\eta_n = \eta_{first}(1 - n \times D_r) \quad \text{(Eq. 7)}$$

where η_{first} is the nominal efficiency at the first year, while η_n is the efficiency calculated at the nth year.

The performance degradation occurring in the PVM stage reduces the DC power, but does not stop the power production unless the DC breakers and disconnectors of the DCS stage interrupt the circuit or the cables fail. In fact, with reference to Figure 7, a single PV generator can contribute to the power generation of the system if the circuit path from the PVM stage to the GCC is closed.
Before connecting to the grid, the DC current is converted into alternating current. The DC/AC inverter of the AC section performs this transformation with an efficiency that depends on the input load. At this stage, inverters can also affect the performance of the system and the algebraic model presented in [59] illustrates this effect:

$$\eta_{inverter} = \frac{P(t)_{AC}}{P(t)_{DC}} = 1 - \frac{P_{loss}}{P(t)_{DC}} \quad \text{(Eq. 8)}$$

The total power produced by the plant is the sum of the AC powers output of the two inverters:

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$$P_{ACS}(t) = P_{ACS1}(t) + P_{ACS2}(t) \qquad \text{(Eq. 9)}$$

For this reason, it is possible to understand that the photovoltaic plant is able to produce energy if at least one of the two PV generators is in operation. To compute the energy produced and measured by the generation meter (GM) before the GCC stage it is possible to integrate the P_{PROD} in the time interval $[t_2, t_1]$:

$$E_{PROD}(t) = \int_{t1}^{t2} P_{ACS}(t)dt \qquad \text{(Eq. 10)}$$

The power transferred to the grid is the power not instantaneously consumed by the utilities connected to the power plant. Therefore it is possible to write the equation:

$$P_{GRID}(t) = P_{ACS}(t) - P_{CONS}(t) \qquad \text{(Eq. 11)}$$

When P_{GRID} is negative, it means that the power plant is not able to satisfy the demand of power for the utilities connected, resulting in a lack of service availability.

The other components involved in a photovoltaic system are protection, cables, breakers, disconnectors and transformers. All these components play an important role in the energy production because if one of them interrupts the circuit path to the GCC, the PV generator in the open path cannot contribute to the power generation. This is a very critical aspect of the production process, in particular when considering the elements of the GCC stage. In fact, if one of the components of the GCC stage interrupts the circuit path, all the power plant stops the production because it gets disconnected from the national grid, causing the complete system unavailability. To determine the impact of these circumstances to all the production process the stochastic fault tree model has to be designed and linked to the deterministic model.

4.1 *Definition of the Stochastic Process*

The fault tree model in Figure 9 describes the failure behavior of the plant. This model is constituted by an OR gate (TE) that takes as input an OR gate (GCC = OR (GPR, ACD, DCB, TRA)) and an AND gate (PV GEN = AND (PV GEN 1, PV GEN 2)), modelling the failure behavior of the PV generators. The plant production unavailability occurs if both PV generators fail or if one of the components of the GCC fails.

Figure 10 shows the failure behavior of a single PV generator.The failure/repair rates of the components are shown in Table 7. Failure rates have been taken from [1]. Note that only the inverter has been modeled as a hybrid basic event whose Weibull probability distribution of failure depends on the aging variable. This latter is bounded to the solar radiation input because the inverter switches on when the solar irradiation is high enough to put the PV strings in operation, with a DC voltage greater than the switch on threshold of the inverter. Otherwise, the inverter stays in stand-by mode, waiting for the sun irradiance to increase (e.g. during the night time).

As for repair rates, it was assumed that electrical components like breakers, disconnectors, string box and protection can be restored to as-good-as-new within two working days after a fault.

According to the agreements with the inverter manufacturer, the repair of the inverter takes between three and four weeks, considering the whole process of inspection, ordering, delivery and replacement. For PV strings it was assumed a periodic inspection would take place every six months.

Table 7: Failure/repair rates and steady state availability of the components of the PV plant.

Figure 9: Fault tree of the PV power plant. PV GEN 1 and PV GEN 2 are represented with the transfer gate symbol (triangle) because these sub-systems are developed into another fault tree model.

Figure 10: Fault tree of a PV generator. The basic event INV is represented with a dashed circle to indicate that it belongs to the subset of the hybrid basic events.

5 COUPLING AND SIMULATION OF THE SHYFTA MODEL

Figure 11 depicts the hybrid-pair model of the case study with the corresponding mapping into a SHyFTA where it is possible to identify the main discrete components of the PV system, the corresponding real time variables $\mathbf{X_i}$ of the deterministic process and the vector $\boldsymbol{\varepsilon}_\mathbf{S}$ encoding the status of the basic events of the stochastic process.

Figure 11: Hybrid-Pair architecture of the case study and corresponding SHyFTA mapping.

X_{IRR} and X_{TA} represent respectively the sun irradiance Irr and the ambient temperature T_a. These two variables are inputs of the model and, according to Eqs. (4-7), affect the power generation and the conversion efficiency of the PVM components. The ACS conversion depends on Eq. (8) and the actual energy produced by the power plant is described by Eqs. (9) and (10). To account for the effects of the stochastic model, the SHyFTA provides a mechanism of synchronization between the variables of the deterministic model and the stochastic events (the basic events) that determine the status of each component. In the stochastic process, the basic events are characterized by two operational states, S_S= {Good, Bad}. The health status of each basic event is an element of the vector $\boldsymbol{\varepsilon}_\mathbf{S}$ that, as input to the deterministic process, realizes the coupling between the basic events of the stochastic process with the corresponding discrete components modelled in the deterministic process. Since it was assumed that components can be only in two possible states, the binary representation can be set as follows:

$$S_{BEi} = \begin{cases} 1, i^{th} \text{ component is working} \\ 0, i^{th} \text{ component is failed} \end{cases}$$

According to this notation, it is now possible to evaluate and rewrite the real variables $X_{PVS1/138}$,$X_{DCG1/2}$, $X_{ACS1/2}$, X_{PROD} and X_{GCC} of the SHyFTA model that correspond with the powers levels generated at the different stages of a PV plant generator.

X_{PVSi} , with i=1,…,138, is the DC power generated by the ith photovoltaic string (each string is comprised of 16 modules, see Table 4) that depends on the status of the ith string S_{PVSi}:

$$X_{PVSi} = \left[\eta I \sin\left(\alpha + \beta_{PVSi}\right) A_{PVSi}\right] \times S_{PVSi} \qquad \text{(Eq. 12)}$$

$X_{DCS1/2}$ are the total DC power of each photovoltaic generator (a DC generator is comprised of 69 strings of the corresponding PVM section)and it includes the loss of DC wiring connections and possible faults of DC protection or fuses:

$$X_{DCS1} = \Sigma_{i=1}^{69} X_{PVSi} \times (S_{SPR1} \times S_{DCD1} \times S_{SPD1}) \qquad \text{(Eq. 13)}$$

$$X_{DCS2} = \Sigma_{i=70}^{138} X_{PVSi} \times (S_{SPR2} \times S_{DCD2} \times S_{SPD2}) \qquad \text{(Eq. 14)}$$

$X_{ACS1/2}$ are the total AC power output of each AC sections and including the efficiency loss of the inverters and possible faults of the AC protections and breakers.

$$X_{ACS1} = \eta_{ACS1} \times X_{DCS1} \times S_{INV1} \times S_{ACB1} \times (S_{GPR} \times S_{ACD} \times S_{DCB} \times S_{TRA}) \quad \text{(Eq. 15)}$$

$$X_{ACS2} = \eta_{ACS2} \times X_{DCS2} \times S_{INV2} \times S_{ACB2} \times (S_{GPR} \times S_{ACD} \times S_{DCB} \times S_{TRA}) \quad \text{(Eq. 16)}$$

It is possible to notice that the components of the stage GCC can break the circuit path towards the grid. When this happens, the inverter stops the DC/AC conversion and the production of the power plant is nullified. In this case, during this outage, $X_{ACS1}(t) = X_{ACS2}(t) = 0$.

X_{ACS} is the total AC power generated by the photovoltaic power plant. It is measured at the exchange meter of production in order to quantify the amount of energy produced that is rewarded with the subsidy tariff of the IPER 2013:

$$X_{ACS} = X_{ACS1} + X_{ACS2} \qquad \text{(Eq. 17)}$$

X_{GRID} is the power exchanged with the grid and is computed as difference between the produced power X_{ACS} and the amount of instantaneous power X_{CONS} requested by the utilities connected to the power plant:

$$X_{GRID} = X_{ACS} - X_{CONS} \qquad \text{(Eq. 18)}$$

Among the variables computed in the deterministic process, Eq. 19 models the counter of the inverter aging of an inverter, $X_{aging} = L$, measuring the amount of time in which an inverter is on.

$$X_{Aging\_INVi} = \int_0^t i_{ON\_INV_i}(t)dt,\ i = 1, 2 \qquad \text{(Eq. 19)}$$

$$i_{ON\_INVi}(t) = \begin{cases} 1, X_{DCSi} > 0 \\ 0, X_{DCSi} = 0 \end{cases} i = 1, 2$$

This value is an input of the Weibull pdf characterizing the failure behavior of the inverter in the stochastic process [see Eq. (2-3)].

The SHyFTA model has been coded in Matlab® to implement a software resolution based on a discrete event Monte Carlo simulation [60]. Several trials must be performed in order to achieve the desired accuracy (or confidence interval) of the measure to compute. For the photovoltaic power plant, the focus is on the power production measured at the generation meter, X_{ACS}. Therefore, at each trial *k* of the Monte Carlo simulation, the output of the SHyFTA model is the time-series $X^k_{ACS}(t)$. When the desired confidence interval is met the simulation is stopped and the mean active power for each sample of the time series is computed as follows:

$$\mathbb{E}[(X_{ACS})] = \frac{1}{N}\left[\sum_{k=1}^{N} X^{k}_{ACS}(t)\right] \text{(Eq. 20)}$$

where N is the number of Monte Carlo trials.

The estimator error associated to the desired confidence interval can be computed as follows [61]:

$$Err = Z_{a/2} \times \frac{\sigma}{\sqrt{N}} \qquad \text{(Eq. 21)}$$

where $Z_{a/2}$ is the confidence coefficient, *a* is the confidence level, σ is the standard deviation of the Monte Carlo simulation and *N* is the number of Monte Carlo trials.

The use of the active power as an estimator of the Monte Carlo simulation has an advantage. In fact, it can be noted that the cumulative error, made up by the instantaneous samples of the time series $X_{ACS}(t)$, corresponds to an energy. In this way, it is possible to provide an appropriate estimation of the active energy aside a confidence interval using the cumulative error of the estimator.

The inputs of the models are the solar irradiance and the ambient temperature acquired by the logging system of the real power plant during 2011-2015. Figure 12 shows the ambient temperature data. In this way, using the same historical time series, it is possible to compare the results of the SHyFTA, the pure deterministic model and the real production data.

Figure 12: Historical time series of the ambient temperature (2011-2015), Syracuse (Italy).

5.1 *Energy production estimation*

In order to test the accuracy of the proposed methodology, the results of the SHyFTA and the deterministic models have been compared with real energy production data, collected by the SCADA system of the photovoltaic plant. The collected data includes the hourly aggregated power, energy, solar irradiance and external temperature for the first four years and half of life, corresponding to 40.173 hours.

For the SHyFTA simulation, a confidence level of 0,99 was set for each data point $X_{ACS}(t)$. There was not set a stopping condition for the simulation and with 10.000 iterations, the cumulative absolute error of the time series sums up to the 0,16%, that corresponds to ±4.681 kWh.

To compute the energy production from the time-series of the estimated active power $X_{ACS}(t)$Eq. (20) must be used. Table 9 displays a comparison among the real data, the deterministic and the SHyFTA models in terms of energy produced and payback generated under the regime of IPER 2011. It is possible to notice that the results of the SHyFTA at the end of the observation period (see last row of Table 8) matches with the real data aside the absolute error of the Monte Carlo simulation (±4.681 kWh). It can be observed that at the beginning of the simulation, the deterministic and the SHyFTA model are very close to the real data and the reason is that at the beginning of the power plant life there are no faults and performance degradation which affect the system. However, after a few months, the gap between the real data and the deterministic model starts to increase, whereas the difference with respect to the SHyFTA remains bounded to a maximum relative error of 2%, as shown in Figure 14 that plot the absolute relative error with respect to real data.

Table 8: Comparison among the real data, the deterministic and the SHyFTA model in terms of energy produced and positive payback generated under the regime of IPER 2011.

Figure 13: Comparison between the energy produced by the deterministic model, the SHyFTA and the real system.

Figure 14: Comparison between the relative error of the deterministic model and the SHyFTA.

At this point, having tested the accuracy of the proposed method, it is possible to forecast the production of energy over 20 years of life in order to provide the owner of the plant with a more accurate estimation of production and economical revenues. To achieve this result, the simulation with the SHyFTA is extended to 20 years assuming that the physical input of the solar radiation and ambient temperature follow the same evolution described by the historical time series of the last 5 years. The Monte Carlo simulation has been set such to respect the same confidence level of the previous simulation. Under this setting, the absolute cumulative error of the time series sums up to 0,18%, that corresponds to ±20.480kWh.

Figure 15 shows the results obtained and Table 9 allows a further comparison between the deterministic and the SHyFTA. In this case, it is possible to recognize at the end of the 20^{th} year, a difference of about 545.000 kWh (±20.480 kWh)of loss of energy productivity. Under the regime of IPER 2011, at the end of the economic investment established at the 20^{th} year from the start of the power plant, this lack of energy production corresponds to a cash short of about 250.000 € (±9.421 €).

Figure 15: Energy production estimation throughout the life time of the power plant (20 years).

Table 9: Comparison between the deterministic and the SHyFTA model throughout the remaining years of the plant life in terms of energy produced and positive payback generated under the regime of IPER 2011.

5.2 *Plant and service availability*

To compute the plant availability, it is possible to use the main principles of the probability theory for union and intersection of independent events, as shown in Eqs. (22) and (23), where $P(BE_i)$ is the probability of the basic event BE_i.

$$P\left(BE_1 \cap BE_2 \cap BE_3 \ldots \cap BE_n\right) = P\left(BE_1\right) \times P\left(BE_2\right) \times P\left(BE_3\right) \times \ldots \times P\left(BE_n\right) = \prod_{i=1}^{n} P(BE_i) \quad \text{(Eq. 22)}$$

$$P\left(BE_1 \cup BE_2 \cup BE_3 \ldots \cup BE_n\right) = P(\Sigma_{i=1}^{n} BE_i) = \sum_{k=1}^{n} (-1)^{k+1} \sum_{\substack{i_1, i_2, \ldots, i_k \\ 1 \le i_1 < i_2 < \ldots < i_k \le n}}^{n} P(BE_{i1} \cap BE_{i2\ldots} \cap BE_{ik}) \quad \text{(Eq. 23)}$$

In the following relationships, $P(E_i)$ corresponds with the unavailability U_x of each component that can be obtained as U_x=1-SSA_x. Table 10 reports the steady state availability for each component of the Fault Tree, with the exception of the inverter that cannot be computed with the same formula, valid for the exponential distributions, $\mu/(\lambda + \mu)$.

The failure behavior of the inverter has been modelled with a piecewise deterministic Markov Process and it has a non-linear relationship with the aging of the inverter.To compute the inverter availability, a dedicated simulation was performed assuming to extend the mission time and the solar radiation to 20 years, by replicating the time-series of the solar radiation and ambient temperature. Figure 16 shows that the steady state availability (SSA) oscillates around the values 0,98±0,001.

Figure 16: Inverter Availability simulated.

Substituting the values of the steady-state availabilities in Table 9, it is now possible to compute the unavailability of each gate and, from bottom up, retrieve the system availability.

$$A = 1 - U_{TE} = 0{,}9999$$

$$U_{TE} = U_{PVGEN} + U_{GCC} - [U_{PVGEN} \times U_{GCC}] = 1e\text{-}5$$

$$U_{GCC} = U_{GPR} + U_{ACD} + U_{DCB} + U_{TRA} - [U_{GPR} \times U_{ACD}] - [U_{GPR} \times U_{DCB}] - [U_{GPR} \times U_{TRA}] - [U_{ACD} \times U_{DCB}] - [U_{ACD} \times U_{TRA}] - [U_{DCB} \times U_{TRA}] + [U_{GPR} \times U_{ACD} \times U_{DCB}] + [U_{GPR} \times U_{ACD} \times U_{TRA}] + [U_{GPR} \times U_{DCB} \times U_{TRA}] + [U_{ACD} \times U_{DCB} \times U_{TRA}] - [U_{GPR} \times U_{ACD} \times U_{DCB} \times U_{TRA}] = 0.1e\text{-}4.$$

$$U_{PVGEN} = U_{PVGEN1} \times U_{PVGEN2} = 5{,}6e\text{-}9$$

For each ith section of the photovoltaic power plant, with i = 1, 2, it is possible to compute the following:

$$U_{PVGENi} = U_{ACSi} + U_{DCSi} - [U_{ACSi} \times U_{DCSi}] = 7{,}5e\text{-}5$$

$$U_{ACSi} = U_{INVi} + U_{SDPi} + U_{ACBi} - [U_{INVi} \times U_{SDPi}] - [U_{INVi} \times U_{ACBi}] - [U_{SDPi} \times U_{ACBi}] + [U_{INVi} \times U_{SDPi} \times U_{ACBi}] = 4{,}5e\text{-}5$$

$$U_{DCSi} = U_{SPRi} + U_{DCDi} + U_{SPDi} + U_{PVMi} - [U_{SPRi} \times U_{DCDi}] - [U_{SPRi} \times U_{SPDi}] - [U_{SPRi} \times U_{PVMi}] - [U_{DCDi} \times U_{SPDi}] - [U_{DCDi} \times U_{PVMi}] - [U_{SPDi} \times U_{PVMi}] + [U_{SPRi} \times U_{DCDi} \times U_{SPDi}] + [U_{SPRi} \times U_{DCDi} \times U_{PVMi}] + [U_{SPRi} \times U_{SPDi} \times U_{PVMi}] + [U_{DCDi} \times U_{SPDi} \times U_{PVMi}] - [U_{SPRi} \times U_{DCDi} \times U_{SPDi} \times U_{PVMi}] = 3e\text{-}5$$

$$U_{PVMi} = \prod_j U_{PVS_j} = 1e\text{-}13, \text{ with } j = \begin{cases} 1, j = 1, \dots, 69 \\ 2, j = 70, \dots, 138 \end{cases}$$

According to these results, is possible to conclude that the SSA of the power plant is very high. An important difference with respect to the work in [16] is that in the presented model the components can be repaired after a fault. Moreover, the power plant is composed of two redundant generating sections (PVGen1 and PVGen2) and both must fail before the system fails. This configuration results in an increased system availability.

For this type of system, a more valuable KPI than reliability or availability of the system is the service availability [54] that measures the probability of the system to satisfy the instantaneous power demand of the connected load. In fact, reliability does not consider restoration and, in these types of applications, this is not realistic. On the other hand, the classic definition of availability, intended as the probability that at the observed time the system will be in production, is not very significant because, as already explained, the complete shut-down of the power plant is very unlikely, as it is constituted by several independent groups of generators with a high availability.

Service availability can be computed as the ratio between the total time in which the photovoltaic power plant is not able to meet the power demand of the company and the total duration of the mission time. To evaluate this KPI, three types of power unavailability must be considered:

i. Unavailability of generated power due to conventional outages of plant and apparatus;
ii. Unavailability of generated power due to source variability (power plant equipment remaining perfectly healthy and operational);
iii. Unavailability of generated power due to outages of plant that arise due to source variability (such as PV panel outages due to differential overheating that arise out of cloud transients).

The SHyFTA model here presented takes into account all the previous effects, although its accuracy (and complexity) can be certainly increased. In fact, the stochastic fault tree model of failure (Figure 8, Figure 9 and Table 7) accounts for the unavailability of type (i); the unavailability of types (ii) and (iii) depend on the real variable X_{IRR} and X_{TA}, input of the deterministic model. Moreover, some of the most dramatic causes of power unavailability of type (iii) are embedded in the deterministic model since the panels and inverter performance, as shown in Eqs. (6)-(9),depend on the variation of the ambient temperature X_{TA}. Certainly, the deterministic model could include many other physical effects that influence the performance of the energy conversion but, the modelling of such mechanisms, is not the main subject of this research paper. To compute the service availability, the SHyFTA model requires as input the daily power demand, as shown in Figure 17a. It is possible to see that it grows during the initial hours of the working day, reaches a peak between 10:00-15:00 and decreases when the production activities are about to finish, at the end of the working day. Figure 17.b shows the schema of the power supply: if the demanded power exceeds the power generated by the power plant, the electrical grid supplies to the difference.

Figure 17.a: daily power demand. Figure 17.b: schema of the power supply.

The results of the SHyFTA match exactly the real scenario (Table 10). It is possible to notice that the service availability is much lower than the system availability and, in the case of renewable power plants, this represents one of the most important disadvantages because energy cannot be easily stored, unless the power plant is provided with a sophisticated system of batteries that, only in recent applications, are becoming popular (e.g. [62, 63]).

Table 10: Comparison between the results of service availability in respect to the demand of Figure 17.

5.3 *Discussion about the reusability of the SHyFTA model and the applicability to other renewable power plants*

The photovoltaic power plant hereby discussed was characterized by fixed panels. Sometimes panels are installed over mechanical systems (called trackers) that are able to follow the direction of the sun irradiation throughout the day. When trackers work correctly it is expected an improvement of the energy production of the power plant. Conversely, a fault of a tracker blocks the solar panel at the position in which the fault has occurred and the high operating time of the system, which has negative influence on the reliability [64]. The conversion process described in Eqs. (4)-(10) is still valid, therefore to include trackers in the SHyFTA model of a photovoltaic power plant, it is possible to add a basic event for each tracker associated with a panel of the PVM stage (Figure 18) and link them with the generic equation of power conversion [cf. Eq. (4)] in the deterministic model.

Figure 18: Fault tree of the PVM section that includes a tracker for each panel of the power plant.

It was observed that, despite very high plant availability, the service availability of such systems is very low. To verify the opportunity of other technical solutions, the SHyFTA could be extended to integrate a system of batteries in the power plant model. The deterministic model should include an additional equation that depends on the charge of the battery that contribute to the power supplying of the internal consumption when the peak power demanded exceeds the instantaneous power generated by the power plant. Accordingly, the fault tree model should include a hybrid basic event associated with the battery (Figure 19a) and the power supply schema should follow the scheme of Figure 19b.

In systems such as concentrated photovoltaic systems the architecture of a module is usually more complex as it includes lenses, a biaxial tracking system, pyrheliometers, heatsinks, etc. In fact, even if the stated efficiency is usually higher than a standard system, the real performance can end up being lower because of random faults occurring in its sophisticated parts [65]. To this aim, the possibility to model such systems with a SHyFTA model linking the fault behavior to the physical equation of the power production can be useful for future studies. Also in this case, the SHyFTA could be implemented to include a number of basic events that accounts for these other components and link their health status to the physical equation of energy conversion such to evaluate the benefit among several combinations of level of service and the related costs of installation and maintenance [39, 66].

Figure 19.a: Fault tree of the power plant that includes a system of battery

Figure 19.b: schema of the power supply with a system of battery.

More generally, the SHyFTA modelling can be applied to other renewable technologies because the model of energy conversion (i.e., the physical laws of the deterministic process) can always be linked with a stochastic fault tree model. In fact, the basic events of a fault tree describe the failure and working interactions of the physical components that participate to the process of energy conversion of the power plant. There have been presented different mathematical models of other renewable technologies (e.g. hydroelectric power plants [67-70], wind farms [71, 72]) that can be used to characterize the model of power conversion and the efficiency of its main components. Other works have investigated the failure behavior of these systems highlighting the dynamic dependencies and aging effects of the main components (e.g. hydro [35, 51, 73] and wind [34, 74] technologies). All these elements can be integrated in a SHyFTA model with algorithms that are able to grasp the uncertainty of the renewable resource (e.g., wind forecasting based on neural networks [75], autoregressive models [76, 77] or Markov chains [78, 79]).

6 CONCLUSIONS

The performance evaluation of a renewable power plant is a complex task because the randomness of the primary resource and its influence on the plant availability can limit the accuracy of traditional deterministic models.For this reason, the need for valuable techniques able to support engineers and risk practitioners with this activity is of increasing interest and it is becoming crucial with the widespread adoption of renewable technologies.

In this paper, a thorough analysis of the up-to-date state-of-the-art has been presented so as to highlight the limitations of traditional models. Namely, existing works are unable to combine in one single model the deterministic process of energy conversion with the stochastic behavior characterizing the plant availability and the intermittency of the primary resource. This limits the capability of such models to account for the variation of the status of a system and its deterioration that are strictly connected with the environmental and the nominal working conditions in which the system operates. To overcome this limitation, a dynamic reliability based methodology is proposed as valuable paradigm. The application of dynamic reliability to model and evaluate the performance of a renewable power plant represents an important novelty of this paper.

Among the several techniques of dynamic reliability, Hybrid Fault Tree Automaton (SHyFTA) has been presented. SHyFTA is a simulation approach that exploits the paradigm of the hybrid-pair modelling [46] offering a structured approach for the resolution of a dynamic reliability problem. This allows modelling the deterministic and stochastic processes independently and coupling them in latter stage with the use of shared variables. In particular, the deterministic process of energy conversion, based on a set of complex mathematical relationships, can be linked with the stochastic behavior of the system using the well-known Dynamic Fault Tree formalism. The main advantage of such technique is the possibility to address the evaluation of a system both in terms of dependability attributes (reliability, availability and maintenance) and performance (production and other relevant KPI, like the service availability). Moreover, a SHyFTA model can be easily redesigned and simulated so as to assess the effect of alternative engineering design decisions on system performance and including design optimization and sensitivity analysis [80]. The case study of a photovoltaic power plant has been discussed and the main steps for the construction of a SHyFTA model have been defined. To demonstrate the accuracy of the results achieved with a SHyFTA simulation over a traditional deterministic model, a comparative analysis has been presented using as benchmark the real data of a photovoltaic power plant. After the initial transient period, the mean error of the SHyFTA model decreases below 2%, while the error of the deterministic model keeps around 6%. Further comparisons between the SHyFTA and the deterministic model have been discussed also in terms of cash short, when estimating the expected productivity throughout the entire lifetime of the power plant (20 years). In this case, it has been shown that the use of the deterministic model is not suggested as it generates an important error in terms of cash short of about 250k€.

Due to the rigorous modelling process that includes components' repair processes, the results obtained in this paper improve the one presented in [16] limited to the reliability evaluation with non-repairable components that, for a renewable power plant, is not the most significant key performance index to consider. With the SHyFTA model, it was possible to compute both the availability of the plant and the related service availability and it was shown that, despite a large plant availability (99,9%), the photovoltaic power plant is not able to offer the same level of service availability (58%) due to the unpredictability of the primary resource and the impossibility to store the unused energy.

The SHyFTA analysis is based on Monte Carlo simulations. Therefore, the accuracy of the results and simulation times can require long computation times before to retrieve results with an acceptable precision. This disadvantage, together with the unavailability of exact models to describe the failure behaviour, represents today the price for a more precise feasibility assessment and performance evaluation of renewable power plant model. However, it can be ascertained that the increase of computing power on the one hand and of big-data analyses on the other will alleviate the impact of the aforementioned limitations.

Future researches will address the opportunity to adopt the methodology for other types of renewable power plants. Among them, wind applications look very promising because the integration of high-frequency sensors for condition-monitoring can provide important data for the modelling of dynamic failure rates of wind turbine components. Additionally, it may be interesting to integrate other uncertainty modelling mechanisms in the proposed approach so as to model uncertain operational states.

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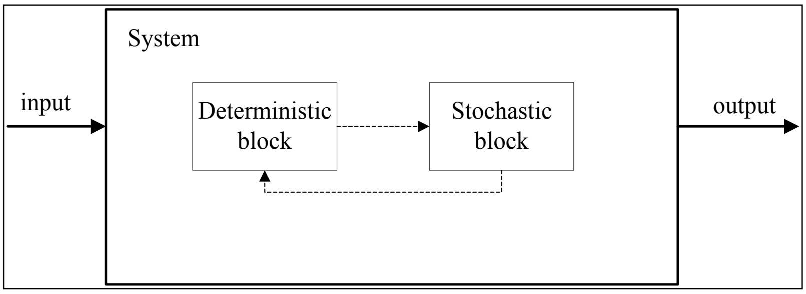

Figure 1: Mutual dependency between the deterministic and the stochastic model.

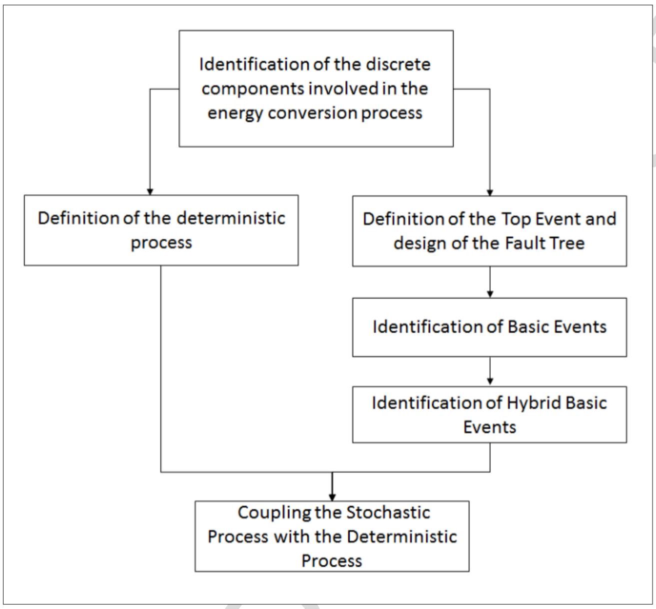

Figure 2: Steps for the construction of a SHyFTA model.

Figure 3: Location of the power plant.

Figure 4: Global horizontal irradiation in Italy.

Figure 5: Map of the power plant and its sections.

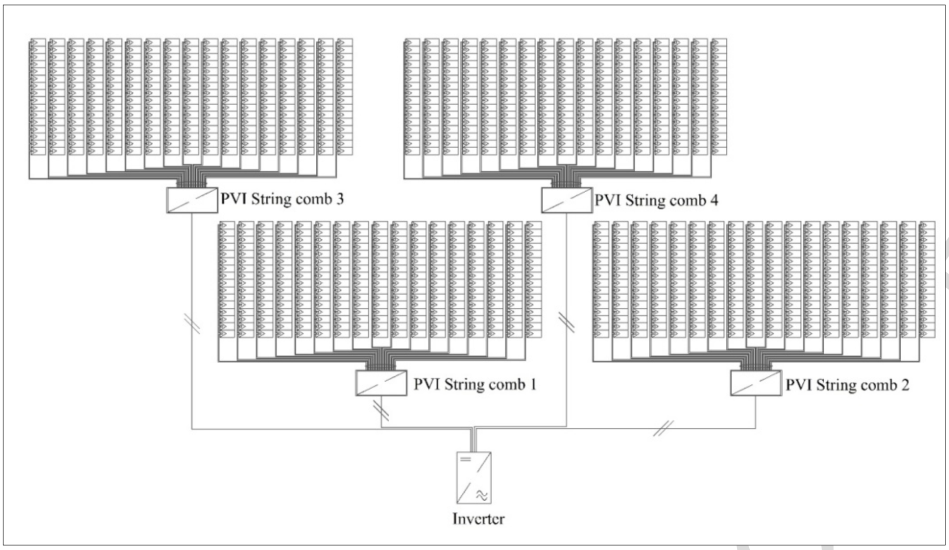

Figure 6: Power Inverter configuration.

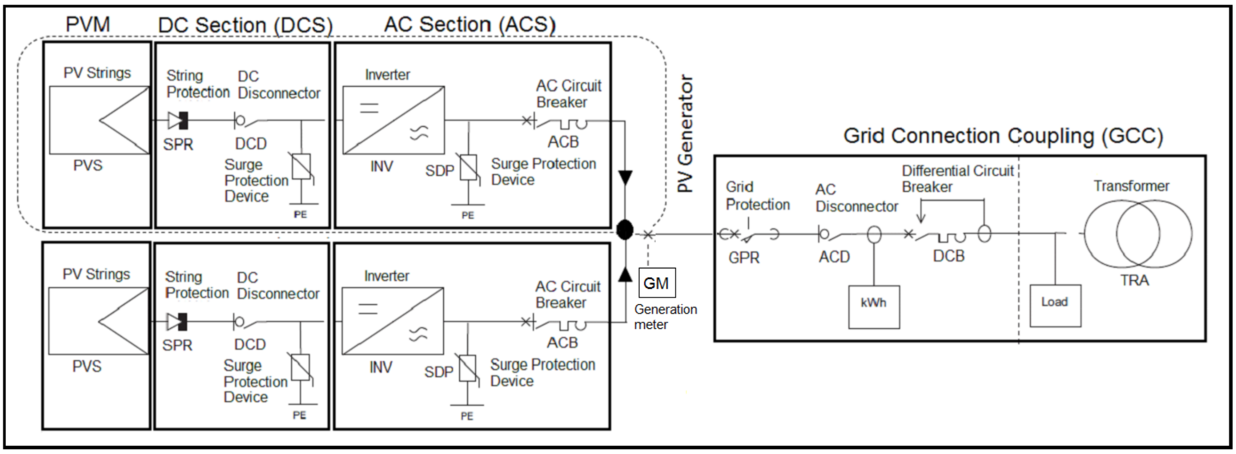

Figure 7: Schematic decomposition of the PV system

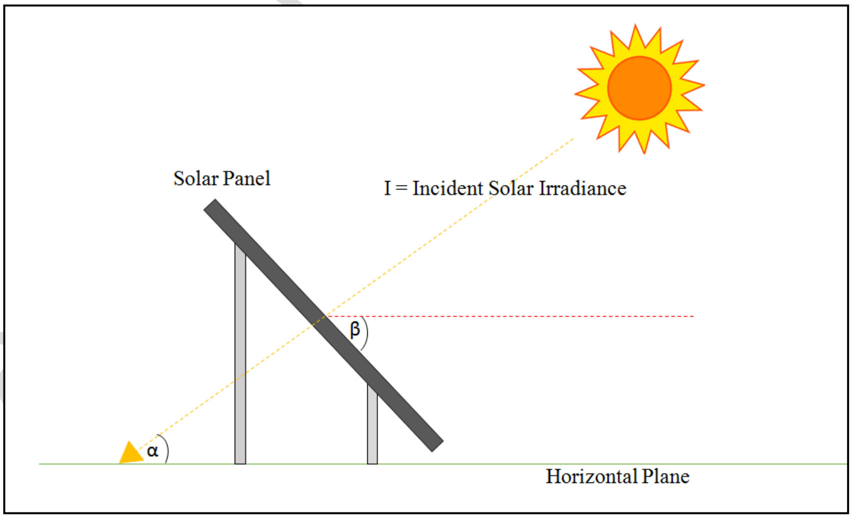

Figure 8: Solar Irradiation, elevation angle α and tilt angle β

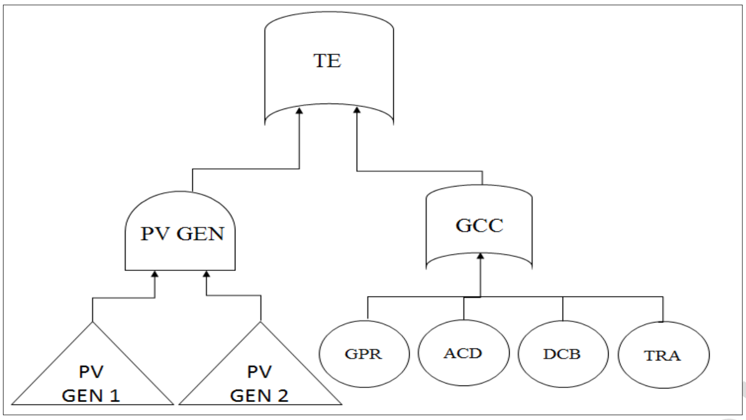

Figure 9: Fault tree of the PV power plant. PV GEN 1 and PV GEN 2 are represented with the transfer gate symbol (triangle) because these sub-systems are developed into another fault tree model.

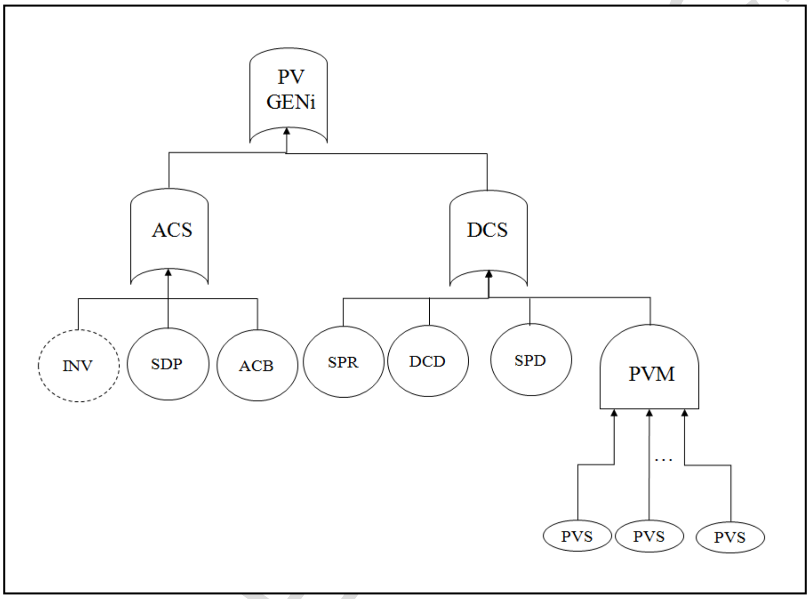

Figure 10: Fault tree of a PV generator. The basic event INV is represented with a dashed circle to indicate that it belongs to the subset of the hybrid basic events.

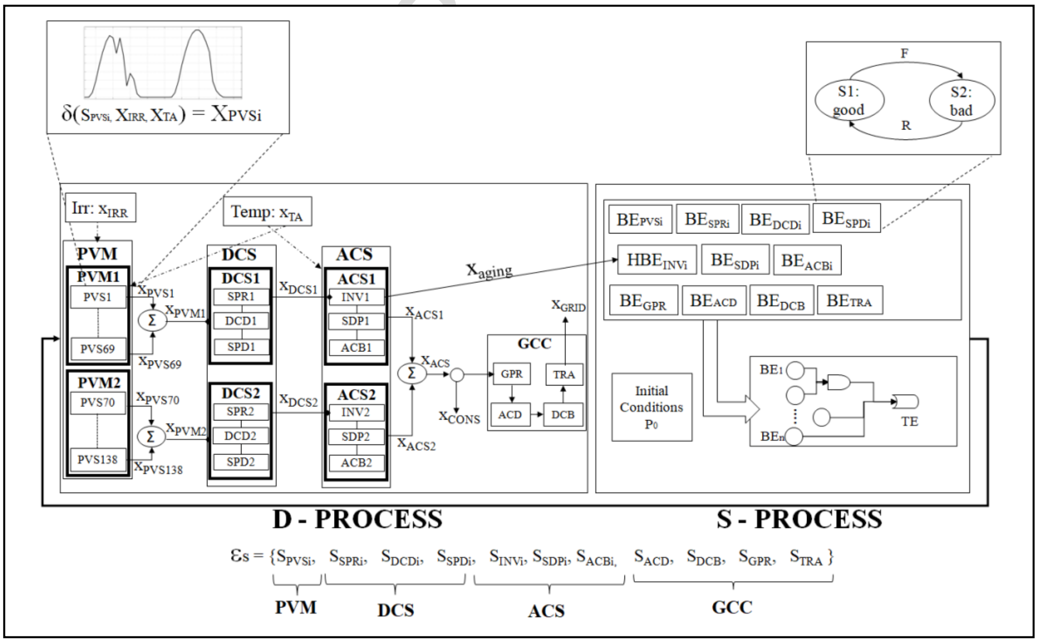

Figure 11: Hybrid-Pair architecture of the case study and corresponding SHyFTA mapping.

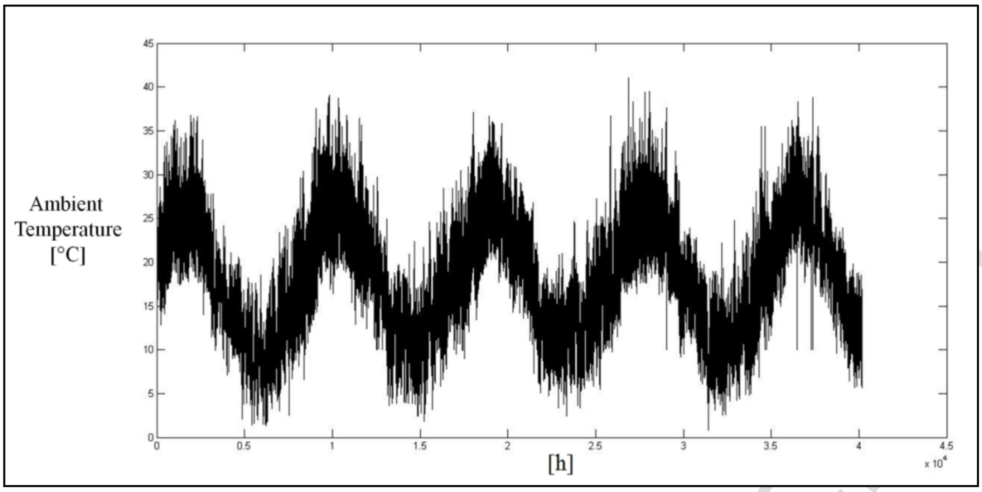

Figure 12: Historical time series of the ambient temperature (2011-2015), Syracuse (Italy).

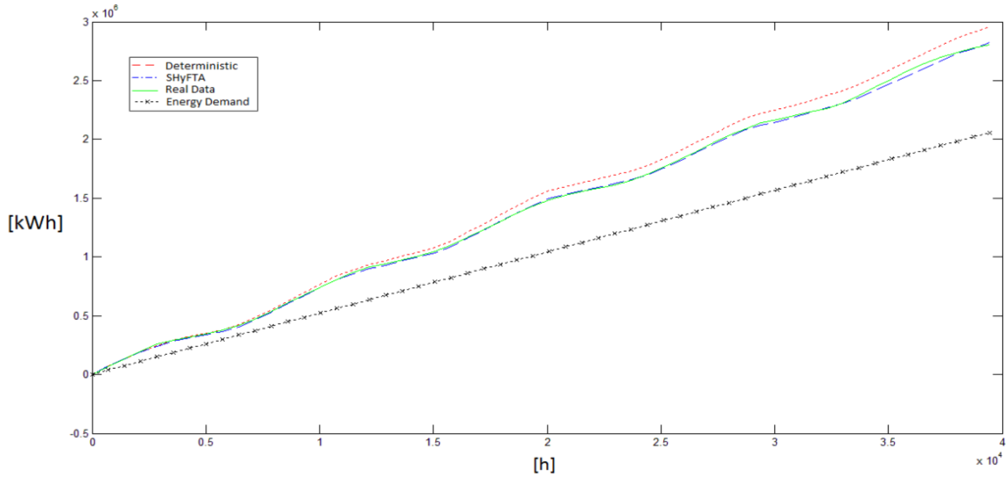

Figure 13:Comparison between the energy produced by the deterministic model, the SHyFTA and the real

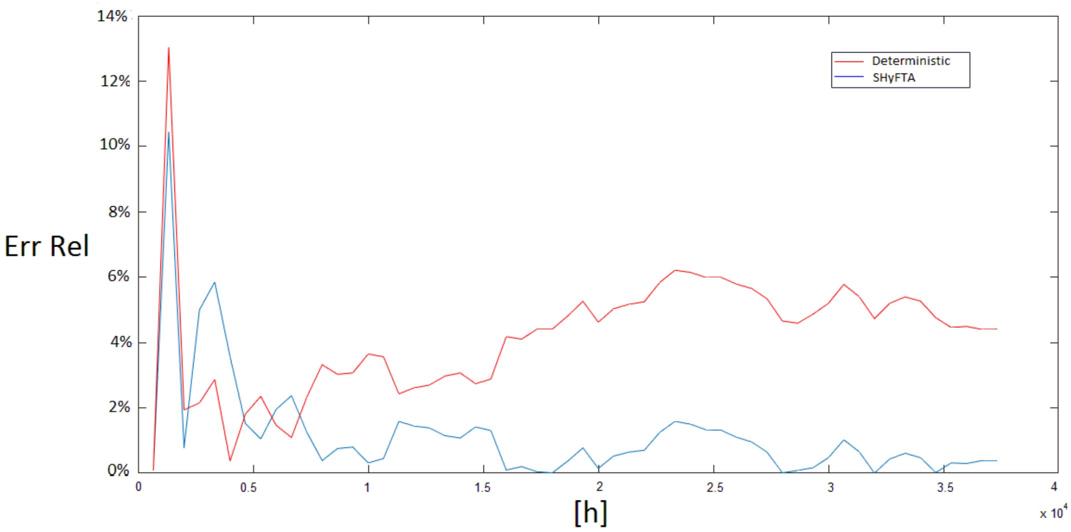

Figure 14: Comparison between the relative error of the deterministic model and the SHyFTA.

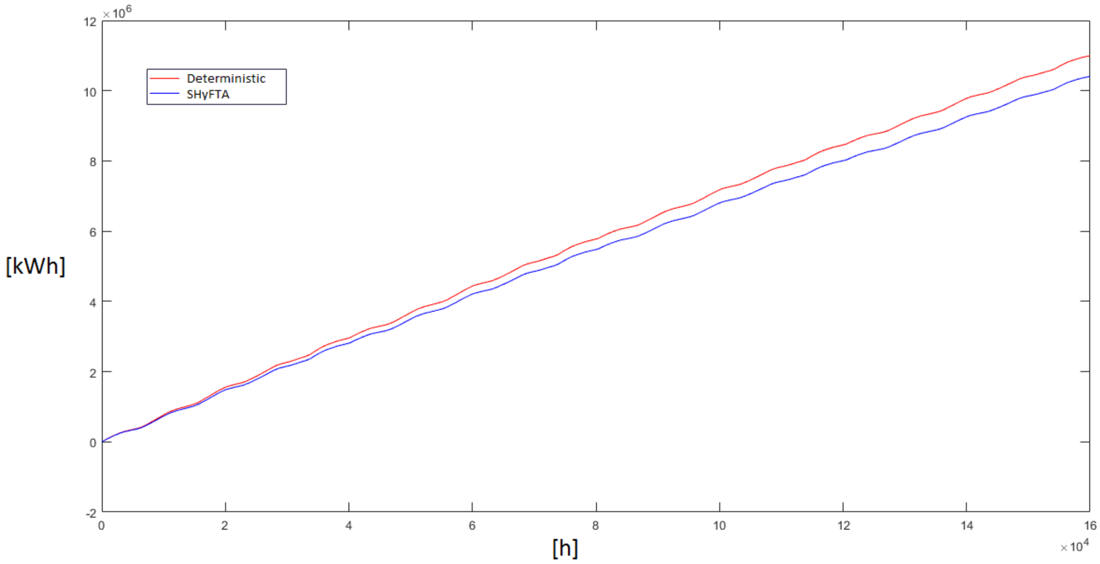

Figure 15: Energy production estimation throughout the life time of the power plant (20 years).

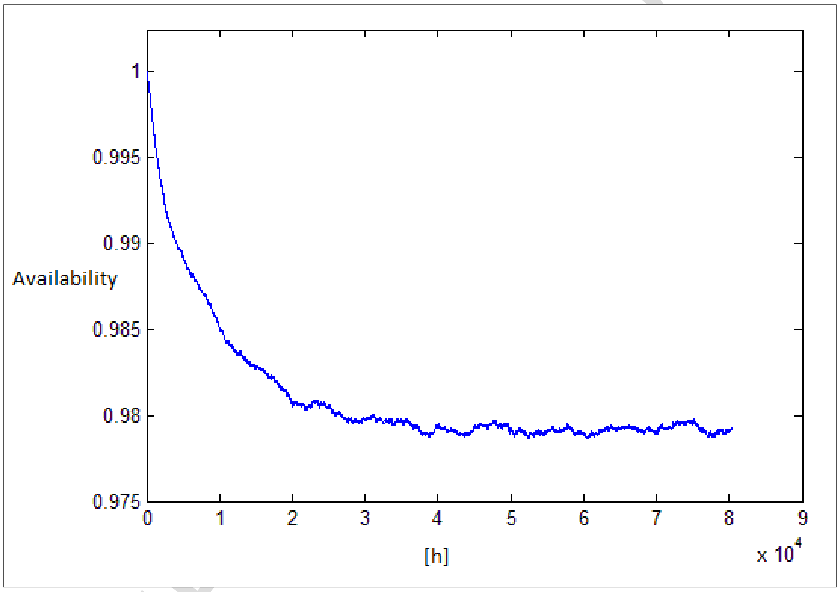

Figure 16: Inverter Availability simulated.

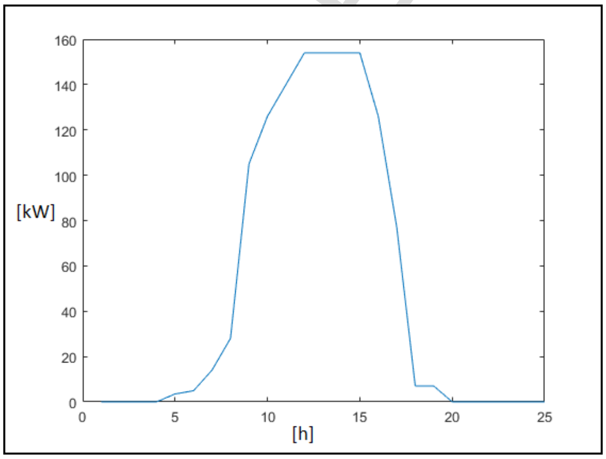

Figure 17.a: daily power demand.

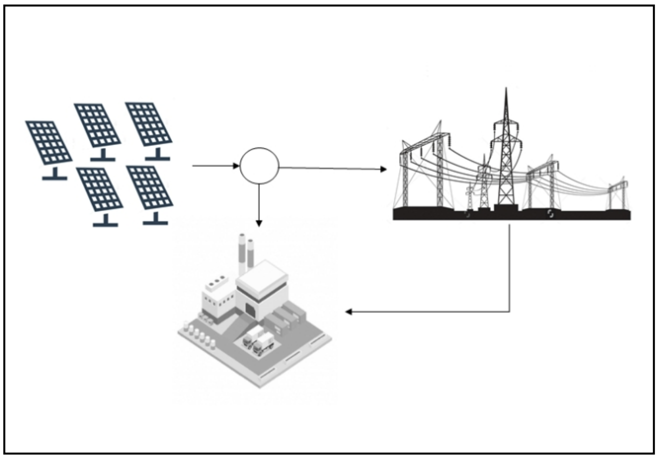

Figure 17.b: schema of the power supply.

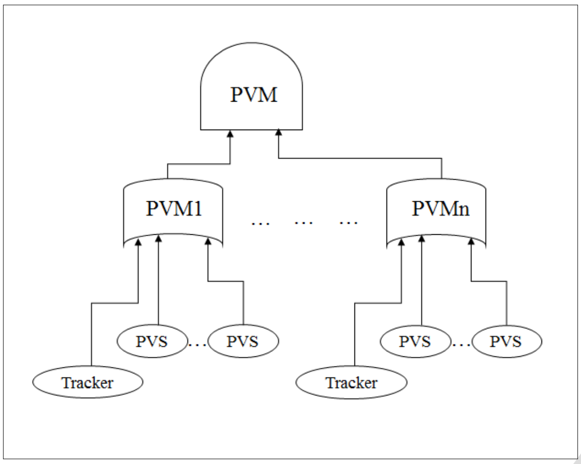

Figure 18: Fault tree of the PVM section that includes a tracker for each panel of the power plant.

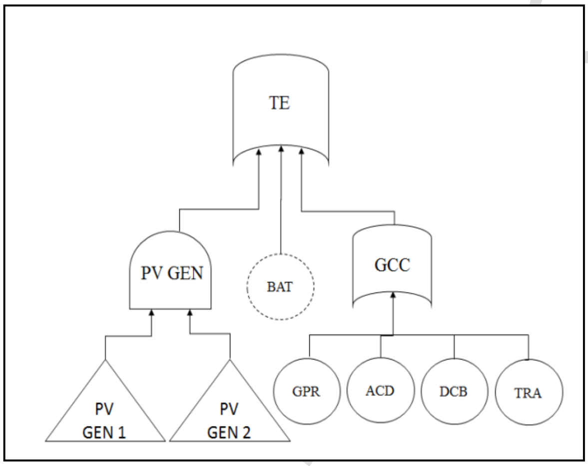

Figure 19.a: Fault tree of the power plant that includes a system of battery

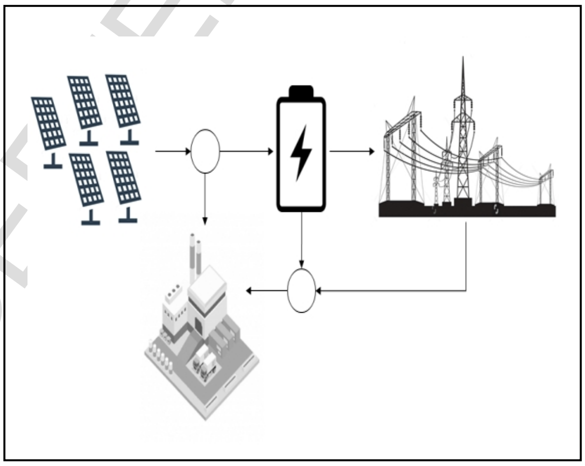

Figure 19b: schema of the power supply with a system of battery.

ON THE USE OF DYNAMIC RELIABILITY FOR AN ACCURATE MODELLING OF RENEWABLE POWER PLANTS

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Research Highlights:

- Review of the state of the art of renewable power plant and reliability modeling
- Modeling steps to design a hybrid dynamic (SHyFTA) model of a renewable power plant
- A real photovoltaic power plant is modelled and results are compared with real data
- The SHyFTA model results more accurate than the deterministic model
- The production throughout the lifetime, service and plant availability are computed

Table 1: Main characteristics of the models used for dependability assessment.

	RELIABILITY ASSESSMENT		DYNAMIC RELIABILITY
	Static Models	**Dynamic Models**	**Hybrid-dynamic Models**
PhysicalProcess	Static working conditions Single-state operating components	Static working conditions Single-state operating components	Dynamic working conditions Multi-state operating components
Stochastic Process	Boolean components Fixed probability of failure Independence of components	Multi-state degradation components Fixed probability of failure Time-event sequence dependencies	Multi-state degradation components Dynamic probability of failure Time-event sequence dependencies
Modelling Techniques	Reliability Block Diagrams Fault Tree	Dynamic Reliability Block Diagrams Dynamic Fault Tree Markov Processes	Stochastic Automaton Models Regime Switching Models* Piecewise Markov Processes*
Satisfied Criteria (Table 1)	c*, d *Performance evaluations limited to reliability/availability in static working scenario	c*, e *Performance evaluations limited to reliability/availability in static working scenario	a, b, c*, d, e *Not intended to evaluate the performance of a system in terms of process output
Computational Costs	*Time-Dependency* Physical Process: No Stochastic Process: No	*Time-Dependency* Physical Process: No Stochastic Process: Yes	*Time-Dependency* Physical Process: Yes Stochastic Process: Yes
Overall	**Low**	**MediumtoHigh**	**HightoVery High**

Table 2: Main physical inputs for different renewable technologies

Renewable Technology	**Physical Input**
Photovoltaic	Sun Irradiance, Temperature
Wind	Wind Speed, Air Density, Temperature
Hydro	Intake Water Flow, Water Level

Table 3: PV system characteristics.

Location	37,1751N 16,1596E
P_{peak}	419,52 kW_p
N° inverters	2
N° strings boxes	4 (per inverter)
N° strings	138
N° modules	2208 (16 for each string)
Azimuth Angle	180°
Tilt Angle (β)	30°

Table 4: PV module main characteristics.

P_{peak}	190 W (Monocrystalline)
Panel efficiency (ŋ)	15%
V_{mp}	37 V
I_{mp}	5,04 A
V_{oc}	45,1 V
I_{sc}	5,35 A
NOCT	45 ± 2° C

Table 5: Inverter main characteristics.

P_{acmax}	220 kW
Voltage range MPPT	$485V<V_{MPPT}<950V$
N° independent MPPT	4
η_{max}	98%
Vacr	320 V
Iacmax	450 A
Idcmax	492 A

Table 6: IPER 2011 Subsidy. Price* is based on an average value of the energy price in the energy market (2011) [43].

Power (kW)	Subsidy	Price*	Total (∑)
1 < P ≤ 3	0,362	0,25	0,612
3 < P ≤ 20	0,339	0,21	0,549
20 < P ≤ 200	0,321	0,18	0,501
200 < P ≤ 1.000	0,314	0,15	0,464

Table 7: Failure/repair rates and steady state availability of the components of the PV plant.

Component		λ:Failure Rate [h^{-1}]	μ: Repair Rate [h^{-1}]	Steady State Availability(SSA) $\frac{\mu}{\lambda+\mu}$
ACB	AC Circuit Breaker	5.71×10^{-6}	2.08×10^{-2}	99.9%
ACD	AC Disconnector	0.034×10^{-6}	2.08×10^{-2}	99.9%
DCB	Diff. Circuit Breaker	5.71×10^{-6}	2.08×10^{-2}	99.9%
DCD	DC Disconnector	0.2×10^{-6}	2.08×10^{-2}	99.9%
GPR	Grid Protection	5.71×10^{-6}	2.08×10^{-2}	99.9%
PVS	PV Strings	2.43×10^{-5}	2.30×10^{-4}	99.8%
SPR	String Protection	0.313×10^{-6}	2.08×10^{-2}	99.9%
SPD	Surge Protection	0.313×10^{-6}	2.08×10^{-2}	99.9%
SDP	Surge Protection	0.313×10^{-6}	2.08×10^{-2}	99.9%
STB	String box	0.015×10^{-3}	2.08×10^{-2}	99.8%
TRA	Transformer	1.4×10^{-6}	2.28×10^{-4}	99.3%
INV	Inverter	Aging Weibull	1.7×10^{-3}	*98% (Simulated)**

* Steady state availability is simulated and shown in Figure 16

Table 8: Comparison among the real data, the deterministic and the SHyFTA model in terms of energy produced and positive payback generated under the regime of IPER 2011.

Year	Real Prod. (kWh)	Payback (€)	Deterministic (kWh)	Payback (€)	SHyFTA (kWh)	Payback (€)
1	534.844	248.168	552.606	256.409	532.777 (±829)	247.208 (±378)
2	1.164.600	540.374	1.213.319	562.980	1.163.503 (±1.909)	539.865 (±879)
3	1.765.200	819.053	1.873.664	869.380	1.791.692 (±3.030)	831.345 (±1.394)
4	2.375.546	1.102.253	2.487.950	1.154.409	2.375.685 (±4.115)	1.102.318 (±1.893)
4.6*	2.806.253	1.302.101	2.929.946	1.359.495	2.809.286 (±4.681)	1.303.509 (±2.153)

Table 9: Comparison between the deterministic and the SHyFTA model throughout the remaining years of the plant life in terms of energy produced and positive payback generated under the regime of IPER 2011.

Year	Deterministic (kWh)	Payback (€)	SHyFTA (kWh)	Payback (€)
5	3.151.996	1.462.526	3.005.940 (±5.166)	1.394.756 (±2.375)
10	6.111.600	2.835.782	5.817.056 (±10.270)	2.699.114 (±4.724)
15	8.955.165	4.155.197	8.516.286 (±15.352)	3.951.557 (±7.062)
20	11.682.162	5.420.523	11.137.157 (±20.480)	5.167.641 (±9.421)

Table 10: Comparison between the results of service availability in respect to the demand of Figure 17.

	Service Availability
Real Data	58.82%
Deterministic Model	59.63%
SHyFTA Model	58.82%