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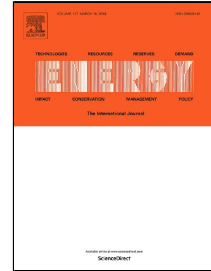
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# Accepted Manuscript

On the use of dynamic reliability for an accurate modelling of renewable power plants

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

3  
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11  
12  
13 ABSTRACT

14  
15 Renewable energies are a key element of the modern sustainable development. They play a key  
16 role in contributing to the reduction of the impact of fossil sources and to the energy supply in remote  
17 areas where the electrical grid cannot be reached.

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

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

32  
33 **Keywords:** Renewable Energy, Stochastic Hybrid Automaton, Availability, Photovoltaic Power Plant, Service  
34 Availability

35  
36 **Nomenclature**

37 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

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

38 Photovoltaic Power Plant

ACB	Alternate current circuit breaker
ACD	Alternate current disconnecter
ACS	Alternate current section
BAT	Battery
DCB	Differential circuit breaker
DCD	Direct current disconnecter

39 SHyFTA Parameters

$\beta$	Shape factor (Weibull function)
$\gamma$	Scale parameter (Weibull function)
$\lambda$	Failure rate
$\mu$	Repair rate

BE	Basic event	$\eta_n$	Efficiency ( $n^{\text{th}}$ year)
HBE	Hybrid basic event	$\eta_{\text{std}}$	Efficiency (standard condition)
		$\rho$	Power coefficient
$Ss^k_i$	$i^{\text{th}}$ stochastic state of $k^{\text{th}}$ basic event:	A	Photovoltaic panel area
	$S_k^1$ : $k^{\text{th}}$ basic event working (good)	$D_r$	Degradation rate
	$S_k^2$ : $k^{\text{th}}$ basic event broken (bad)	E	Energy
		G	Global solar irradiance
		Irr	Incident solar irradiance
$X_i$	$i^{\text{th}}$ real time variable:	L	Aging
$X_{\text{AGING\_INV}i}$	Aging $i^{\text{th}}$ inverter	$P_k$	Power ( $k^{\text{th}}$ section of power plant)
$X_{\text{ACGi}}$	AC Power $i^{\text{th}}$ generator	$P_{\text{AC}}$	Alternate current power
$X_{\text{ACS}}$	Total AC Power generated	$P_{\text{DC}}$	Direct current power
$X_{\text{CONS}}$	Power consumed by utilities	$P_{\text{loss}}$	Power loss
$X_{\text{DCGi}}$	DC Power $i^{\text{th}}$ generator	$T_a$	Ambient temperature
$X_{\text{TA}}$	Ambient temperature	$T_c$	Solar module temperature
$X_{\text{GRID}}$	Power output to the grid	$T_{c,\text{std}}$	Solar module temperature (standard condition)
$X_{\text{IRR}}$	Solar irradiance		
$X_{\text{PVSi}}$	Power $i^{\text{th}}$ photovoltaic string		

### Physical Process

$\alpha$	Elevation angle
$\beta$	Tilt angle
$\eta$	Efficiency
$\eta_m$	Solar panel efficiency
$\eta_{\text{first}}$	Efficiency (first year)
$\eta_{\text{inverter}}$	Inverter efficiency

### Stochastic Process

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

1

2

3

## 4 1 INTRODUCTION

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

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

22 An exhaustive feasibility assessment and performance evaluation of a renewable power plant  
23 should model the physical process of the energy conversion, account for the variability of the primary  
24 resource and its effects on the system availability, model the performance deterioration caused by the

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

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

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

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

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

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

## 49 2 RELATED WORKS

51 To the best of the authors' knowledge, previous literature has not yet proposed any modeling  
52 formalism which is able to combine in a unified model the deterministic and the stochastic processes  
53 that affect the performance of a power plant. However, it is possible to find several works that address

1 the modelling of deterministic and stochastic processes independently. For instance, the design and  
 2 the study of renewable power plants with deterministic approaches are object of several academic  
 3 courses and handbooks [17, 18].

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

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

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

30  
 31  
 32 Table 1: Main characteristics of the models used for dependability assessment.  
 33

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

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

51 As displayed in Table 1, both static and dynamic reliability modes are based on the hypothesis  
 52 that working conditions are fixed so that components can operate into their nominal state of operation  
 53 (single-state) and can be characterized with a fixed function of failure probability. This is an ideal  
 54 assumption because environmental factors and operation conditions may change, affecting the

1 performance of the system. In renewable power plants this is even more critical because the operating  
 2 conditions (and thus the failure characteristics) are continuously influenced by the randomness of the  
 3 renewable resource.

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

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

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

### 24 25 3 HYBRID-PAIR MODELLING OF RENEWABLE POWER PLANTS: CONCEPT AND 26 IMPLEMENTATION OF A STOCHASTIC HYBRID FAULT TREE AUTOMATON

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

30 Dynamic reliability defines a mathematical framework which is able to combine deterministic  
 31 (e.g., process of energy transformation) and stochastic (e.g., process of failure of a system) models  
 32 [12]. Dynamic reliability makes use of non-linear functions to adapt the system failure probability  
 33 according to the system operation conditions. This leads to more accurate reliability modelling able  
 34 to account for environmental and operational changes of the working conditions. Moreover, recent  
 35 works have shown its potential as a tool for the dimensioning of a system [46] and the understanding  
 36 of other aspects of the life cycle of a system that characterizes the regime operations, like availability  
 37 and maintenance.

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

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

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

1 described with a repairable dynamic fault tree (RDFT) [49] for an easy implementation and evaluation  
2 of the failure model of the system [50].

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

10 Figure 1: Mutual dependency between the deterministic and the stochastic model.  
11  
12

### 13 3.1 Stochastic hybrid fault tree automaton (SHyFTA)

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

16 The SHyFTA is a 13-uplet  $(S, \mathcal{E}, X, Y, \delta, H, G, F, P, GA, BE, T, C)$ , where:

- 17 •  $S$  is a finite set of discrete states  $\{S_D, S_S\}$ .  $S_D$  is the subset of deterministic states and  $S_S$  is the  
18 subset of stochastic states.
- 19 •  $\mathcal{E}$  is a finite set of events  $\{\mathcal{E}_D, \mathcal{E}_S\}$ , where  $\mathcal{E}_D$  is the subset of deterministic events and  $\mathcal{E}_S$  is the  
20 subset of stochastic events.
- 21 •  $X$  is a finite set of real variables evolving in time  $\{x_1, \dots, x_n\}$ .
- 22 •  $Y$  is a finite set of arcs of the form  $(s, \varepsilon_j, G_k, s')$  where  $s$  and  $s'$  are, respectively, the origin and  
23 the destination states of the arc  $k$ ,  $\varepsilon_j$  is the event associated with this arc,  $G_k$  is the guard condition  
24 on the real variable  $X$  in state  $s$ .
- 25 •  $\delta: S \times X \rightarrow (\mathbb{R}^{n^+} \rightarrow \mathbb{R})$  is a function of activities, describing the evolution of real variables in each  
26 discrete state.
- 27 •  $H$  is a finite set of clocks on  $\mathbb{R}$  that identify the firing of a deterministic or a stochastic event.
- 28 •  $F: H \times S \times X \rightarrow (\mathbb{R}^{n^+} \rightarrow [0, 1])$  is a set of applications that associate a distribution function to the  
29 stochastic events  $\mathcal{E}_S$ , according to the clock  $H$ , the system evolution  $X$  and the discrete state  $S$ .
- 30 •  $P$  is the instantaneous probability to be in  $s_i \in S_S$ ;
- 31 •  $GA$  is the finite set of gates of the fault tree model.
- 32 •  $BE$  is the finite set of basic events of the fault tree model. The set  $BE$  contains a subset called  
33 Hybrid Basic Events (HBE) whose failure distribution depends on the evolution of the system  
34 and varies continuously in time. This type of basic event accounts for the multi-state nature of a  
35 component, namely those systems whose failure characteristics are not static in time but vary  
36 dynamically according to the operational conditions that, in turn, affect reliability and  
37 performance. These events are characterized by a non-static pdf through a set of functions  $f_i \in F$ ,  
38  $f_i: H \times S \times X \rightarrow (\mathbb{R}^{n^+} \rightarrow [0, 1])$ .
- 39 •  $TE$  is the top event of the fault tree and corresponds with the output of the main gate.
- 40 •  $C$  is the set of connections between gates and basic events.

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

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



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

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

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

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

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

The Weibull probability density function in Eq. (3) can be generalized when the scaling factor  $\gamma(L, X, S)$  is a function of the evolution  $X = \{x_1, \dots, x_n\}$  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,

1 the basic event is referred as hybrid. Otherwise, the basic event must be characterized with the pdf  
2 provided by the component manufacturer that is generally static.

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

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

#### 18 4 CASE STUDY: A PHOTOVOLTAIC POWER PLANT

20 There have been proposed different fault tree models of renewable power plants that can be used  
21 as reference models to build up a SHyFTA [16, 32-35]. In this paper, the case study of a photovoltaic  
22 power plant is presented. The analyzed power plant is a grid-connected photovoltaic power plant with  
23 no trackers implemented by a private company in 2011, located in Sicily close to Syracuse (see Figure  
24 3 and Table 3).

25  
26 Table 3: PV system characteristics.

27  
28  
29 The power plant is characterized by a peak power,  $P_{peak} = 419,5$  kW and by two identical DC/AC  
30 inverters of 220 kW<sub>p</sub>. There are 4 string boxes for each inverter: 3 accommodate 17 strings and 1  
31 accommodates 18 strings. The strings are connected in parallel while the modules are in series  
32 (Figures 4 and 5). Tables 4-5 summarize the main characteristics of the system.

33  
34 Table 4: PV module main characteristics.

35  
36 Table 5: Inverter main characteristics.

37  
38  
39  
40 To be compliant with the Italian Producer Electrical Regulation (IPER) of 2011 (Terzo Conto  
41 Energia [55]), the power plant is connected to the national grid. The IPER states that the power plant  
42 must stop in case of disconnection from the national grid and forbids the use of energy storage  
43 systems. There is a strong economic advantage for adhering to the IPER of 2011. In fact, for the first  
44 20 years of life of the power plant, there is a fixed economic subsidy for all the energy produced.  
45 Moreover, the energy not instantaneously consumed by the producer is tracked and sold with a price  
46 dictated by the energy market. Therefore, the power plant contributes to the company activities by  
47 supplying the internal consumption and providing a profit due to the economic incentive (subsidy)  
48 and the sale of the energy not consumed. Table 6 shows the value of the Subsidy (it is fixed by the  
49 IPER [53]) and the corresponding price of buy/sell per one kWh of energy. This latter is a rough value  
50 of the energy price in the energy market (2011). The column Total is the sum of the previous  
51 contributes and it is used to estimate the payback generated by the energy produced by the power  
52 plant.

1 Table 6: IPER 2011 Subsidy. Price\* is based on an average value of the energy price in the energy market  
2 (2011) [43].  
3

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

10  
11 Figure 4: Global horizontal irradiation in Italy.

12  
13 With reference to Figures 5, 6 and 7, it is possible to identify the main components of the  
14 photovoltaic power plant.

15  
16 Figure 5: Map of the power plant and its sections.

17  
18 Figure 6: Power Inverter configuration.

19  
20 The components of the photovoltaic power plant can be grouped into the following functional  
21 blocks (Figure 7):  
22

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

30  
31 Figure 7: Schematic decomposition of the PV system  
32

33 Next, we apply the steps discussed in Section 2 to build up the SHyFTA model under the following  
34 assumptions:

- 35 1- The physical variables, input of the model, are the ambient temperature and sun irradiance;
- 36 2- The hourly aggregated samples of the physical variables are extracted by the SCADA of the  
37 PV power plant;
- 38 3- The randomness of the physical variables is achieved by applying a random seasonal variation  
39 component at each iteration of the simulation;
- 40 4- It is assumed that the inverter switches on when the output power at the PVM stage is greater  
41 than zero (during the daily time). This affects the aging of the inverter.
- 42 5- In the deterministic model, performance degradations occur only for the photovoltaic panels  
43 and for the inverters.
- 44 6- In the stochastic model, the components of the photovoltaic power plant can be only in two  
45 possible states (S1: good or working, S2: bad or failed).
- 46 7- Failure rates of all the components except inverters are constant [16];
- 47 8- The inverter failure rate is not constant and is subjected only to an aging process;
- 48 9- Repair rates of all the components are constant;
- 49 10- Restoration of a component brings the component back to as-good-as-new state.

#### 50 51 4.1 Definition of the Deterministic Process

52 The photovoltaic conversion starts in the PVM stage where PV modules capture the solar  
53 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:

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

As shown in Figure,  $I_{rr}$  is the incident solar irradiance [ $\text{W}/\text{m}^2$ ];  $\alpha$  is the elevation angle and  $\beta$  is the tilt angle of the module/string measured from the horizontal. Finally,  $A$  is the area of the module [ $\text{m}^2$ ] and  $\eta$  is the system efficiency that is always less than 1.

Figure 8: Solar Irradiation, elevation angle  $\alpha$  and tilt angle  $\beta$

The total efficiency can be expressed as:

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

where  $\eta_i$  is the number of loss effects considered at each  $i^{\text{th}}$  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,  $\eta_m$ , by considering the variation of the temperature [54]:

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

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

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

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

where  $\eta_{\text{first}}$  is the nominal efficiency at the first year, while  $\eta_n$  is the efficiency calculated at the  $n^{\text{th}}$  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:

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

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

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

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  $[t_2, t_1]$ :

$$E_{PROD}(t) = \int_{t_1}^{t_2} P_{ACS}(t) dt \quad (\text{Eq. 10})$$

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:

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

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.

1  
2 5 COUPLING AND SIMULATION OF THE SHYFTA MODEL

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

7  
8 Figure 11: Hybrid-Pair architecture of the case study and corresponding SHyFTA mapping.  
9

10  $X_{IRR}$  and  $X_{TA}$  represent respectively the sun irradiance  $I_{rr}$  and the ambient temperature  $T_a$ . These  
11 two variables are inputs of the model and, according to Eqs. (4-7), affect the power generation and  
12 the conversion efficiency of the PVM components. The ACS conversion depends on Eq. (8) and the  
13 actual energy produced by the power plant is described by Eqs. (9) and (10). To account for the effects  
14 of the stochastic model, the SHyFTA provides a mechanism of synchronization between the variables  
15 of the deterministic model and the stochastic events (the basic events) that determine the status of  
16 each component. In the stochastic process, the basic events are characterized by two operational  
17 states,  $S_S = \{\text{Good, Bad}\}$ . The health status of each basic event is an element of the vector  $\mathbf{E}_S$  that, as  
18 input to the deterministic process, realizes the coupling between the basic events of the stochastic  
19 process with the corresponding discrete components modelled in the deterministic process. Since it  
20 was assumed that components can be only in two possible states, the binary representation can be set  
21 as follows:  
22

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

23  
24 According to this notation, it is now possible to evaluate and rewrite the real variables  
25  $X_{PVS1/138}$ ,  $X_{DCG1/2}$ ,  $X_{ACS1/2}$ ,  $X_{PROD}$  and  $X_{GCC}$  of the SHyFTA model that correspond with the powers  
26 levels generated at the different stages of a PV plant generator.

27  $X_{PVS_i}$ , with  $i=1, \dots, 138$ , is the DC power generated by the  $i^{\text{th}}$  photovoltaic string (each string is  
28 comprised of 16 modules, see Table 4) that depends on the status of the  $i^{\text{th}}$  string  $S_{PVS_i}$ :  
29

$$X_{PVS_i} = [\eta I_{sin}(\alpha + \beta_{PVS_i}) A_{PVS_i}] \times S_{PVS_i} \quad (\text{Eq. 12})$$

30  
31  
32  $X_{DCS1/2}$  are the total DC power of each photovoltaic generator (a DC generator is comprised of  
33 69 strings of the corresponding PVM section) and it includes the loss of DC wiring connections and  
34 possible faults of DC protection or fuses:  
35

$$X_{DCS1} = \sum_{i=1}^{69} X_{PVS_i} \times (S_{SPR1} \times S_{DCD1} \times S_{SPD1}) \quad (\text{Eq. 13})$$

$$X_{DCS2} = \sum_{i=70}^{138} X_{PVS_i} \times (S_{SPR2} \times S_{DCD2} \times S_{SPD2}) \quad (\text{Eq. 14})$$

36  
37  
38  
39  
40  $X_{ACS1/2}$  are the total AC power output of each AC sections and including the efficiency loss of  
41 the inverters and possible faults of the AC protections and breakers.  
42

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

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

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

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

$$7 \quad X_{ACS} = X_{ACS1} + X_{ACS2} \quad (\text{Eq. 17})$$

8  
 9  
 10  $X_{GRID}$  is the power exchanged with the grid and is computed as difference between the produced  
 11 power  $X_{ACS}$  and the amount of instantaneous power  $X_{CONS}$  requested by the utilities connected to the  
 12 power plant:

$$13 \quad X_{GRID} = X_{ACS} - X_{CONS} \quad (\text{Eq. 18})$$

14  
 15  
 16 Among the variables computed in the deterministic process, Eq. 19 models the counter of the  
 17 inverter aging of an inverter,  $X_{aging} = L$ , measuring the amount of time in which an inverter is on.

$$18 \quad X_{Aging\_INVi} = \int_0^t i_{ON\_INVi}(t) dt, \quad i = 1, 2 \quad (\text{Eq. 19})$$

$$19 \quad i_{ON\_INVi}(t) = \begin{cases} 1, & X_{DCSi} > 0 \\ 0, & X_{DCSi} = 0 \end{cases} \quad i = 1, 2$$

20  
 21  
 22 This value is an input of the Weibull pdf characterizing the failure behavior of the inverter in the  
 23 stochastic process [see Eq. (2-3)].

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

$$31 \quad \mathbb{E}[X_{ACS}] = \frac{1}{N} \left[ \sum_{k=1}^N X_{ACS}^k(t) \right] \quad (\text{Eq. 20})$$

32 where  $N$  is the number of Monte Carlo trials.

33 The estimator error associated to the desired confidence interval can be computed as follows  
 34 [61]:

$$35 \quad Err = Z_{a/2} \times \frac{\sigma}{\sqrt{N}} \quad (\text{Eq. 21})$$

36  
 37 where  $Z_{a/2}$  is the confidence coefficient,  $a$  is the confidence level,  $\sigma$  is the standard deviation of the  
 38 Monte Carlo simulation and  $N$  is the number of Monte Carlo trials.

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

43 The inputs of the models are the solar irradiance and the ambient temperature acquired by the  
 44 logging system of the real power plant during 2011-2015. Figure 12 shows the ambient temperature  
 45 data. In this way, using the same historical time series, it is possible to compare the results of the  
 46 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  $\pm 4.681$  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 ( $\pm 4.681$  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  $\pm 20.480$  kWh.

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<sup>th</sup> year, a difference of about 545.000 kWh ( $\pm 20.480$  kWh) of loss of energy productivity. Under the regime of IPER 2011, at the end of the economic investment established at the 20<sup>th</sup> year from the start of the power plant, this lack of energy production corresponds to a cash short of about 250.000 € ( $\pm 9.421$  €).

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



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

### 3 5.2 Plant and service availability

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

$$9 \quad P(BE_1 \cap BE_2 \cap BE_3 \dots \cap BE_n) = \quad (Eq. 22)$$

$$10 \quad P(BE_1) \times P(BE_2) \times P(BE_3) \times \dots \times P(BE_n) = \prod_{i=1}^n P(BE_i)$$

$$14 \quad P(BE_1 \cup BE_2 \cup BE_3 \dots \cup BE_n) = P(\sum_{i=1}^n BE_i) = \quad (Eq. 23)$$

$$15 \quad \sum_{k=1}^n (-1)^{k+1} \sum_{\substack{i_1, i_2, \dots, i_k \\ 1 \leq i_1 < i_2 < \dots < i_k \leq n}} P(BE_{i_1} \cap BE_{i_2} \dots \cap BE_{i_k})$$

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

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

25 Figure 16: Inverter Availability simulated.

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

$$31 \quad A = 1 - U_{TE} = 0,9999$$

$$32 \quad U_{TE} = U_{PVGEN} + U_{GCC} - [U_{PVGEN} \times U_{GCC}] = 1e-5$$

$$33 \quad U_{GCC} = U_{GPR} + U_{ACD} + U_{DCB} + U_{TRA} - [U_{GPR} \times U_{ACD}] - [U_{GPR} \times U_{DCB}] - [U_{GPR} \times U_{TRA}] - [U_{ACD} \times$$

$$34 \quad U_{DCB}] - [U_{ACD} \times U_{TRA}] - [U_{DCB} \times U_{TRA}] + [U_{GPR} \times U_{ACD} \times U_{DCB}] + [U_{GPR} \times U_{ACD} \times U_{TRA}] + [$$

$$35 \quad U_{GPR} \times U_{DCB} \times U_{TRA}] + [U_{ACD} \times U_{DCB} \times U_{TRA}] - [U_{GPR} \times U_{ACD} \times U_{DCB} \times U_{TRA}] =$$

$$36 \quad 0.1e-4.$$

$$37 \quad U_{PVGEN} = U_{PVGEN1} \times U_{PVGEN2} = 5,6e-9$$

38

1 For each  $i^{\text{th}}$  section of the photovoltaic power plant, with  $i = 1, 2$ , it is possible to compute the  
 2 following:

$$3 \quad U_{\text{PVGEni}} = U_{\text{ACSi}} + U_{\text{DCSi}} - [U_{\text{ACSi}} \times U_{\text{DCSi}}] = 7,5e-5$$

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

$$5 \quad U_{\text{SDPi}} \times U_{\text{ACBi}}] = 4,5e-5$$

$$6 \quad U_{\text{DCSi}} = U_{\text{SPRi}} + U_{\text{DCDi}} + U_{\text{SPDi}} + U_{\text{PVMi}} - [U_{\text{SPRi}} \times U_{\text{DCDi}}] - [U_{\text{SPRi}} \times U_{\text{SPDi}}] - [U_{\text{SPRi}} \times U_{\text{PVMi}}] - [$$

$$7 \quad U_{\text{DCDi}} \times U_{\text{SPDi}}] - [U_{\text{DCDi}} \times U_{\text{PVMi}}] - [U_{\text{SPDi}} \times U_{\text{PVMi}}] + [U_{\text{SPRi}} \times U_{\text{DCDi}} \times U_{\text{SPDi}}] + [$$

$$8 \quad U_{\text{SPRi}} \times U_{\text{DCDi}} \times U_{\text{PVMi}}] + [U_{\text{SPRi}} \times U_{\text{SPDi}} \times U_{\text{PVMi}}] + [U_{\text{DCDi}} \times U_{\text{SPDi}} \times U_{\text{PVMi}}] - [$$

$$9 \quad U_{\text{SPRi}} \times U_{\text{DCDi}} \times U_{\text{SPDi}} \times U_{\text{PVMi}}] = 3e-5$$

$$10 \quad U_{\text{PVMi}} = \prod_j U_{\text{PVS}_j} = 1e-13, \text{ with } j = \begin{cases} 1, j = 1, \dots, 69 \\ 2, j = 70, \dots, 138 \end{cases}$$

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

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

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

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

31 The SHyFTA model here presented takes into account all the previous effects, although its  
 32 accuracy (and complexity) can be certainly increased. In fact, the stochastic fault tree model of failure  
 33 (Figure 8, Figure 9 and Table 7) accounts for the unavailability of type (i); the unavailability of types  
 34 (ii) and (iii) depend on the real variable  $X_{\text{IRR}}$  and  $X_{\text{TA}}$ , input of the deterministic model. Moreover,  
 35 some of the most dramatic causes of power unavailability of type (iii) are embedded in the  
 36 deterministic model since the panels and inverter performance, as shown in Eqs. (6)-(9), depend on  
 37 the variation of the ambient temperature  $X_{\text{TA}}$ . Certainly, the deterministic model could include many  
 38 other physical effects that influence the performance of the energy conversion but, the modelling of  
 39 such mechanisms, is not the main subject of this research paper. To compute the service availability,  
 40 the SHyFTA model requires as input the daily power demand, as shown in Figure 17a. It is possible  
 41 to see that it grows during the initial hours of the working day, reaches a peak between 10:00-15:00  
 42 and decreases when the production activities are about to finish, at the end of the working day. Figure  
 43 17.b shows the schema of the power supply: if the demanded power exceeds the power generated by  
 44 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

1 and working interactions of the physical components that participate to the process of energy  
2 conversion of the power plant. There have been presented different mathematical models of other  
3 renewable technologies (e.g. hydroelectric power plants [67-70], wind farms [71, 72]) that can be  
4 used to characterize the model of power conversion and the efficiency of its main components. Other  
5 works have investigated the failure behavior of these systems highlighting the dynamic dependencies  
6 and aging effects of the main components (e.g. hydro [35, 51, 73] and wind [34, 74] technologies).  
7 All these elements can be integrated in a SHyFTA model with algorithms that are able to grasp the  
8 uncertainty of the renewable resource (e.g., wind forecasting based on neural networks [75],  
9 autoregressive models [76, 77] or Markov chains [78, 79]).

## 10 6 CONCLUSIONS

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

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

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

47 Due to the rigorous modelling process that includes components' repair processes, the results  
48 obtained in this paper improve the one presented in [16] limited to the reliability evaluation with non-  
49 repairable components that, for a renewable power plant, is not the most significant key performance  
50 index to consider. With the SHyFTA model, it was possible to compute both the availability of the  
51 plant and the related service availability and it was shown that, despite a large plant availability  
52 (99,9%), the photovoltaic power plant is not able to offer the same level of service availability (58%)  
53 due to the unpredictability of the primary resource and the impossibility to store the unused energy.

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

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

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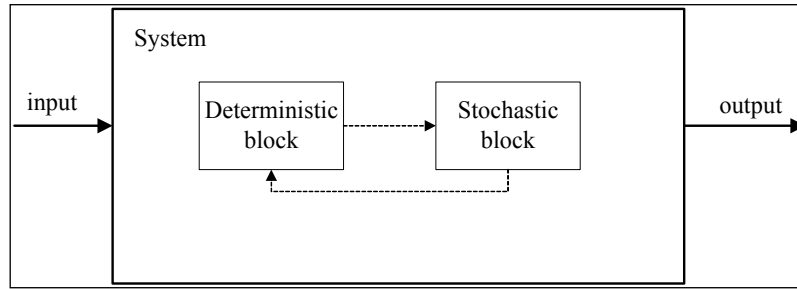


Figure 1: Mutual dependency between the deterministic and the stochastic model.

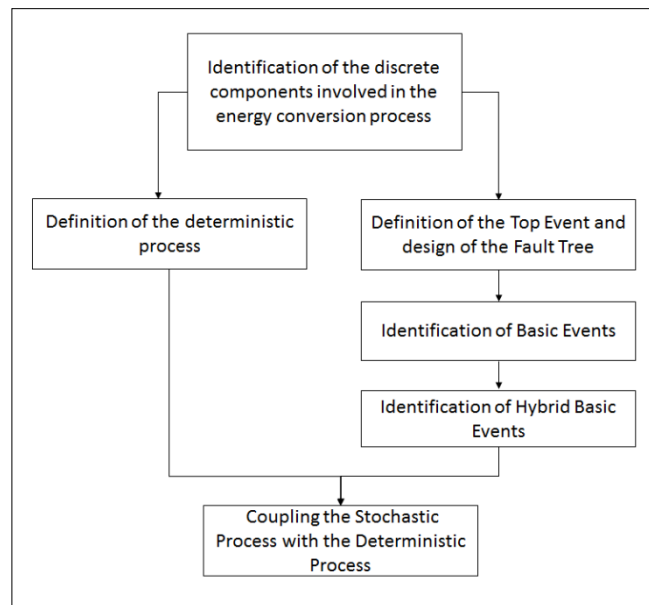


Figure 2: Steps for the construction of a SHyFTA model.

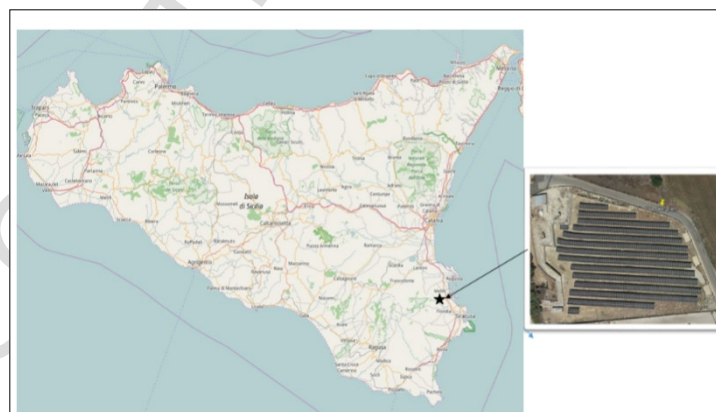


Figure 3: Location of the power plant.



Figure 4: Global horizontal irradiation in Italy.



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

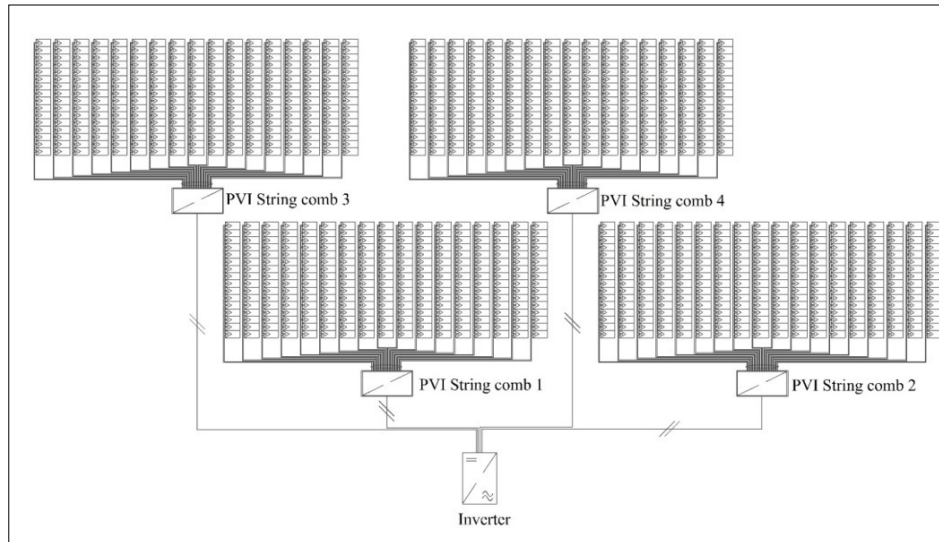


Figure 6: Power Inverter configuration.

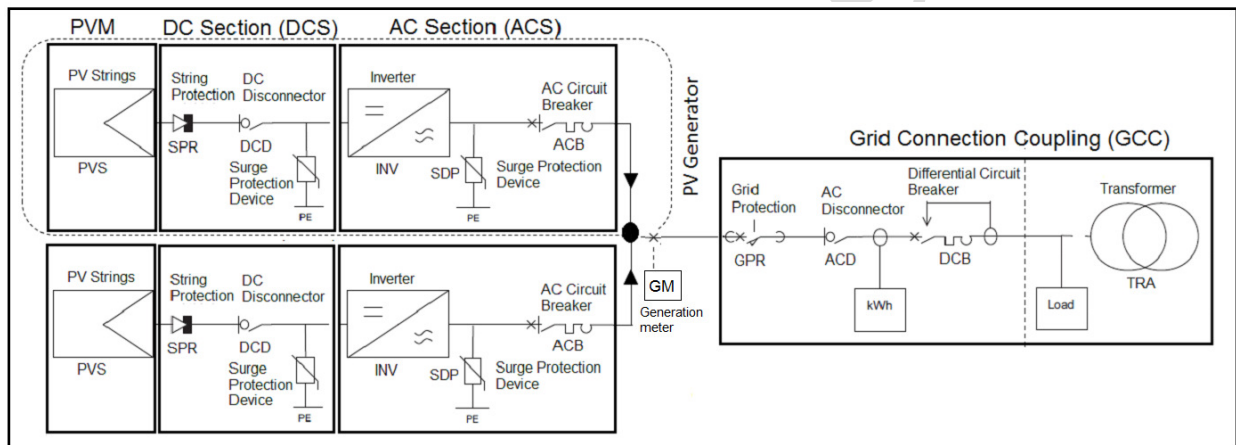
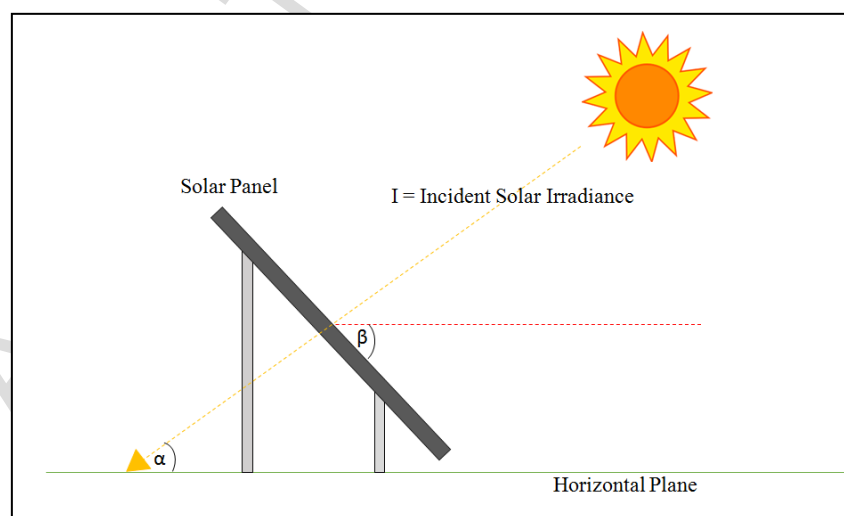


Figure 7: Schematic decomposition of the PV system

Figure 8: Solar Irradiation, elevation angle  $\alpha$  and tilt angle  $\beta$

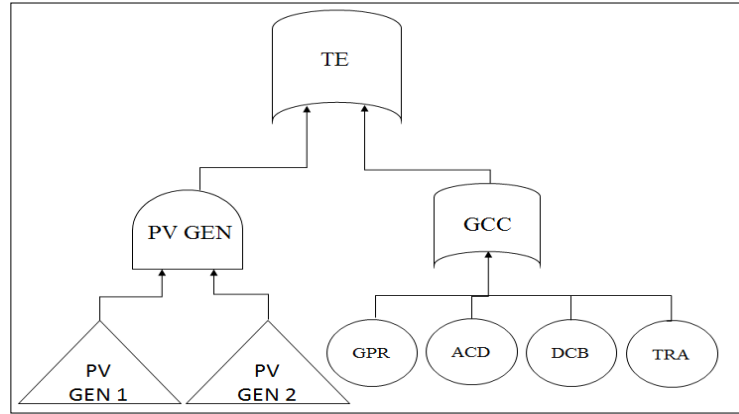


Figure 9: Fault tree of the PV power plant. PV GEN 1 and PV GEN 2 are represented with the transfer gate symbol (triangle) because these sub-systems are developed into another fault tree model.

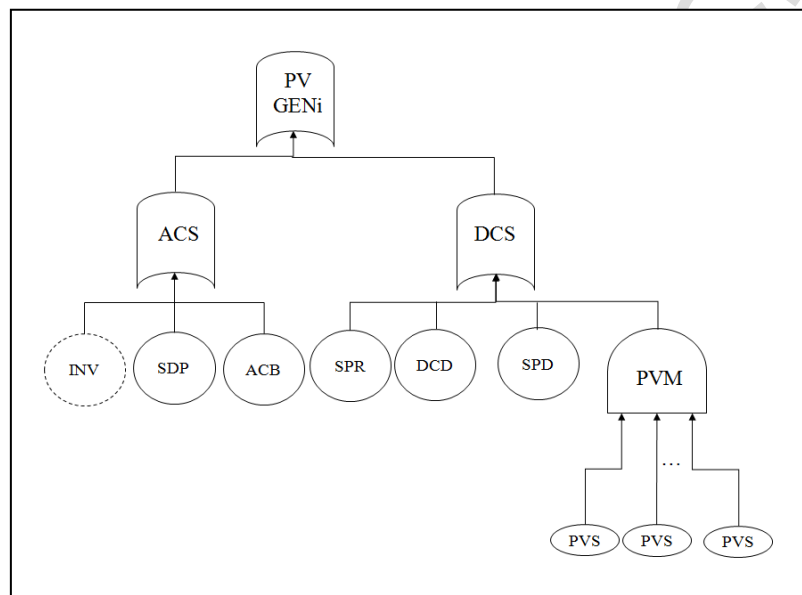


Figure 10: Fault tree of a PV generator. The basic event INV is represented with a dashed circle to indicate that it belongs to the subset of the hybrid basic events.

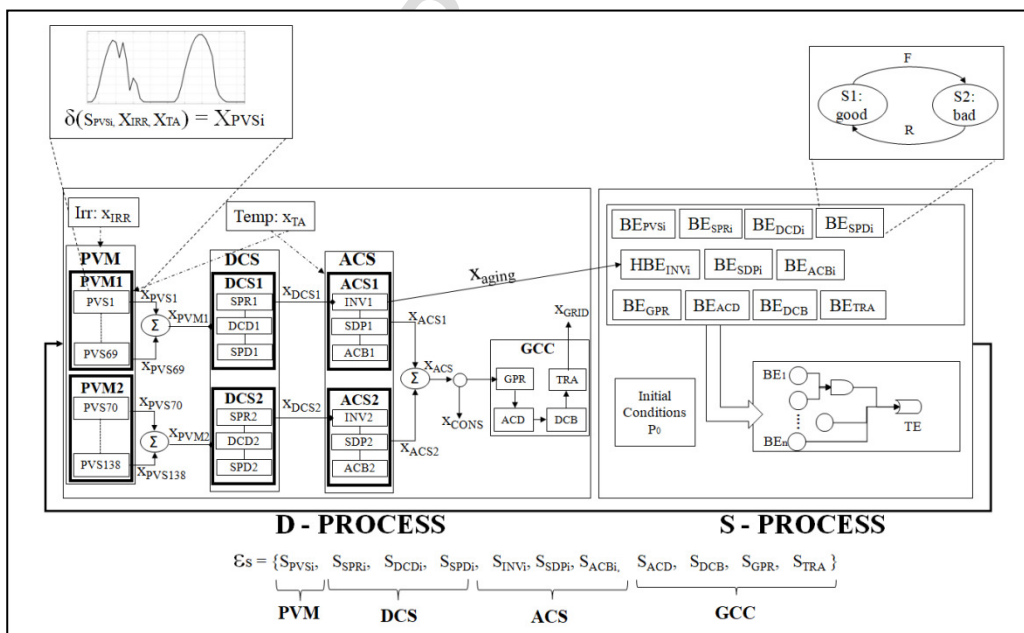


Figure 11: Hybrid-Pair architecture of the case study and corresponding SHyFTA mapping.

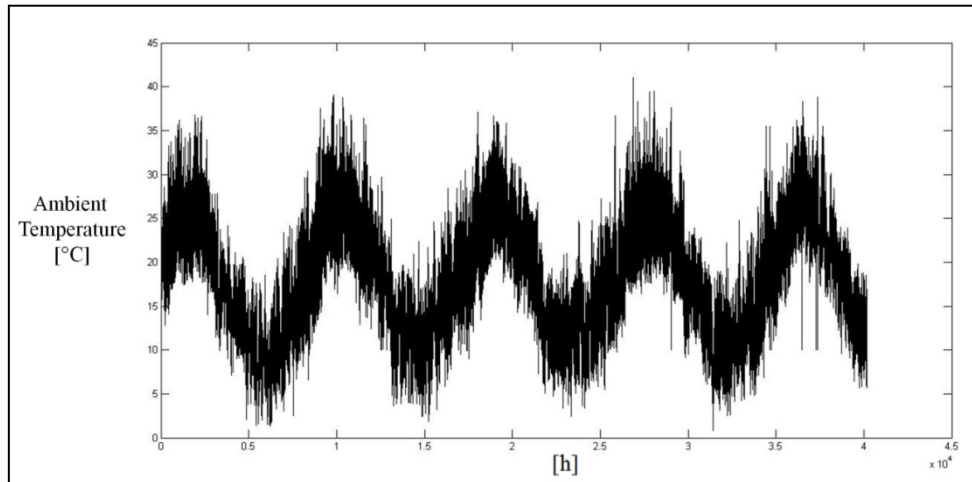


Figure 12: Historical time series of the ambient temperature (2011-2015), Syracuse (Italy).

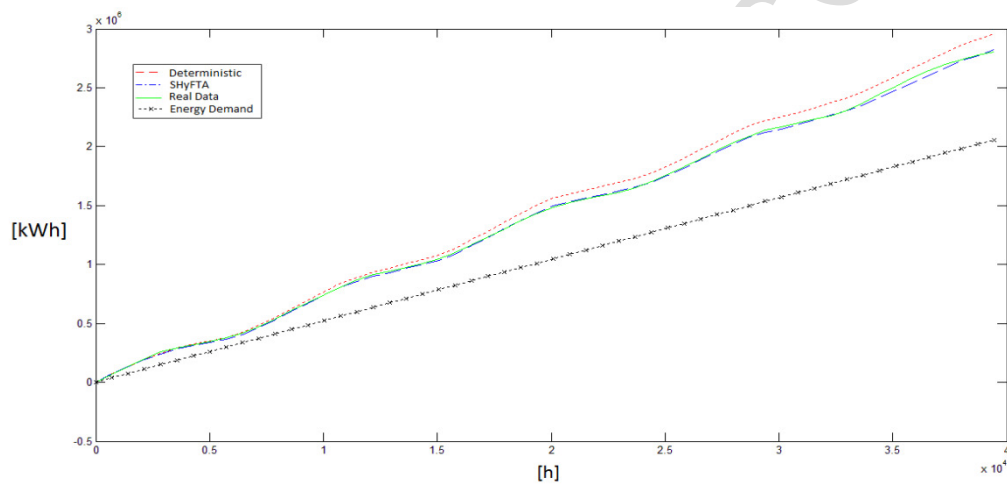


Figure 13: Comparison between the energy produced by the deterministic model, the SHyFTA and the real

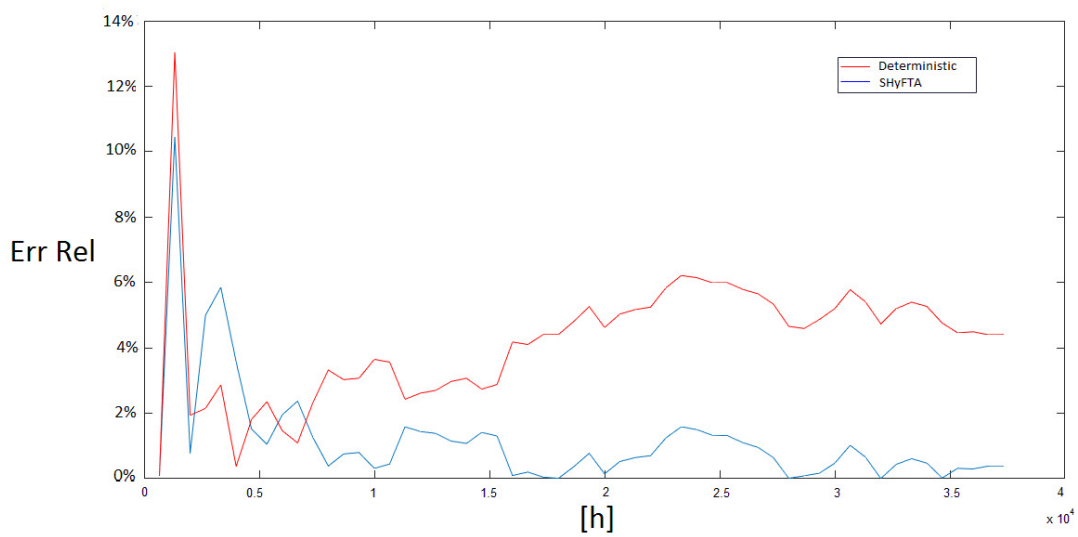


Figure 14: Comparison between the relative error of the deterministic model and the SHyFTA.

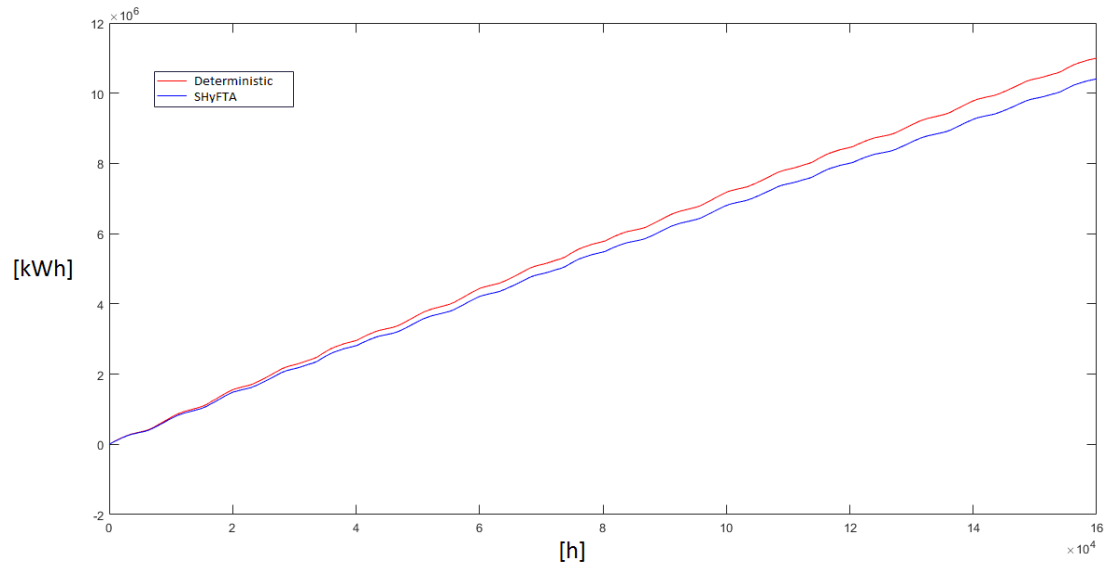


Figure 15: Energy production estimation throughout the life time of the power plant (20 years).

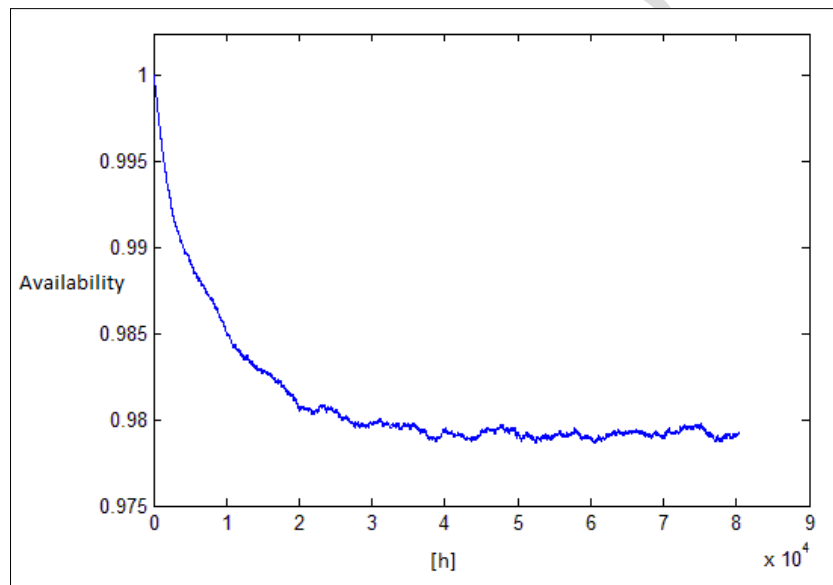


Figure 16: Inverter Availability simulated.

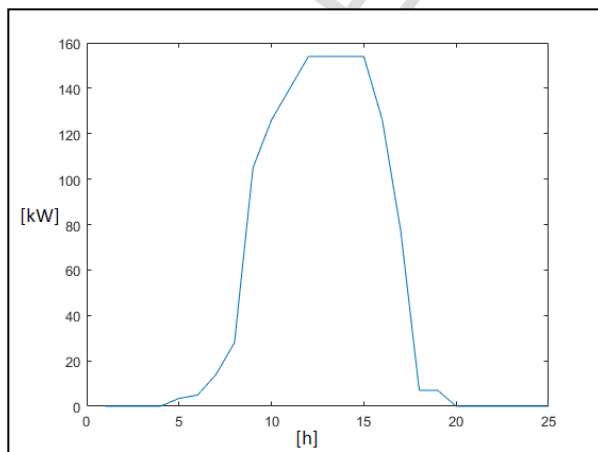


Figure 17.a: daily power demand.

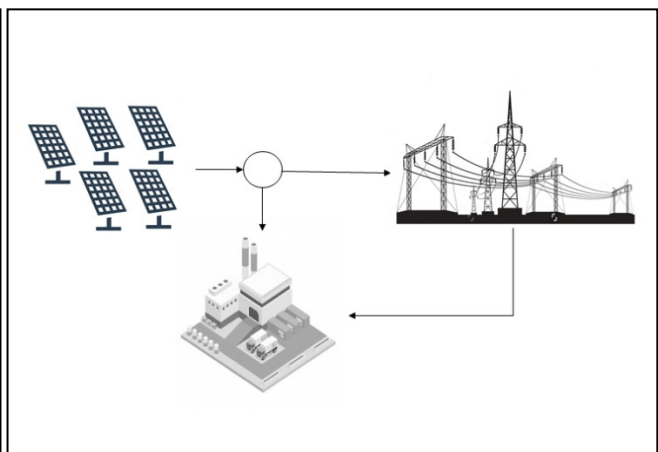


Figure 17.b: schema of the power supply.

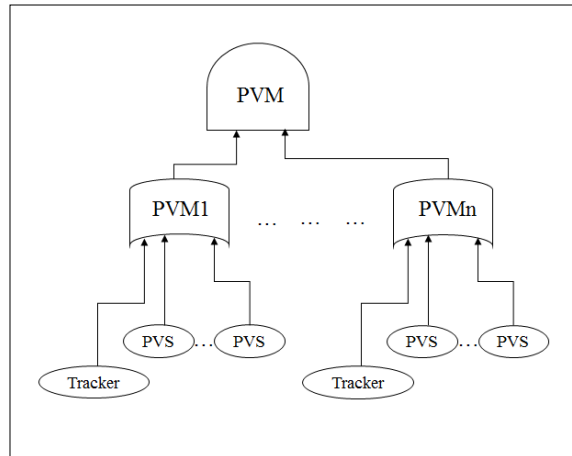


Figure 18: Fault tree of the PVM section that includes a tracker for each panel of the power plant.

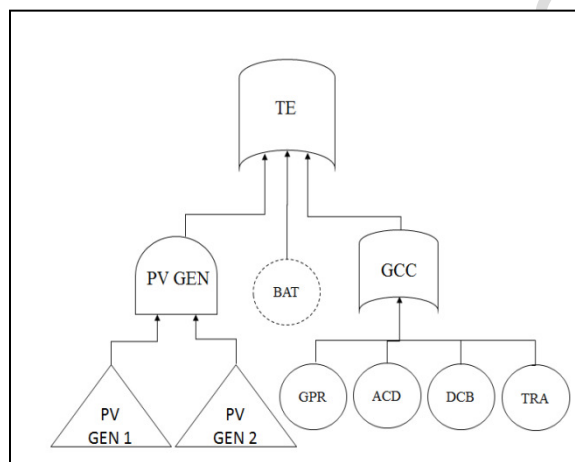


Figure 19.a: Fault tree of the power plant that includes a system of battery

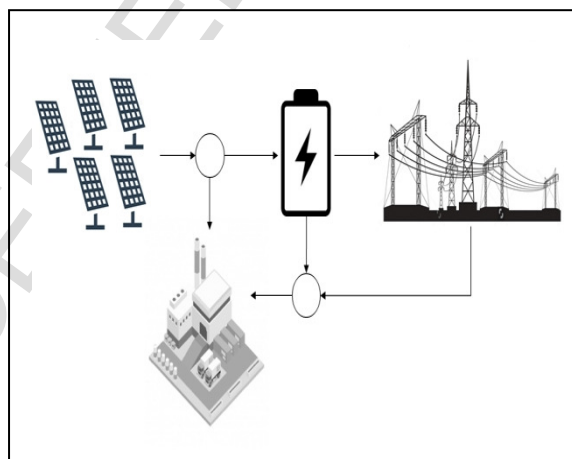


Figure 19b: schema of the power supply with a system of battery.



## 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
<b>Physical Process</b>	Static working conditions Single-state operating components	Static working conditions Single-state operating components	Dynamic working conditions Multi-state operating components
<b>Stochastic Process</b>	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
<b>Modelling Techniques</b>	Reliability Block Diagrams Fault Tree	Dynamic Reliability Block Diagrams Dynamic Fault Tree Markov Processes	Stochastic Automaton Models Regime Switching Models* Piecewise Markov Processes*
<b>Satisfied Criteria (Table 1)</b>	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
<b>Computational Costs</b>	<i>Time-Dependency</i> Physical Process: No Stochastic Process: No	<i>Time-Dependency</i> Physical Process: No Stochastic Process: Yes	<i>Time-Dependency</i> Physical Process: Yes Stochastic Process: Yes
<b>Overall</b>	<b>Low</b>	<b>Medium to High</b>	<b>High to Very High</b>

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 <sub>p</sub>
N° inverters	2
N° strings boxes	4 (per inverter)
N° strings	138
N° modules	2208 (16 for each string)
Azimuth Angle	180°
Tilt Angle ( $\beta$ )	30°

Table 4: PV module main characteristics.

$P_{peak}$	190 W (Monocrystalline)
Panel efficiency ( $\eta$ )	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
$\eta_{max}$	98%
$V_{acr}$	320 V
$I_{acmax}$	450 A
$I_{dcmax}$	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 (Σ)
$1 < P \leq 3$	0,362	0,25	0,612
$3 < P \leq 20$	0,339	0,21	0,549
$20 < P \leq 200$	0,321	0,18	0,501
$200 < P \leq 1.000$	0,314	0,15	0,464

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

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