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Reliability Assessment In Microgrids: Comparison Of Modeling Methods

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ABSTRACT
Modern society faces an unsustainable energy system. Therefore, innovative solutions have emerged to modernize distribution systems in recent years. The concept of Microgrids is vital within these solutions since the implementation of these would improve the quality of supply, efficiency, and reliability and provide cleaner energy at lower costs. Despite its advantages, researchers in Microgrids currently face significant challenges. An example of this is the evaluation of the reliability of distribution systems with Microgrids applications, which corresponds to one of the most critical and complex challenges encountered. This paper studies a collection of methods reported in the literature for modeling stochastic systems. Advantages and disadvantages are reported there. This presents a selection of the method that could best adapt in the case of Microgrids. Finally, the selected method is implemented in a case study.

Keywords: Distributed Generation, Markov, Microgrids, Monte Carlo Simulation

1. INTRODUCTION

Reliability theory is used in most of the areas that electricity distribution companies handle: conceptual design, equipment acquisition, operating decisions, maintenance and spare parts policies, and evaluation of the status and performance of the distribution system (DS) or its subsystems. Said reliability theory is based on probabilistic methods for the reliability evaluation of the DS. The probabilistic methods mentioned above have been widely developed; despite this, there is no single formula or method. The method used and the resulting equations depend on the problem and assumptions. At this point, it is necessary to remember that many assumptions must be made for practical applications of probability and statistical theory. In addition, it must be considered that the analysis's validity is directly related to the validity of the models used to represent the system [1], [2].

The rest of this work is organized in the following way: in section 2, different reported stochastic modeling methods are studied, identifying their advantages, disadvantages, applications, and trends. Finally, the Monte Carlo sequential simulation method is selected, given its adaptation to the needs of the problem. Monte Carlo simulation is then implemented in a case study in section 3. Possible future work is presented later in section 4. Finally, the conclusions are presented in Section 5.

2. METHODS FOR RELIABILITY ASSESSMENT IN DS

According to literature reports, the methods could be divided into two categories, analytical and Monte Carlo simulation (MCS) methods. Table 1 shows the two categories' advantages, disadvantages, and applications.

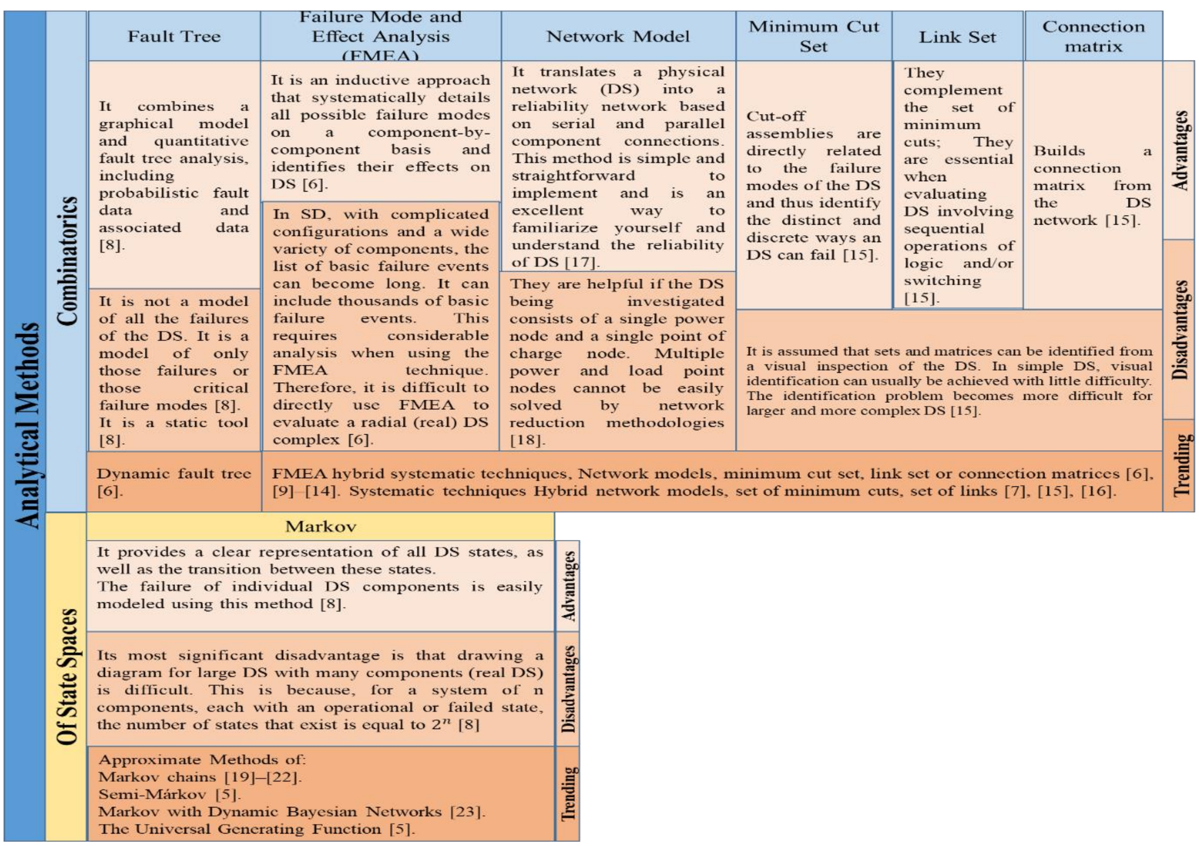
Table 1: Methods Advantages-Disadvantages-Application

Methods	Advantages	Disadvantages	Application
Analytical	These are extremely useful for evaluating the expected values of indices and have been used for years to help planners make planning and operating decisions.	They do not provide the probability distributions of the indices; these are important because they provide information about events that rarely occur but can have severe effects on the system. These events, which can quickly occur in real life, can be disregarded if probability distributions are not provided [1], [3]–[7].	Analytical methods are more efficient if complex operating conditions are not considered and/or the probabilities of component failure are minimal (i.e., the system is very reliable).
MCS	They provide the probability distributions of the indices. In theory, MCS can consider virtually all aspects and contingencies inherent in an DS's planning, design, and operation. These include random events such as load variations and the generation, interruptions, and repairs of elements represented by probability distributions.	Computing Time. Provide an estimate of the expected values of the indices.	When complex operating conditions are involved and/or the number of severe events is relatively large, Monte Carlo methods are often preferable.

2.1 Analytical Methods

These represent the system using mathematical models based on probability theory. Most of these techniques are formalized methods for transforming the system's logical functioning, or the system's topology, into a structure consisting solely of components, paths, or branches in series and parallel, using mathematical expressions to determine reliability indices. It should be noted that several of the methods are very similar in concept. The main difference between them is the formal or logical presentation of the method and not the essential underlying concept. There are two types of these, combinatorial models and state space models. Figure 1 shows the most developed basic analytical methods for evaluating reliability in DS and their advantages and disadvantages. Table 1 and Figure 1 follow the crucial disadvantage of analytical methods. It is that they become unfeasible for (real) complex DSs. However, analytical methods have an essential role in the reliability evaluation of DS, the trend (see Figure 1) is to use advanced (approximate) methods, which can be hybrids between different methods. These advanced methods highlight the advantages and mitigate the disadvantages of fundamental methods. The following section presents, as an example, one of the most progressive approaches today [7].

Figure 1: Analytical Methods Advantages-Disadvantages-Trends



2.2 Approximate analytical method of Failure Mode and Effects Analysis (FMEA)/ Minimum Shear Set

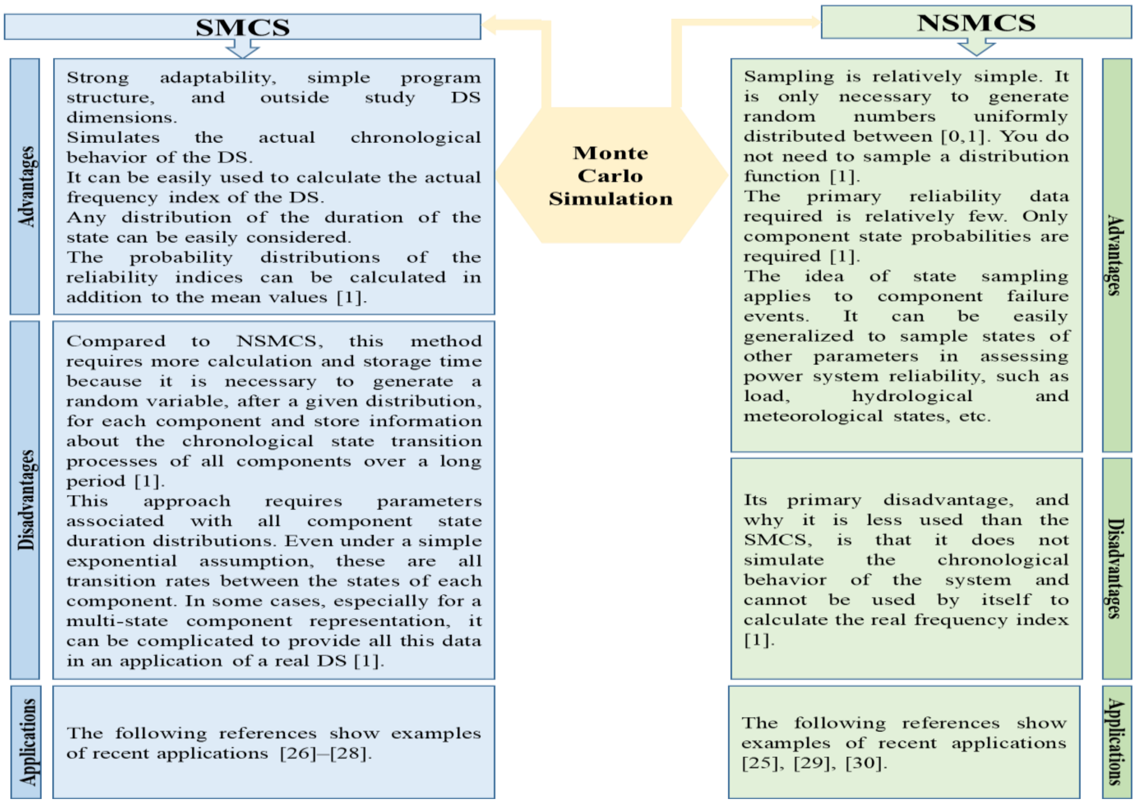
The FMEA is an inductive approach that systematically details all possible failure modes on a component-by-component basis; it is often possible to identify the failure modes of the DS from a visual inspection. Minimum cut sets identify failure modes when impossible since these are directly related [6], [7].

Each overlapping cut is effectively a set of similar elements, and its effect can be evaluated using the equations for parallel components (using the network modeling method). In addition, since each of the superseding outages will cause DS failures, all overlapping interrupts are effectively serial from a reliability standpoint. Therefore, the indices of the system can be evaluated by applying the equations for the serial components (using the network modeling method) To combine all overlapping interrupts [6], [7]. An example of the method discussed above can be found in J. Faulin et al. [6]. It is important to note that this method has been used to evaluate a wide range of radial DSs. However, this has evolved to treat modern DSs even more complex as DS with Microgrids (MG).

2.3 Monte Carlo Simulation.

The Monte Carlo method is the general designation for stochastic simulation using random numbers. In the reliability assessment utilizing MCS, the indices are estimated, simulating the real process and the random behavior of the system. Therefore, the method treats the problem as a series of experiments [3]. In theory, MCS can consider virtually all aspects and contingencies inherent in an DS's planning, design, and operation. These include random events such as load variations and the generation, interruptions, and repairs of elements represented by probability distributions, etc. There are mainly two types of standard MCS, Monte Carlo sequential simulation (SMCS) and non-sequential Monte Carlo simulation (NSMCS) [1], [5-7], [24]. Figure 2 shows the two types of simulation and their advantages, disadvantages and some applications in DS with MGs.

Figure 2: Types of MCS Advantages-Disadvantages-Applications



2.4 Sequential Monte Carlo Simulation (SMCS)

It is based on sampling the state's duration for each system's component from its corresponding probability distribution. In this method, the time state transition processes of each system component are first simulated by sampling. The next step is to combine these results to create the chronological state transition process for the entire system. This is achieved using the probability distributions of state duration for each component. In a two-state component representation, these are the functions of distributing the duration of the operation and repair state and are generally assumed to be exponential. Other distributions, however, can be easily used [1], [25]. The sequential method can be summarized in the following steps:

Step 1: Specify the initial state of each component. In general, it is assumed that all components are initially in a state of success or operation.

Step 2: The duration of each component residing in its current state is sampled from its probability distribution. For example, an exponentially distributed random variable has the probability density function.

$$f(t) = \lambda e^{-\lambda t} \quad (1)$$

Where $\boldsymbol{\lambda}$ is the failure rate of the component, Its cumulative probability distribution function is

$$F(t) = 1 - e^{-\lambda t} \tag{2}$$

At this point, it is necessary to generate the random variables; the processes for generating random variables distributed in non-uniform ways can be categorized into three techniques: the reverse transformation method, the composition method, and the rejection transformation method R. Billinton and W. Li describe these methods [1]. Using the reverse transform method in equation (2), the random time variable for failure TTF is given by:

$$\mathrm{TTF} = -\frac{1}{\lambda}\ln(1 - \mathrm{U}) \tag{3}$$

Where **U** is a uniformly distributed random number obtained from a pseudo-random number generator, there are currently many pseudo-random number generator methods R. Billinton and W. Li describe some basic methods [1]. Since $\mathbf{1-U}$ is evenly distributed in the same way as **U** in the interval $[\mathbf{0}, \mathbf{1}]$, equation (3) would remain

$$\mathrm{TTF} = -\frac{1}{\lambda}\ln(\mathrm{U}) \tag{4}$$

Equation (4) is used if the current state is active and, as mentioned above, $\boldsymbol{\lambda}$ is the component's failure rate. But if the current state is idle, $\boldsymbol{\lambda}$ is replaced by $\boldsymbol{\mu}$, which is the repair rate of the component, and **TTF** is replaced by the time to repair **TTR**.

$$\mathrm{TTR} = -\frac{1}{\mu}\ln(\mathrm{U}) \tag{5}$$

Step 3: Step 2 is repeated in the given period, i.e., usually one year, and the sampling values of each state duration are recorded for all components. The chronological system state transition process can be obtained by combining the state transition processes of the chronological component of all components.

Step 4: The last step is performing a system scan to get the necessary reliability indices for all the different system states.

2.5 Method Selection

For selecting the method, it is important to emphasize that it is vital to have a complete understanding of the SD when introducing MGs since probability theory is simply a tool that will allow transforming the knowledge of the SD into a prediction of its probable future behavior. Only after achieving this understanding and considering the information in Table 1, and figure 2 and 3 for this research was the SMCS technique selected.

Below are the most important characteristics of SD with MG, which led to such a decision.

- DSs with real MG are large-scale systems involving complex operating conditions.
- In the reliability assessment of DSs when MGs are introduced, it is necessary to model the variable behavior of the load concerning time.
- The nature of photovoltaic and wind energy production in MGs is random and intermittent.
- The representation of energy storage systems (ESS) in reliability studies requires a particular model because their behavior is not Markovian due to their operational characteristics.

In addition, this selection is supported by the bibliographic review carried out in [2], of the review concerning the methods used, for the evaluation of reliability in DS with MG, it was obtained that: Of 85 documents analyzed, 41 (48.2%) of them used some of the analytical methods and 44 (51.8%) used the MCS method. Among the research studies using MCS, 40 (90.9%) used SMCS and 4 (9.1%) used NSMCS. Consequently, with 47.1%, the SMCS is the most used technique currently for the reliability evaluation of DS with MG.

3. APPLICATION EXAMPLE

The primary indices required to evaluate the reliability of distribution networks are the average failure rate $\boldsymbol{\lambda_i}$, the average or interruption time $\mathbf{r_i}$, and the average annual interruption time $\mathbf{U_i}$, which are calculated with equations (6), (7), and (8), respectively.

$$\lambda_i = \sum_{j=1}^{n} \lambda_j \tag{6}$$

$$U_i = \sum_{j=1}^{n} \lambda_j * r_j \tag{7}$$

$$r_i = \frac{U_i}{\lambda_i} \tag{8}$$

Where n is the total number of components affecting charging point **i** [1].

These can then be extended to evaluate the overall performance indices of the distribution system. For example, the Average System Interruption Frequency Index (interruptions/system customer/year) (SAIFI) and the energy not supplied index (kWh/year) (ENS) are calculated with equations 9 and 10, respectively.

$$\mathbf{SAIFI} = \frac{\sum_{i \epsilon R} \lambda_i N_i}{\sum_{i \epsilon R} N_i} \tag{9}$$

Where λ_i and N_i are the average failure rate and the number of clients at charging point i, respectively; is the set of charging points in the system R.

$$\mathbf{ENS} = \sum_{i \epsilon R} \mathrm{P}_{ai} \mathrm{U}_{i} \tag{10}$$

Where $\mathbf{P_{ai}}$ is the average load (en kW) connected to the charging point $\mathbf{i}$.

The principle for calculating this set of indices using an SMCS approach is described in section 2.4. This principle focuses on randomly sampling the uptimes and downtimes of each component to produce a simulated sequence of component uptime and downtime. Sufficient sequences are simulated to produce a representative picture of the system's overall behavior. This principle can easily be extended to encompass distribution systems. Figure 3 shows the RBTS BUS 2 test system, a distribution system commonly used in reliability assessment applications [19].

On the other hand, Figure 4 presents a flowchart for the reliability evaluation of distribution systems by the SMCS method. The flow diagram in Figure 4 was coded in MATLAB, using data from the RBTS B US 2 test system given in [19]. The system was simulated by calculating two of the indices discussed above. The SMCS results were compared with the results obtained by R. Allan et al. [19], which made the analysis of this system by the analytical method; as can be seen in Table 2, the percentage of error obtained when comparing the SMCS with the analytical method is low. Therefore, it can be said that the results of the SMCS are satisfactory.

Figure 3: RBTS BUS 2 Distribution System

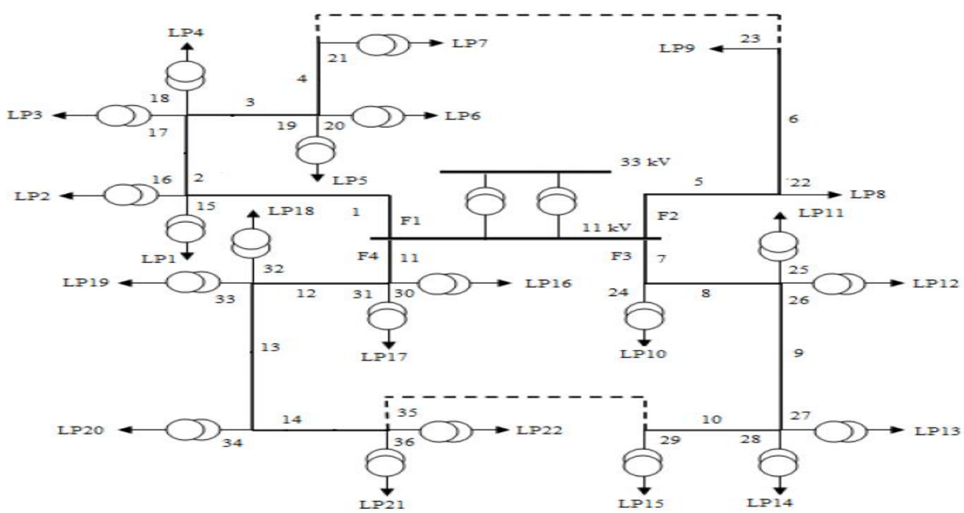


Figure 4: Flowchart- Reliability assessment of distribution systems by the SMCS method

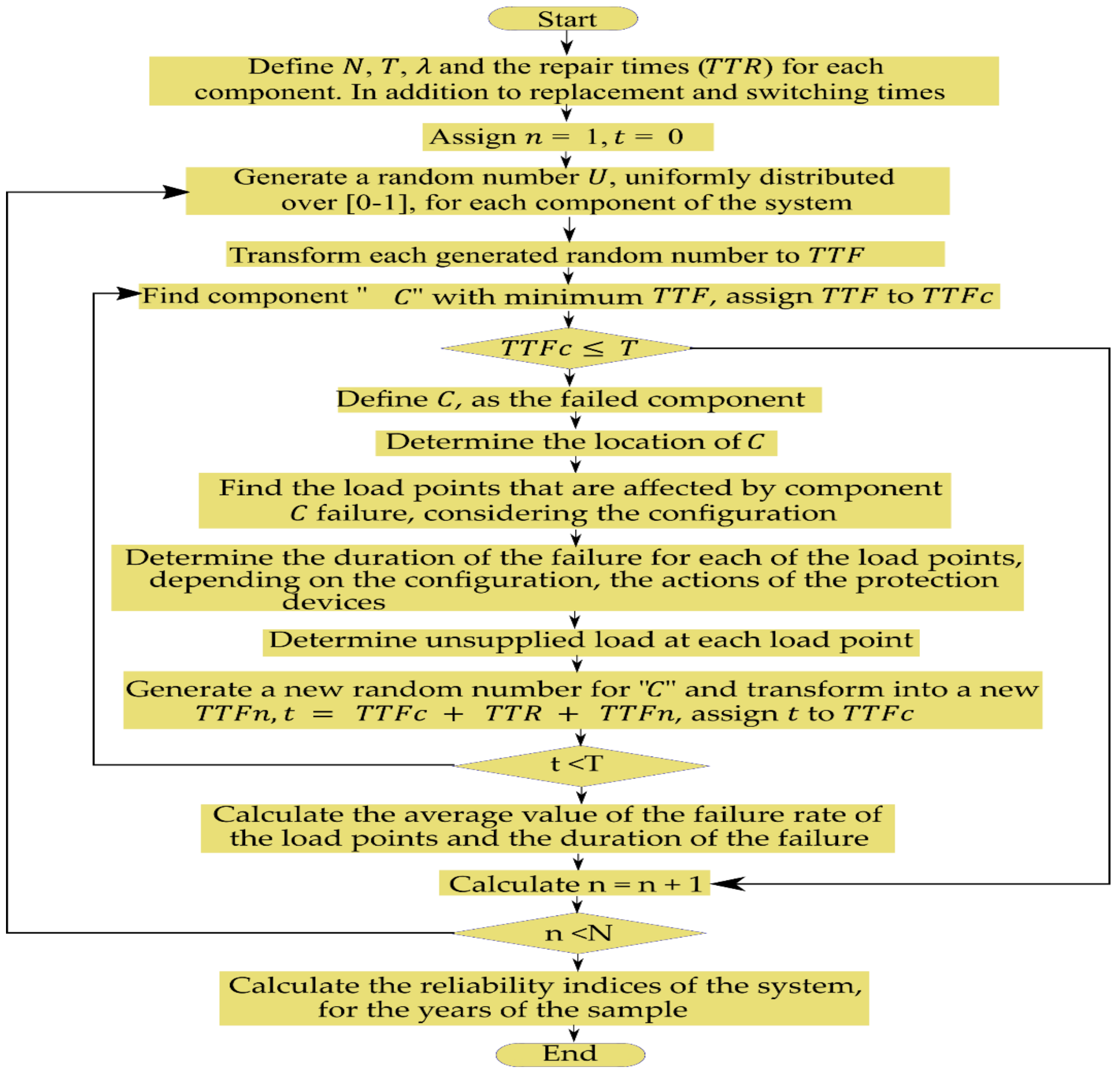


Table 2: Comparison of SMCS with the analytical method

	SAIFI			ENS (MW)		
Feeder	SMCS	Analytical method	% Error	SMCS	Analytical method	% Error
F1	0.2468	0.248	-0.48	13.034	13.172	-1.047
F2	0.1384	0.14	-1.14	1.11	1.122	-1.081
F3	0.2464	0.25	-1.44	11.079	11.203	-1.119
F4	0.2481	0.247	0.44	12.195	12.248	-0.434

4. FUTURE WORK

Once the reliability evaluation methods have been studied and the SMCS has been selected, the next step is to model the real DS with MG applications and analyze the impact of MGs applications on the reliability of the DS, applications such as conventional distributed generation, photovoltaic or wind renewable distributed generation, ESS, control systems, protection systems among others.

5. CONCLUSIONS

Reliability assessment methods in DS with MG have been studied, and their advantages, disadvantages, applications, and trends have been analyzed. Showing that, for large-scale systems and when complex operating conditions are involved, this being the case of DSs with MGs, the Monte Carlo simulation method is often preferable over analytical methods. This is due to the following characteristics: strong adaptability, simple program structure, and irrelevant study system dimensions.

In the reliability assessment of DSs when MGs are introduced, it is necessary to model the variable behavior of the load concerning time—being the ideal SMCS to represent these factors that vary over time.

Since the production of photovoltaic energy and wind energy in the MGs are random and intermittent, it is not easy to evaluate the power supply capacity of this distributed generation using an analytical method. To avoid the complexities of analytical methods, the SMCS is more suitable for improving reliability in DS. When MGs are introduced. In addition, this method can simulate the random output of DGs in a time sequence, managing to establish a more realistic probability model.

Table 1 and Figure 1 follow the crucial disadvantage of analytical methods. It is that they become unfeasible for (natural) complex DSs. However, analytical methods have an essential role to play in the reliability evaluation of DS. The tendency (see Figure 1) is to use advanced (approximate) methods, which can be hybrids between different methods. These advanced methods highlight the advantages and mitigate the disadvantages of fundamental methods. Among the advanced methods are (the approximate analytical Method (FMEA)/ Minimum Cut Set, dynamic fault tree, approximate methods of Markov chains, and Method of the universal generating function).

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