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Definition of maintenance policies in power systems

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Resumo

Palavras Chave: **Fiabilidade, manutenção, Monte Carlo, taxa de avarias;**

Nesta tese é apresentada uma nova aplicação das simulações de Monte Carlo no âmbito da avaliação da fiabilidade de sistemas elétricos de energia. A técnica desenvolvida pertence aos métodos de simulação que, hoje em dia, são extremamente utilizados. Para além disso, vários novos aspetos vão ser introduzidos no processo de simulação típico, a fim de alcançar uma abordagem realista para a análise da fiabilidade de sistemas elétricos de energia.

Geralmente, na avaliação da fiabilidade de sistemas elétricos de energia, é necessário construir o ciclo de vida de cada um dos componentes que compõem os sistemas. Deste modo, um processo cronológico tem de ser desenvolvido. Grande parte dos estudos seguem uma distribuição exponencial para gerar esses ciclos de vida, através do uso de uma taxa de avarias λ constante. Contudo, a taxa de avarias λ de um componente elétrico não é constante. Ela varia com o passar do tempo. A taxa de avarias λ de um componente elétrico é caracterizada por diferentes regiões. O início de vida destes componentes é caracterizado por uma taxa de avarias decrescente, graças à correção de alguns problemas de fabrico. Depois, os componentes entram na sua fase de vida útil, a qual se caracteriza por uma taxa de avarias constante. Finalmente, com o natural processo de degradação, a taxa de avarias começa a aumentar. Portanto, o uso de uma taxa de avarias λ constante não ilustra uma situação real. Assim, nesta tese, um método de simulação baseado no típico método sequencial de Monte Carlo é desenvolvido, a fim de se incorporar esta nova particularidade: taxa de avarias variável. Para alcançar este objetivo, várias mudanças são produzidas no algoritmo típico de um Monte Carlo sequencial.

Ao introduzir-se, nesta tese, a existência de uma taxa de avarias variável, passou-se também, a incluir o processo de degradação que os componentes de um sistema elétrico sofrem. Por conseguinte, outro aspeto muito importante na avaliação da fiabilidade de sistemas elétricos de energia é tratado: as políticas de manutenção. Esta tese apresenta três diferentes aplicações de Monte Carlo que correspondem a três diferentes políticas de manutenção: manutenção reativa, manutenção preventiva e manutenção preditiva. A inclusão deste novo aspeto tem um objetivo: a melhoria dos índices de fiabilidade, através da extensão do período de vida útil dos componentes.

Os resultados obtidos com as três diferentes aplicações de Monte Carlo vão ser comparados e, uma análise de custo-eficiência vai ser realizada, a fim de descobrir qual o melhor processo de manutenção.

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Abstract

***Index Terms: Failure Rate*, maintenance, Monte Carlo, reliability;**

This thesis presents a new application of the Monte Carlo simulations in power systems reliability evaluation. The developed technique belongs to the simulation methods that are, nowadays, widely used. Moreover, several new aspects will be introduced in the typical simulation process in order to achieve a realistic approach in the power systems reliability analysis.

Usually, in the assessment of power systems reliability, the development of the life cycle of the components that compose the power systems is necessary. Therefore, a chronological process needs to be developed. Most of studies follows an exponential distribution to generate the life cycle of the components of a power system, by using a constant failure rate λ. However, the failure rate λ of an electrical component isn't constant. It varies with the elapse of time. The failure rate λ of an electrical component is characterized for three different regions. The beginning of an electrical component life is characterized for a decreasing failure rate, thanks to the rectification of some debugging problems. Then, the electrical components enter on the useful life period, which is characterized for a constant failure rate. Finally, with the natural degradation process, the failure rate starts to increase. Therefore, the use of a non constant failure rate λ doesn't illustrate the real situation. So, in this thesis, a sequential Monte Carlo based method is developed in order to incorporate this new particularity: the variable failure rate. To reach this goal, several changes are produced in the typical Monte Carlo algorithm.

By introducing, in this thesis, the existence of a variable failure rate, the process of degradation of the components of a power system is also included. Therefore, another very important aspect in the power systems reliability evaluation is treated: the maintenance policies. This thesis presents three different Monte Carlo applications that correspond to three different maintenance policies: reactive maintenance, preventive maintenance and predictive maintenance. The inclusion of this new aspect has one goal: the improvement of the reliability indices through the extension of the useful life period of the components.

The results obtained with the three different Monte Carlo applications will be compared and, a cost-efficiency analysis will be made in order to find the best maintenance procedure.

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List of acronyms and symbols

List of acronyms

EIR	Energy Index of Reliability
EPNS	Expected Power Not Supplied
FEUP	Faculty of Engineering of University of Porto
FOR	Forced Outage Rate
F&D	Frequency and Duration
IEEE	Institute of Electric and Electronic Engineers
INESC	Institute for Systems and Computer Engineering of Porto
LOEE	Loss of Energy Expectation
LOLD	Loss of Load Duration
LOLE	Loss of Load Expectation
LOLF	Loss of Load Frequency
LOLP	Loss of Load Probability
MCS	Monte Carlo simulations
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
PB	Population Based
RTS	Reliability Test System

Listo f symbols

λ	Failure rate
μ	Repair rate
β	Variation coefficient

Chapter 1

Introduction

In this Chapter, a brief overview about the addressed problem will be presented. First, the general guidelines about the importance of the maintenance policies for the power systems will be given. Then, the purpose of this thesis will be explained. Finally, the organization of this thesis will be presented.

1.1 The Importance of Maintenance Policies for Power Systems Reliability

One of the major goals for producers and distributors of electric power is to reach the maximum asset performance. In order to reach this objective, it's necessary to find the optimal balance between the maintenance policies and power systems reliability. In the one hand, the suppliers must meet the demands from customers and regulators. Therefore, the suppliers need to ensure a certain level of reliability in order to give a proper quality of supply to the clients. In the other hand, the suppliers intend to minimize the life cycle cost of the components. One way to reach this goal is by minimizing the maintenance actions. So, the decision maker has to find the best trade-off between the cost and the benefits of maintenance policies. So, it's our goal, in this thesis, the study the impacts of maintenance policies in the power systems reliability and in the overall budget of the suppliers.

There are different maintenance policies and, each one of them, have their own advantages and disadvantages. However, the main goal of these maintenance plans is exactly the same: the extension of the useful life period of the components. By extending the useful life of the components, the degradation process of the components is delayed. In other words, the components suffer the consequences of the elapse of time in a later stage of their lives. Obviously, the decrease of the reliability indices through the implementation of maintenance activities is the illustration of this consequence. So, a well constructed and performed maintenance plan will bring important improvements for the power systems reliability.

Until now, the positive effects of maintenance upon the power systems reliability were the only object of study. However, some maintenance activities can bring some problems. Sometimes, deficient maintenance procedures can occur. Thanks to these deficient procedures, some components fail before return to their useful life periods. Therefore, some deficient maintenance actions can be the reason for premature failures. This aspect will be also studied in the following Chapters.

To sum up, a better the maintenance plan will have as consequence greater benefits for the power systems reliability. Therefore, the problem lies on the maintenance costs and on the budget of the supplier. In this thesis, this problem will be studied and solutions will be developed.

1.2 The purpose of this thesis

Most of reliability studies consider that the components of a power system have a constant failure rate λ. This approximation is used for many studies because of its simplicity. However, this assumption doesn't translate the real evolution of the failure rate of an electrical component. The failure rate λ of an electrical component can be described for the well known "bathtub curve". Therefore, one of the purposes of this thesis is to measure the impact of the implementation of a variable failure rate λ. Using this new approach, we will understand how far, most of reliability studies, are from reality. In order to achieve this goal, a new sequential Monte Carlo approach will be developed. This new approach will be based on a typical sequential Monte Carlo algorithm [1], but some changes will be produced on it [2]. By considering a non constant failure rate, the exponential distribution won't be valid any longer. In order to surpass this problem, the cumulative distribution function $Q(t)$ will be developed. Through this curve, the generation of the operation times of the components will be possible.

Maximum asset performance is one of the major goals for electric power system managers. One of the most important aspects to achieve this goal is the maintenance optimization. In truth, the inclusion of maintenance policies in a power system is an area that requires the development of new optimization models. The identification of the right moments to perform the maintenance actions, as well as, the identification of the components, in which the maintenance actions should occur, can lead to significant improvements on the reliability indices. In a perfect world, the maintenance policies would lead to a significant decrease of the customers interruptions and, in the other hand, wouldn't have any impact on the budget of the suppliers. Unfortunately, this world doesn't exist. Actually, the improvements of the reliability indices through the implementation of maintenance plans have as consequence the increase of the maintenance costs. Therefore, another purpose of this thesis is to study the inclusion of different maintenance policies and try to find the perfect balance between the customers interruptions and the maintenance costs. Most of studies [3], [4] and [5] try to find the optimal level of maintenance, but respecting only one objective, as for example the minimization of the expected energy not supplied (EENS).

In order to achieve this second purpose, two more Monte Carlo applications will be developed. One of them will include the well known preventive maintenance policy. In the other hand, the predictive maintenance will be implemented in the other Monte Carlo application. The implementation of a preventive plan will depend on the definition of a schedule for the maintenance procedures. The predictive maintenance actions will be performed according to the degradation state of the components.

The proposed methodologies will be tested in the evaluation of the reliability of a world-wide benchmark power system in order to have a basis of comparison with the results of a typical Monte Carlo process.

1.3 Organization of this thesis

In Chapter 2, the traditional methods of reliability adequacy evaluation will be presented. First, the analytical methods will be distinguished from the probabilistic methods. Among the probabilistic methods, the focus will be on the simulation approach, since this thesis will be based on a typical simulation process. Finally, an overview of the most widely known maintenance procedures will be performed. The main advantages and disadvantages of each one of these maintenance processes will be presented.

In Chapter 3, the typical sequential Monte Carlo algorithm will be described. Then, new aspects will be added to the typical methodology in order to reach a more realistic approach. Therefore, the constant failure rate λ will be replaced for the well known "bathtub curve". After this, the explanation about how the times of operation of each component will be generated will be made. Subsequently, a brief overview about the reliability indices of the problem addressed in this thesis will be performed. Next, the introduction of the maintenance policies will be carried out. The implementation of the maintenance policies will bring several changes for the Monte Carlo algorithm.

In Chapter 4, the results of the proposed methodologies will be presented and analyzed. This Chapter will allow to verify if the practice matches with the theory.

Finally, in Chapter 5, the main conclusions of this work will be withdrawn and some suggestions for future work will be described.

Chapter 2

State of the art

In this Chapter, a review about the state of the art of power systems reliability assessment techniques will be presented. This type of analysis requires a certain level of knowledge about power systems, reliability concepts and probability distributions. More information about these aspects can be found in [2]. Nevertheless, these studies will guide us to the main goal of evaluating the power systems reliability.

Several methods to solve reliability problems are described in the literature of this area. In this Chapter, a quick journey through each one of them will be made in order to find out their advantages and disadvantages.

Firstly, an analysis of two different approaches that allows the evaluation of the adequacy of the generating capacity will be made: the deterministic approach and the probabilistic approach. Moreover, the probabilistic approach will be divided into two different methods: the enumeration and the simulation methods. Finally, three different maintenance techniques will be presented: reactive, preventive and predictive maintenance. The inclusion of maintenance in the evaluation of the reliability of power systems is one of the main focus of this thesis and, for that reason, the aspects related to the maintenance techniques will be deeply studied.

2.1 - The deterministic approach

Several techniques were developed in order to evaluate the power systems reliability. As mentioned before, the two approaches to be analyzed are: the deterministic approach and the probabilistic approach.

It is now known that the systems behavior is stochastic and, for that reason, the evaluation of such systems should be made by probabilistic techniques. But, until the 30's, this knowledge was unknown. Therefore, during decades, the deterministic approach [6] was the main technique for the assessment of power systems reliability.

The deterministic approach is a very simple method that allows the measure of the reliability of a power system. Basically, this approach uses information about the past experience of the systems to set a pre-specified rule that will allow assessing the electrical power system reliability. So, it is easy to understand that this approach is very subjective because different systems will have different criteria depending on its internal organization.

A well-known example is Planning Generating Capacity [7]. Another criterion that is widely used by the companies is the calculation of the static reserve. The static reserve is the difference between the generating capacity and the expected maximum demand, using as reference the capacity of the largest generating unit.

Although still used, this approach is not compatible with the present. The problem is that deterministic risk criteria such as “percentage reserve” or “loss of largest unit” don’t define the true risk in the system consistently. A detailed analysis of a power system will show that the variation in true risk depends on the forced outage rate, the number of units and the load demand. The deterministic approach cannot take into account these factors. The fact that the deterministic approach does not take into account how systems work, how components fail and the existence of a variable load leads to often unnecessary spending of money and resources. Moreover, this approach can also lead to the existence of under-investments. This may have as a consequence a high number of interruptions. Since the deterministic approach has as its main concern the security of the supply, robustness is its major advantage.

In spite of these disadvantages, a significant part of the present planning, design, and operational criteria are based on deterministic approaches.

2.2 - The probabilistic approach

The probabilistic approach [7] is the most solid mode to evaluate power systems reliability. If we want to consider uncertainties that, usually, are related with these types of systems, it´s necessary to use a probabilistic approach. Stochastic models allow to incorporate these uncertainties. Uncertainties as the components state, the weather state, the hydrological resources state and the load state can be modeled by this type of processes.

Markov processes are the well-known reference, in which the conditional probability of failure or repair, during any fixed interval of time, is constant. This implies that the failure and repair rates of components are associated with exponential distributions [8].

In the following Chapters, a new particularity will be shown: the use of non constant transition rates between states. Obviously, the exponential distribution will be replaced by a different approach.

The use of an exponential distribution to represent the duration of the system events gives to the Markov models a certain level of mathematical elegance. It allows the inclusion of different system states. The Markov approach can be used for a wide range of reliability problems, including systems that are either non-repairable or repairable and are either series connected, parallel redundant or standby redundant.

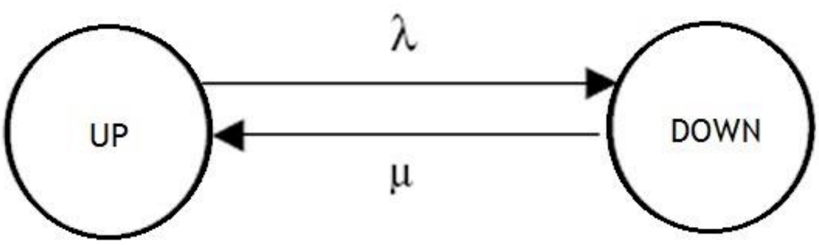


Figure 2.1 - Markov model composed by two states, where λ is he expected failure rate and $\boldsymbol{\mu}$ is the expected repair rate.

As said before, the exponential or strictly the negative exponential distribution is probably the most widely known and used distribution in reliability evaluation of power systems. However, the use of this type of distribution to model the duration of components repairs isn´t consensual. The lognormal distribution that is related to the normal distribution can, for example, be a good fit to model components repair times and, consequently, is becoming an important distribution in the assessment of reparable systems. There are other non exponential distributions, like the Weibull or the Rayleigh that can represent, as well, good models. The implementation of these distributions is well described in [2]. Furthermore, in [9] and [10], the inclusion of non exponential distribution in the Markov models is studied.

Analytical and simulation are the two different methods that compose the probabilistic approach. Both methods have the goal of calculate the system reliability indices. As expected, the analytical methods appeal to a mathematical model in order to calculate the mean value of these indices. In spite of the low computational effort that these methods require, with the development of computer technology, these began to be used less and less. Moreover, the application of this approach to complex systems isn't feasible. Several simplifications had to be made in order to apply analytical methods to this type of systems. Unfortunately, these assumptions and simplifications lead to some unrealistic results.

The simulation processes are all frequently and loosely referred as Monte Carlo Simulations (MCS). Strictly, this is incorrect, since MCS really relates to a process that is completely random in all respects. However, many processes are related to time and, therefore, do not possess all the random characteristics needed to use a true Monte Carlo. The process, however, is stochastic and can be analyzed using stochastic simulations. Despite the stated previously, the term MCS is used widely for all types of simulation processes. Unlike the analytical methods, MCS estimates the reliability indices using a random sampling of scenarios. For this reason, MCS constitutes a solid method to evaluate the reliability in more complex power systems. One of its main advantages is that is able to incorporate electrical and non electrical characteristics and a few system dependencies.

2.2.1 - The analytical methods

In order to assess the reliability of a power system through the evaluation of the system reliability indices, two different approaches can be clearly defined: the basic probability methods and the frequency and duration methods (F&D) [7].

Basic probability methods use the concept of unavailability, which is the probability of finding the unit on forced outage at some distant time in the future. This probability is historically known as the unit forced outage rate (FOR). Usually, FOR is computed, assuming a two state homogeneous Markov model (O-Operating State; F-Failure State). This model is characterized by its simplicity and is directly applicable to a base load generating unit which is either operating or forced out of service. The construction of the well-known Capacity Outage Probability Table is related to the concept of unavailability. This table is no more no less than a simple array of capacity levels and the associated probabilities of existence. To each one of these capacity levels, we associate different system states with their own probability. The calculation of the table is basically the enumeration of all capacity levels that represent different system configurations and their probability of occurrence. The result is the discrete probability distribution of an interruption occurrence. As a curiosity, if all the units in a system were identical, the constructed table could be easily obtained using the binomial distribution [2].

In fact, the use of this method for very large systems can become very demanding in terms of the time spent. Fortunately, it is possible to decrease the computational effort by omitting all capacity outages for which the cumulative probability is less than a specified amount. Therefore, the Capacity Outage Probability Table can be truncated. Another method used to decrease the computational effort is to reduce the number of discrete capacity outage levels by grouping the units into identical capacity groups prior to combining or by rounding the table to discrete levels after combining.

The next step in this analytical approach is a discrete convolution between all the entrances of the constructed table and the system load curve. For that, first, it is necessary to build the cumulative load model. This can be done by the arrangement, in a descending order, of the individual peak loads. Then, with the Capacity Outage Probability Table and the load diagram, it is possible to calculate known indices as LOLP and LOLE. Therefore, the technique to calculate the loss of load risk can be summarized as:

1. Successively simulate the loss of capacity for each row of the Capacity Outage Probability Table;
2. Check, on the load diagram, the number of hours, days or weeks (depending on the base of the load diagram) for which it is expected that the load peak exceeds the available capacity of the system;
3. Weigh each number of hours, days or weeks for the loss of capacity probability associated with them;
4. Add the individual values of the loss of load probability to achieve the system loss of load probability;

Furthermore, if the calculation is made in days, there is a risk () in days per year. If the calculation is made in terms of percentage, the obtained value (dividing by 100%) is the LOLP.

The mathematical formula that can summarize the described method is:

$$LOLP = \sum_{i=1}^{n} p(X_i) * p(L > X_{max} - X_i) \tag{2.1}$$

where $LOLP$ is the Loss of Load Probability, one of the most important reliability indices, $p(X_i)$ is the probability of the capacity loss being X_i(MW), X_{max} is the total installed capacity (MW), $p(L > X_{max} - X_i)$ is the probability that the peak load L exceeds the available capacity of the state i and n is the number of states or, in other words, the dimension of the Capacity Outage Probability Table.

So, this is the basic analysis that can be made in order to calculate reliability indices. But, other characteristics can be introduced in this method such as: the FOR uncertainty, the effect of scheduled maintenance and the uncertainty in the load forecast [7]. Moreover, through this method it is possible to calculate energy indices. Actually, the total energy consumed in the studied period can be obtained through the area bellow the load curve.

The basic indices calculated by the previous method are the expected number of days (or hours) in a given period in which the load exceeded the available capacity y and the expected value of energy not supplied in the period due to the lack of installed capacity. However, these indices don´t give information about the frequency of occurrence of an insufficient capacity condition and about the expected duration of these outages. The F&D methods are able to provide indices that indicate these specificities. Therefore, this is the major advantage of this method. The disadvantage lies on the most advanced and complicated mathematics that this method involves.

The F&D method requires additional system data and knowledge about some concepts. First of all, it is very important to have deeply knowledge about frequency and state transition concepts. Moreover, this method needs data about the transition rates between the states that compose the homogeneous Markov model. This data is added to the information that is used in the basic probability methods, particularly, the concepts of availability and unavailability. Like the basic probability methods, through a discrete convolution between the system load curve and the recursive constructed generation model, the calculation of the reliability indices can be done. Another important specification is that this technique also allows to incorporate the uncertainty on the load forecast [6][7].

The adequacy of the generating capacity in a power system is normally improved by interconnecting the system to another power system. The increasing of the interconnected systems must be taken into account due to the effect of adjacent areas in the reliability analysis. The probability array method and the equivalent assisting method are to different approaches to calculate the LOLE indices in interconnected systems. [7]

2.2.2 - The simulation methods – Monte Carlo

Simulation methods are based on Monte Carlo simulations [1][6]. As previously stated, the simulation techniques, often known as Monte Carlo simulation, estimate the reliability indices using a random sampling of scenarios. The Monte Carlo simulation can take basically two major types: chronological/sequential simulation and not chronological simulation.

The non chronological approach simulates the basic intervals of the system lifetime by choosing intervals randomly. On the other hand, the sequential approach simulates the basic intervals in chronological order.

In the non chronological simulation, the evaluation of systems reliability matches the accounting of photos or snapshots that result from the observation system. These photos or snapshots will find the system in several states. There is no place, therefore, to consider operating and failure times, but only probabilities to find the equipments in failure mode.

Chronological simulation is meant to represent the course of life of the electrical system. Therefore, not only it simulates the times until each equipment fail but also the times of their repair. In chronological models, the simulation follows the line of temporal development and therefore we can use the metaphor of the film in opposition to a collection of photos. Therefore, the life cycle of a power system can be obtained through the combination of the life cycles of each component [11]. In order to develop a chronological simulation is not enough to know the unavailability (probability of failure) of the components of the system, the so called F.O.R. It's necessary, for each of them, to know the failure density function. This function is associated with the operating and failure (repair) times. The exponential function is the most used to model these times. In this thesis, another approach to calculate the operating times will be used [2].

The most appropriate of these two approaches depends on system effects and the goals of the analyses. There are some system problems for which one basic interval has a significant effect on the next interval, and this can have a consequential significant impact on the reliability indices being evaluated. One example is the effect of hydrogeneration: the ability to use water in one interval of time can be greatly affected by how the water was used in previous intervals and the amount of rainfall and water infeed in these previous intervals.

It follows from this discussion that the sequential approach will always work and the random approach is more restrictive. However, it is generally, but not universally, found that the random approach is less time consuming.

The computational effort, in number of draws, to be held is not affected by the size of the system under examination or its complexity. For this reason, the Monte Carlo method is appropriate to the study of complex cases, such as correlated loads, common cause failures and operating strategies. The variance of the variable under estimation influences the number of needed samples for a certain level of accuracy.

The Monte Carlo simulations remain the most common method used for reliability assessment. This statistical method, although much older, began to gain importance with the increasing of the computational power in the early 80s. The adoption of new and efficient techniques for convergence acceleration also contributed to the widespread use of this method. These techniques are related to the development of variance reduction processes.

Nevertheless, the computational effort is considerably affected by the desired degree of confidence. For example, to calculate a LOLP around 0.001, with a precision of 30%, the number of samples needed is about 10 000. On the other hand, to calculate the same value of LOLP, but with a precision of 3%, the number of samples required increases to a million. Note that, in general, the number of iterations needed to obtain the desired accuracy is different according to the variable in observation. Each variable has its own variance. For this reason, it is perfectly possible to reach a desired accuracy for a certain reliability index and be necessary to extend the simulation to achieve convergence of other reliability index.

Furthermore, the computational effort is affected by the magnitude of the value to be calculated and by the system reliability [6]. In relation to the first aspect, the number of samples required to estimate a small value of p (indices of reliability), for the same level of confidence, is bigger than for estimating a higher p value. Regarding the system reliability, the number of samples necessary to assure that a certain indices, for very reliable systems, has the desired degree of confidence can be very large.

Monte Carlo methods can be divided according to how system states are sampled. If the sample of a certain system state takes into account the previous state, the method is called sequential. Therefore, in this Monte Carlo method, the chronology of the events must be taken into account. Instead, if the sampling is independent from the previous system state, the MCS method is called non-chronological. In other words, in this type of method, a state space representation is used for the sampling.

Considering the above points, the great advantage of the sequential Monte Carlo is the possibility to include chronological issues. For instance, if the probability distributions of state duration and frequency are required, these can only be evaluated explicitly if the chronology of the process is simulated. The representation of renewable resources is other example of the importance of chronological Monte Carlo processes [12]. As it is known, renewable resources have the particularity of having production levels quite variable. Wind power and hydrogeneration are two examples of that. In both cases, there are two different types of series that can represent the resources behavior: synthetic and historical series. Therefore, the sequential Monte Carlo approach is designed to, for each year of the simulation, choose a series. Usually, the process is base on a uniform distribution.

It´s now time to analyze two different techniques that explain how to develop a Monte Carlo simulation. The State Duration Sampling Method and the State Sampling Method [7][10] are two different approaches related to the chronological Monte Carlo simulation and to the non-chronological Monte Carlo simulation, respectively.

2.2.2.1 - State Duration Sampling Method

The first step to take in this method is to simulate the cycle of operation-failure of each component. So, in order to develop the lifetime line of each component, it´s necessary to sample their times to fail and times to repair, according to the probability distribution that rules these phenomena. Therefore, considering the above mentions, it’s been assumed that the components operation is constituted by two states. Nevertheless, this approach can be extended to a multiple state model. If this case was considered, it would be necessary the sampling of the time for all possible transitions from the current state. Thus, after calculating the time of operation of all components of the system (the initial state), it´s time to find the lowest of these values, which corresponds to the 1st component to fail. For this component is generated a new repair time (represents state 2). This process is repeated until the desired accuracy is reached. Having drawn the lifetime line for each component, it’s possible to follow her and go-checking, at each time, if the capacity of the system is sufficient to supply the load. At the end of each sampling, the variance of the desired reliability indices is updated.

As stated before, the sequential simulation stops when the desired accuracy is reached. It is, therefore, traditional, to establish a stopping criterion or convergence of a Monte Carlo simulation [7]. Thus, it is defined a relative uncertainty, based on a variation coefficient β, such that:

$$\beta^2 = \frac{V(F)}{E(F)} \tag{2.2}$$

or, according to the standard deviation $\sigma(F)$:

$$\beta = \frac{\sigma(F)}{E(F)} \tag{2.3}$$

where F is the index under estimation, $E(F)$ is the estimated expectation of the index, $V(F)$ and $\sigma(F)$ are the variance and the standard deviation of the estimated expectation.

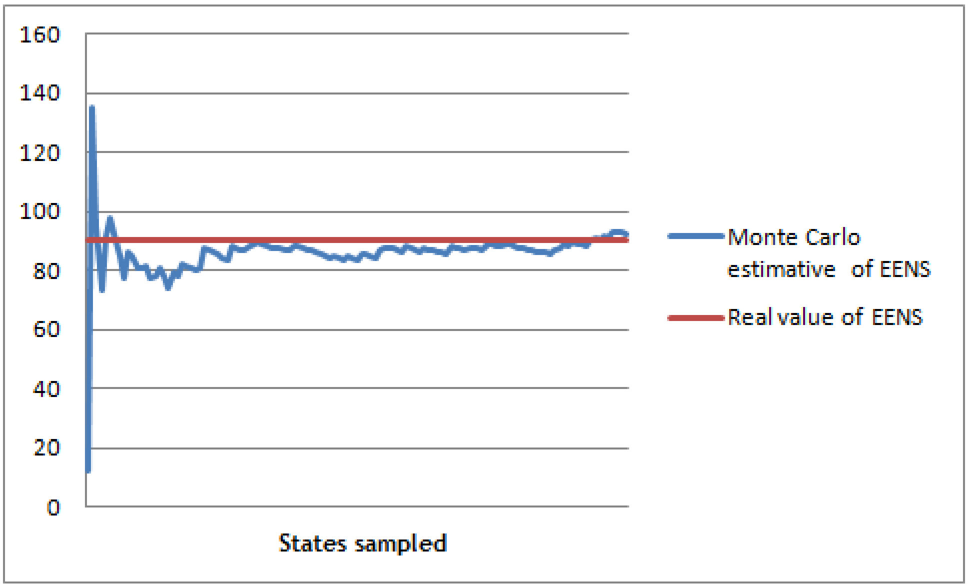


Figure 2.2 - Example of the evolution of the estimative of EENS, a reliability index, using Monte Carlo methods

The major advantages of this method are as follows:

1. Frequency indices can be calculated in a easy way;
2. Non-exponential distributions can model the unit state durations;
3. Peaking unit operating cycle can be modeled;

2.2.2.2 - State Sampling method

In the State Sampling method, the availability of a system element (line, generator, transformer) is modeled as a random variable that can reside in two states. The system element can be found in failure mode with an associated probability of P or in operating mode with an associated probability of 1-P. P represents the unavailability of the element. This probability is known as FOR. The traditional way to fix, during the state sampling, the state of operation or failure of the components is from a pseudo-random number generator that provides an uniformly distributed number in a [0,1] range. Thereafter, the generated number is compared with the unit FOR. If the random number is inferior to the unit FOR, the unit is considered unavailable otherwise it is considered available. Therefore, the system state would be obtained by repeating this operation for each component. This principle can be extended to any number of states. So, it´s possible to apply this principle to a multiple state unit model or to a derated state unit model [7].

In a non chronological approach, the evaluation of the reliability indices has a different treatment. As matter of fact, superimposition of the load curve is no longer possible. So, the first idea that comes to mind to evaluate the reliability indices is the comparison between the sample and all periods of time of the chronological load curve. This constitutes a huge problem in terms of computation effort. The most straightforward method for the evaluation of the reliability indices is based on the sampling of load states according to a multistep model. To use this method is necessary to numerate the load levels, in descending order, to form a cumulative load model.

Other approaches can be used in order to decrease the computational effort. The following two are examples of that:

- Sample load states according to the load cumulative distribution function;
- Implementation of cluster techniques in order to create a multistep model of the annual load curve.

These approaches are described in detail in [7]. Comparatively to what happens in the state duration method, the calculation of frequency indices isn´t so simple. Moreover, the use of non-exponential distributions to model unit state durations is very complicated. However, it has the following advantages:

1. It requires less computing time and memory storage than the state duration sampling method, particularly for large-scale systems
2. It doesn´t require data regarding to transition rates between different states

The major concern in Monte Carlo methods is the excessive time that the simulations need to achieve the specified level of convergence. Especially in very reliable systems, the convergence of the simulation can last for long periods. This is due to the large number of sample that has to be drawn in order to achieve the condition of convergence. Therefore, the methodologies to reduce the computational effort and the number of draws, keeping the same precision β, are based on the variance reduction of the estimated expectation. These methodologies are known as “Variance Reduction techniques”.

Control Variates, Importance Sampling, Stratified Sampling, Antithetic Variates and Dagger Sampling are five of these techniques. In [1], these techniques are explained in detail.

2.2.2.3 - The Control Variates technique

The Control Variates technique [1][6] assumes that it is possible, through an analytical method that is independent of the Monte Carlo process, to calculate an approximation for the value that is to be determined.

This Variance Reduction technique can be used to assess system indices of a composite generation and transmission system. Therefore, Monte Carlo simulation is only used to calculate the difference between the solution of the problem and the approximated value. As it is possible to observe in equation 2.4, the achievement of a high convergence “speed” depends on the correlation between the variable that is intended to estimate and calculated analytical value. As matter of fact, the most important step in this technique is the choice of a correct control variable, which is the calculated approximation.

$$acceleration = \frac{N}{N^*} = \frac{1}{1-\rho^2} \tag{2.4}$$

where N is the initial number of draws, and N^* represents the number of necessary draws after the application of these process. ρ is the correlation coefficient.
Thus, the higher the correlation, the greater the acceleration introduced by the Control Variates technique.

2.2.2.4 - The Importance Sampling technique

Importance sampling is a procedure for changing the probability density function of sampling in such a way that the events which make greater contributions to the simulations results have greater occurrence probability [1][6]. Therefore, by deforming the density function, it is possible to increase the probability of important events and reduce it for those which are irrelevant. As an example, for the evaluation of power systems reliability, the important events are those which are the cause of load curtailment.

The use of a previous known auxiliary probability density function, obtained by an analytical method, is an extremely important step of this process. The success of this method rests on the approximation between the original probability density function and the auxiliary probability function. It is as if the analytical model “explains" much of the variance found, and, therefore, the focus should be on the assessment of the unexplained part. Thus, this process can reduce the variance without altering the mean value.

It is, therefore, easy to understand that the use of the combination of the previously described methods and Monte Carlo methods can bring great benefits in accelerating the convergence of the process.

2.3 - The Maintenance Programs

Maintenance practices are an essential step of the planning, construction and operation of a power system. Looking at the maintenance policies that, currently, are presented by the companies, it´s possible to say that most of them see these procedures as actions associated with the failure of equipment. The definition of maintenance in the dictionary is: “the work of keeping something in proper condition; upkeep.” This would imply that the aim of maintenance activities should be the continuously prevention of components state. In other words, these practices should be taken in order to prevent a component from failing or to repair normal equipment degradation. Unfortunately, data obtained in many studies prove that the main concern of companies is their economic requirements, while also adhering to the constraints set by system and customer requirements. This fact means that companies prefer to wait until a component failure and, only after this, they take the necessary measures to replace the normal operation.

Ideally, maintenance is designed to maintain equipment and systems in efficiently conditions of operation. Therefore, the operation should run without problems for at least designed life of the components. As such, the operation of a component is a time based-function. The shape of the hazard rate curve is often referred as a bathtub curve. This can be divided into three different regions: infant mortality, useful life and wear-out periods.

Region 1 is characterized by the decrease of the hazard rate as function of time or age. The high failure rate associated with this region is linked to manufacturing errors or improper design. This region is followed by a nearly constant failure rate and is known as the useful life period or normal operating phase. In this region failures occur purely by chance and this is the only region in which the exponential distribution is valid. There are other studies that relate the failures in this region to a deficient plan of operations and maintenance [13]. It is also agreed that the development of a correct plan of maintenance encompassing preventive or predictive technologies can extend this period [13][14]. The third region represents the wear-out or fatigue phase and it is characterized by a rapidly increasing of the hazard rate with time. These three regions can also be identified in figure 2.3, which shows the evolution of the failure rate with time and in figure 2.4, which illustrates an example of the failure density function.

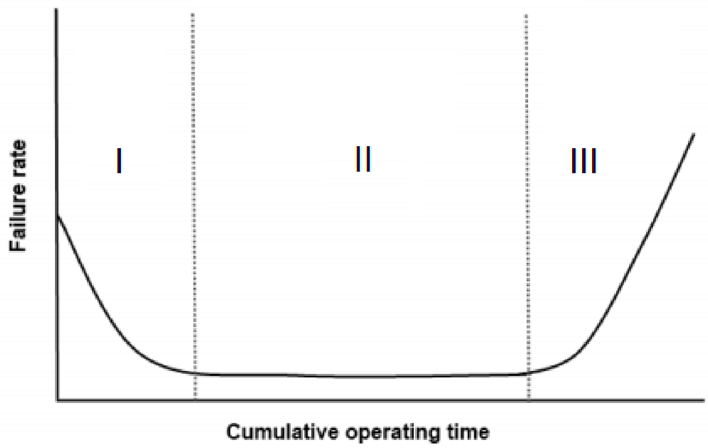


Figure 2.3 - Typical electronic component failure rate λ as a function of age

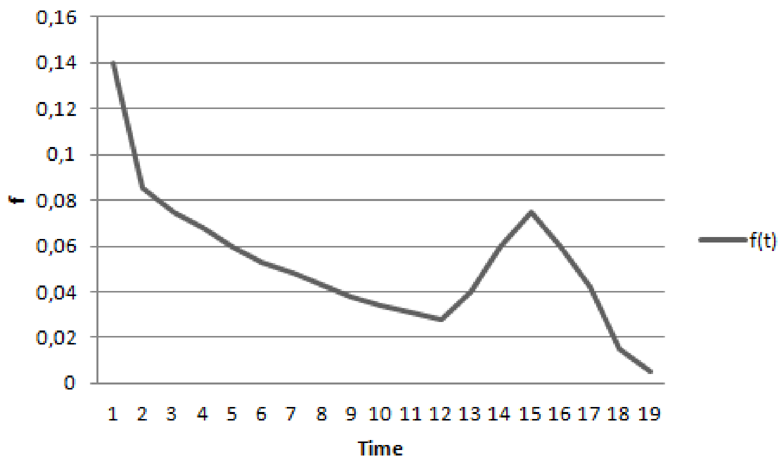


Figure 2.4 - Illustration of a failure density function for a typical electronic component failure rate

The necessary data to construct these two functions was obtained from [2]. As can be seen in figure 2.4, region two follows a good approximation to a negative exponential curve which can be extrapolated in both directions. Region one shows values significantly greater than those that would be obtained if the exponential curve has applied form zero. In the third region, the failures density function increases and finally decreases towards zero. The failure density function that represents, in this example, the third region can often be approximated to a normal distribution. The gamma and Weibull distributions are other distributions that normally represent this region. More details about this and other distributions and their shaping parameters can be seen in [2].

Many components and systems, including power systems components can extend their useful life period. To achieve this goal, the companies need to expend some of their budget in the correct maintenance actions.

Belts need adjustment, alignment needs to be maintained, proper lubrication on rotating equipment is required, and so on. For these specific reasons, maintenance is an indispensable part in the life cycle of a system.

In the next sections, different maintenance techniques will be analyzed. Thus, we will realize that companies should expend the necessary resources to maintenance activities.

2.3.1 - Reactive maintenance

Reactive Maintenance procedure is basically a mode in which maintenance action is not taken. In this method, there are no concerns to keep or to extend the originally designed lifetime of the components. Some studies indicate that this type of maintenance is still predominant [13].

It is difficult to find advantages in this kind of maintenance. It can be seen as double-edge sword. On the one hand, the main thought in the companies plan of strategy is: “if we set apart the maintenance program, we are saving money until some component has a failure. Furthermore, we increase the budget that can be spent in other fields.” That can be seen has an advantage, but the problem lies on the other edge of the sword. When the companies set apart the maintenance, they forget that they are shortening the life of the equipment. This, actually, implies more frequent replacements. Obviously, this means that the systems would become less reliable. Moreover, the failure of a certain device can cause a failure of a second one. Therefore, the lack of a proactive maintenance program can lead to unexpected costs.

The disadvantages of this type of maintenance do not end here. For example, if a failure occurs in a critical device of the system, the operation needs to be replaced in a quick way. The result is an increase of the costs caused by the maintenance overtime cost. Furthermore, the stock of materials required for the reparations will be much larger.

Summarizing, the labor cost associated with repair will probably be higher than implementing a different maintenance program. A multi-objective approach that tries to find the perfect balance between reactive maintenances and preventive maintenance can be found in [15].

2.3.2 - Preventive maintenance

The main goal of preventive maintenance is to control the degradation of the components in a power system. As result of this, the useful life of these components can be sustained or extended. In order to achieve this, this type of maintenance is based on time schedules. This means that will be pre-defined moments, in which maintenance actions will occur. Therefore, if the companies have a look to the bigger picture, they will see that in exchange of the necessary resources for a proper preventive maintenance program, they will get reliable systems by extending the useful life of the components. In addition, as stated before, the application of a proactive plan of maintenance will allow to save money. This type of maintenance is fully described in [13]. Moreover, a methodology to optimize the maintenance schedules can be found in [16].

Estimates indicate that, with this type of policies, these savings can reach 12 to 18% on average, comparatively, with a purely reactive maintenance.

The real implementation of preventive maintenance can take different forms. Some programs are extremely limited and consist of only lubrication and minor adjustments. More exhaustive programs encompass repairs, lubrication, adjustments, and machine rebuilds for all critical plant machinery. The common denominator for all of these preventive maintenance programs is the scheduling guideline—time.

Despite the advantages mentioned above, preventive maintenance isn´t an optimal maintenance plan. In order to happen, it would imply that the correct components were maintained, at the correct time and with the correct maintenance activities.

The mean-time-to-failure (MTTF) or bathtub curve indicates the probability of failure of the components. In preventive maintenance management, machine repairs or rebuildings are scheduled based on MTTF static. The normal result of using MTTF statistics to schedule maintenance is either unnecessary repairs or catastrophic failures. It’s true that components require some periodical maintenance actions (lubrification; filter change; etc), but sometimes this kind of actions can take place, although they can become unnecessary. This is due to the fact that this type of maintenance depends on a schedule and not on the state of degradation of the components. Independently of this, this type of policies will usually result in less components failures. It´s possible to make a translation of this fact into cost savings.

Other interesting studies about preventive maintenance can be found on the literature. In [17] the implementation of a minimal preventive maintenance is studied and, in [18], the introduction of a more complete procedure of preventive maintenance is analyzed.

2.3.3 - Predictive Maintenance

Unlike the preventive maintenance, predictive maintenance isn't a time-driven program [13][14]. Instead, it can be considered as a condition-driven preventive maintenance program. Actually, the MTTF or loss of efficiency for each machine and system is determined by the following indicators: direct monitoring of the mechanical condition, system efficiency and vibration monitoring. Thus, the condition that leads to predictive maintenance actions is related to the state of degradation of the components.

The main goals of this type of maintenance are, on the one hand, to take maintenance actions only when necessary and, on the other hand, to prevent the degradation state of a certain component from becoming irreversible.

The predictive maintenance can assume many forms: may be linked to the analysis of the vibration of rotating machinery, or to the monitoring of the infrared image of electrical equipments, or the analysis of oil lubrication. All these aspects are analyzed in [14]. The common premise of predictive maintenance is that regular monitoring of the actual mechanical condition, operating efficiency, and other indicators of the operating condition of the system will provide the data required to ensure the maximum interval between repairs and minimize the number and cost of unscheduled outages. Predictive maintenance is much more, however. It uses the actual operating condition of plant equipment and systems to optimize total plant operation.

In most cases, time-driven maintenance programs, do not allow a thorough analysis of the current condition and performance of the plant equipment. These programs are based on scheduled maintenances. The final decision in preventive or reactive programs must be made on the basis of intuition and the personal experience of the maintenance manager. The most quoted and well-known case is the change of oil in vehicles. The oil is changed according to the number of years of the vehicle or according to the number of miles made. So, there is not any concern about the real state of the oil. If the followed methodology led to a serious evaluation of the components state, the lifetime of these would be extended, without the existence of unnecessary maintenance actions. This is the fundamental difference between predictive maintenance and preventive maintenance, whereby predictive maintenance is used to define needed maintenance task based on quantified material/equipment condition. Therefore, predictive maintenance makes use of diagnostic equipment and specialized staff in order to evaluate the systems performance. It is also important to notice that the goal of this equipment is to provide factual data on the actual mechanical condition of each component and the operating efficiency of each system process. With this kind of data, the maintenance manager is able to schedule maintenance activities at the right time.

The advantages of this kind of maintenance comparatively with preventive policies are of particular interest. First of all, the implementation of predictive policies allows to minimize

or delete overtime cost and to minimize inventory and order parts. Moreover, it allows to optimize the operation of the equipment, saving energy cost and increasing plant reliability. It is estimated that the application of this policy over the preventive management can provide savings between 8 to 12%. Comparatively to a reactive program, this type of maintenance can reach between 30 to 40% in savings.
In table 2.1, it's possible to observe, in terms of percentage, some important characteristics that indicate industrial average savings resultant from the implementation of a proactive, correct and functional predictive maintenance program.

Table 2.1 – Comparison between predictive maintenance and the others maintenance plans.

Savings Type	Savings Percentage
Return on investment	10 times
Elimination of breakdowns	70 to 75%
Reduction in maintenance costs	25 to 30%
Reduction in downtime	35 to 45%
Increase in production	20 to 25%

The data used to construct this table can be found in [13]. Despite all these advantages, it is to predict the existence of some problems associated with this type of maintenance. The main one is, undoubtedly, the initial investment that needs to be done. Program development will require some resources that have a significant influence in the global budget. These resources are related to well-trained staff and to diagnoses equipment.

There are five different techniques that encompass a normal process of predictive maintenance:

- Vibration Monitoring
- Process Parameter Monitoring
- Thermography
- Tribology
- Visual Inspection

The sets of data that help the maintenance manager to find the correct moments to apply a certain maintenance action can be obtained through the use of these techniques. Vibration monitoring is the most common technique because of the mechanical pieces that compose a major part of the equipment of a power system. However, this process doesn´t allow to identify all the possible problems that may exist in these systems So, it´s crucial in a predictive maintenance plan to have equipment able to provide all the five different techniques. Each one of these techniques is explained in greater detail as well as the different types of maintenance in [14]. In [19] a predictive maintenance plan is applied to a deteriorating system.

In addition to the maintenance policies presented here, there are plenty of others, but that will not be the focus of this thesis. The Total Productive Maintenance [14] and the

Reliability Centered Maintenance [20] are examples of other important maintenance processes.

2.4 - Conclusions

In this Chapter it was carried out an overview of the power systems reliability evaluation nowadays. Thus, it was presented an important study of the actual state of the art. As it was seen, the use of a deterministic or probabilistic approach is completely different. The main conclusion to retain on this topic is the stochastic nature of the power systems. Therefore, the implementation of a deterministic approach doesn't consider the existence of the cycle of operation in the system components. Despite the robustness presented by this method, it can lead to waste financial resources. On the other hand, the probabilistic methods are capable to consider this behavior and, thanks to increased computational capabilities, they are also able to analyze very large systems. As the probabilistic methods, it was possible to distinguish two different approaches: the enumeration and the simulation methods. The first one led to a purely mathematical model and, as it was seen, allows calculating the exact value of the reliability indices. The main reason because this approach is much less used is related to the analysis of very large systems. As an analytical method, the analysis of such systems becomes much more complicated. Therefore, the simulation methods are the most widely used. These provide the mean values of the reliability indices through a sampling process. Another important conclusion to retain is the fact that, usually, these methods consider a constant failure rate and, therefore, the exponential distribution is used to the draw of the operating and repair times. In the following chapters, we will realize that this thesis will follow a different approach. The large number of samples needed to achieve the specified level of convergence (β) can be decreased through the use of the presented variance reduction techniques.

The issue of maintenance was then introduced. This will be one of the main themes of this thesis. Three different types of maintenance policies were presented: reactive, preventive and predictive maintenance. It was concluded that the application of an elaborate and proactive maintenance plan can lead to significant savings, in a long term. Theoretically, predictive maintenance proves more advantageous. Nevertheless, the initial investment associated with it is very high.

In this thesis, these questions will be explored using a Sequential Monte Carlo as method of reference. It is also important to refer that the failure rate of the components will be considered not constant and that the different maintenance policies will be subject of study.

Chapter 3

Modeling the problem with sequential Monte Carlo

In this Chapter, a Sequential Monte Carlo algorithm, which allows to calculate some important reliability indices and, therefore, allows to evaluate power systems reliability will be presented.

As it was seen, Monte Carlo methods are based on a probabilistic approach. Thus, they are capable of translating the stochastic nature, which the components of a power system present. Therefore, Monte Carlo methods appeals to the use of a sampling process, being the main goal to translate the global behavior of a system, through a significant set of samples. Through this, this approach avoids the use of analytical methods in very large systems, which would be very problematic. It also should be noticed that the use of a sequential approach allows the construction of the life cycle of the components. Throughout this study will be shown that the addressed problem requires the use of a chronological method that implements this feature.

First, a typical sequential Monte Carlo algorithm will be analyzed, showing the main differences from a non-chronological approach. Following this, the proposed sequential Monte Carlo algorithm will be described. This part is particularly important because it will show a different approach when compared to a traditional Monte Carlo. Last, but not least, the inclusion of different maintenance techniques in the algorithm will be described.

3.1 - Formal description of sequential Monte Carlo

In the previous Chapter, the guidelines of a Monte Carlo method were introduced. Two different simulation types were presented: the chronological one and the non-chronological. In fact, these two types of simulation have an identical base structure, despite their differences. Thus, the reliability evaluation process of a power system, through a Monte Carlo method, can be schematized as follows:

Monte Carlo Procedure method

Initialize system data: MTTF, MTTR, pre-specified β, etc

Do

NS:=0;

Repeat

Simulate a new state $x_i \in X$ using $P(x)$ distribution; NS=NS+1;
Calculate the test function $F(x_i)$ for the state x_i;
Estimate the expected value $\hat{E}(F)$;
Evaluate the uncertainty of the estimator, $V\left(\hat{E}(F)\right)$;

Until the coefficient of variation β is reached:

End Monte Carlo method

where NS is the number of samples that are evaluated, x_i is a simulated system state that belongs to the system possible states vector X, $P(x)$ is the associated probability distribution and $F(x)$ is the test function that allows to evaluate power systems performances. $F(x)$ can represent, for example, ENS.

However, a comparison between these two approaches was made. In the non chronological simulation, the evaluation of systems reliability was compared to the accounting of photos, while the chronological simulation was compared to a film that explains the life of the system. These are different approaches with differences in their algorithms, too. State sampling method and state duration sampling are two techniques that were previously presented and that explain these differences [7]. The perception of the differences between these two approaches is very important in this thesis. Therefore, it will be possible to understand the reason why the constructed algorithm follows a chronological Monte Carlo.

In a non-chronological process, each sample is independent of the other. Contrary to what happens in the chronological process, this approach only needs the F.O.R of each component to find the actual components state. On the other hand, the chronological approach simulates the cycle of operation-failure of each component and, therefore, each component state has a direct relation with the previous one. Obviously, this algorithm is a bit more complex since more data are needed. In this approach, it is necessary the knowledge about the probability distribution that will allow to find the operating and the repair times of each component.

There are two particular features which special attention should be given in this thesis. First, the failure rate of the components will not be considered constant. Therefore, it is intended to simulate the existence of the three phases of the life of a component that were already mentioned. These three different stages occur sequentially according to the elapse of the components life time. Thus, it is necessary to take into account the chronology of the events. Another important goal of this thesis is the implementation of different types of maintenance to a power system. It is known that the maintenance of a given component occurs in specific periods of its life. If the maintenance policy is based on preventive processes, these periods are pre-specified. If the maintenance policy is based on predictive processes, these periods depend on the actual state of components. Regardless of the mentioned above, to apply a maintenance plan, it is essential to be aware of the temporal chronology. Therefore, the reasons presented above explain why the Monte Carlo method developed was based on a chronological simulation.

The general scheme of a typical chronological Monte Carlo process will now be presented:

1. Simulate the operating times for each component of the system, according to the probability distribution used. This constitutes the initial state of the system.

2. Identify the lowest simulated time. The corresponding component will be called F.

3. Update the system load for this particular moment.

4. State evaluation. According to the current state of each component, the load curtailment is calculated.

5. Update the reliability indices accumulators

6. Simulate a new operating or repair time to the component F. The type of simulated time depends on the previous state of the component F. Therefore, if component F was in operational mode, this means that this component is the next to fail. Thus, a repair time will be generated.

7. Update the components F state and its lifetime.

8. Evaluate the lifetime of the system. Tests if the system has already completed one year and make the necessary updates, including the update of the coefficient of variation β.

9. Evaluate the coefficient of variation β. If convergence has not been reached, return to step 2. Otherwise, proceed to calculate the expected values and distributions of reliability indices and finish the process.

In sequential Monte Carlo, a life cycle is simulated for each component of the system, as figure 3.1 shows. Having this step done, it is possible to check, at each time, if there is load curtailment or not. Then, the reliability indices can be calculated.

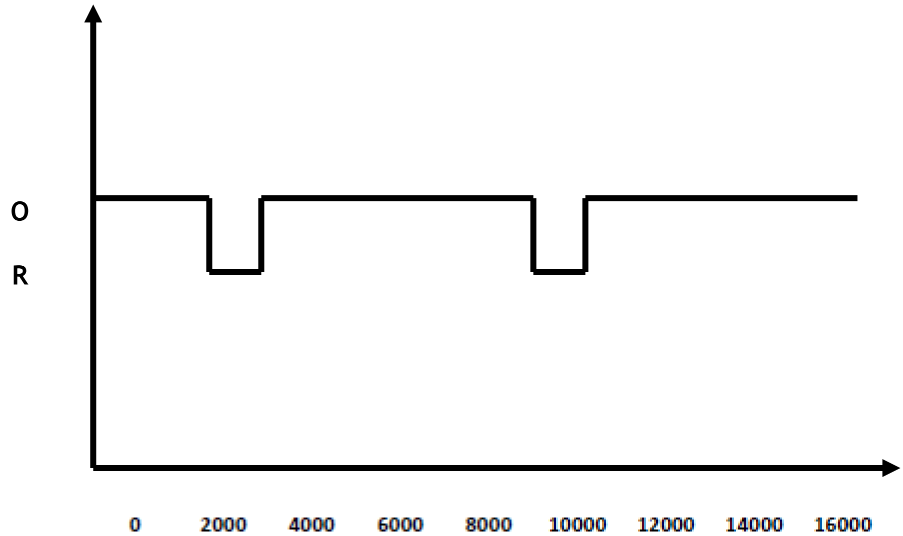


Figure 3.1 – Typical up/down sequence (life cycle) for a given electrical component, where O is Operational mode and R is Repair mode.

As it was seen in the previous algorithm, the simulation the operation and repair times are dependent on the probability distribution associated to them. To analyze this topic, it is important to review some general reliability functions. In reliability terminology, the cumulative distribution function $Q(t)$ is known as the cumulative failure distribution. In reliability assessment, many problems don´t use this distribution. Instead, they use the probability of surviving in a given period of time, $R(t)$. Obviously, these two functions are complementary. So, $R(t)$ also known as the survivor function is equal to:

$$R(t) = 1 - Q(t) \tag{3.1}$$

In reliability evaluation, the probability density function is called failure density function, $f(t)$, and results from the derivative of $Q(t)$:

$$f(t) = \frac{dQ(t)}{dt} = -\frac{dR(t)}{dt} \tag{3.2}$$

Furthermore, it is known that:

$$\lambda(t) = \frac{f(t)}{R(t)} \tag{3.3}$$

Which, from equations 3.2 and 3.3:

$$\lambda(t) = -\frac{1}{R(t)} * \frac{dR(t)}{dt} \tag{3.4}$$

Finally, from the integration of equation 3.4:

$$\int_{1}^{R(t)} \frac{1}{R(t)} * dR(t) = \int_{0}^{t} -\lambda(t)dt \tag{3.5a}$$

$$\ln R(t) = \int_{0}^{t} -\lambda(t)dt \tag{3.5b}$$

$$R(t) = \exp[\int_{0}^{t} -\lambda(t)dt\,] \tag{3.5c}$$

Equation 3.5 c) is the general equation to calculate the survivor function through the components failure rates. In typical Monte Carlo processes, the hazard rate is considered constant. Therefore, it is assumed that the system components remain in the useful life period throughout their lives. So, the infant mortality and wear-out periods are not considered. Later in this thesis, we will realize that this fact can lead to considerable variations on the reliability indices. Considering a constant and time independent failure rate, the survivor function simplifies to:

$$R(t) = e^{-\lambda t} \tag{3.6}$$

This special case is known as the exponential distribution and it is the most widely used probability distribution in reliability evaluation problems. Due to this distribution, the Monte Carlo simulation becomes much simpler. By using the exponential distribution inverse, the operation and repair times can be obtained as follows:

$$T_f = -\frac{1}{\lambda} * \ln(y) \tag{3.7}$$

where T_f means time to fail, which is the same that the time while the component worked in operational mode. λ is the constant failure rate (failures/year) and y is an uniformly distributed number in a [0,1].

$$T_r = -\frac{1}{\mu} * \ln(y) \tag{3.8}$$

where T_r means time to fail, which is the same that the time while the component worked in operational mode. μ is the constant repair rate ($year^{-1}$) and y is an uniformly distributed number in a [0,1].

There are other distributions that can be used in a reliability problem [2]. The gamma or the Weibull distributions are examples of that.

In the next sections, the use of a non constant failure rate will transform this problem into something more complex.

This is, therefore, a very important part of a Monte Carlo process, but not the only one as it's possible to observe in the previous algorithm. The state evaluation is other important part. In this phase, the influence of the different system states in the load loss is analyzed. Furthermore, the Monte Carlo process only ends when the coefficient of variation β is reached. The coefficient choice is one of the most important steps in the process. Actually, a small β, such as 1% can lead to a very long simulation, since the number of samples will be very large. On the other hand, the reliability index will be obtained with an excellent precision level.

In a Monte Carlo process, a confidence interval is established. If a 95% confidence interval is established, in 95% of cases, the established interval will contain the true value. The width of the confidence interval is a measure of the accuracy of our estimate. This is a particular advantage of the Monte Carlo processes. For example, evolutionary algorithms aren't yet capable of establishing a confidence interval.

3.2 - The sequential Monte Carlo reliability algorithm

In this thesis, several sequential Monte Carlo algorithms were developed. The main differences between them are: the failures rates that can be constant or not and the implementation or not of maintenance programs. Each one of these algorithms has their own particularities. Therefore, one of the goals of this section is to clarify those specifications.

First, the proposed algorithm for a typical sequential Monte Carlo process will be presented. In these types of processes, it is common to use a two-state homogeneous Markov model. Moreover, it's usual to assume that all units are base load units. Furthermore, usually, the failure and repair rates are considered constant. As it was seen in the previous Chapter, the use of a constant and independent of time λ led to a special case known as the exponential distribution. Considering these facts, the state transitions in this Markov model will follow an exponential distribution.

The "story of life" of each specific unit is as a source of information. Statistical data can be obtained from it, allowing us to compute the failure and repair rates. Therefore, according to the exponential distribution:

$$\lambda = \frac{1}{MTTF}, \tag{3.11}$$

$$\mu = \frac{1}{MTTR}, \tag{3.12}$$

where λ is the expected failure rate, $MTTF$ is the Mean Time To Failure, μ is the expected repair rate and $MTTR$ is the Mean Time To Repair.

Taking into account these facts, the probability of finding the unit up can be defined as follows:

$$P_{up} = \frac{MTTF}{MTTF + MTTR}. \tag{3.13}$$

Moreover, the F.O.R or the probability of finding the unit down can be obtained from the following expression:

$$P_{down} = \frac{MTTR}{MTTF + MTTR}\,. \tag{3.14}$$

Most of the times, Monte Carlo processes require considerable computational effort. For this reason, it is important to develop some methods that allow to decrease the computational effort. Usually, in the presented Markov model, some generating units have the same characteristics. The expected failure and repair rates and the generating capacity are examples of those characteristics. Therefore, these units can be treated together, instead of separately. In this thesis, this particularity is used in the generating system that will be presented in the next Chapter. This system that is composed for 32 generators was arranged in 9 different groups of equal generators.

It's now time to analyze a different sequential Monte Carlo algorithm. Most reliability studies consider that the components of a power system have a constant failure rate. In this new approach, a non constant failure rate will be used. Therefore, some of the characteristics that were presented previously, for a typical Monte Carlo process, must be forgotten. For example, all the simplifications that were introduced by the exponential distribution will no longer take place.

In power systems reliability literature, some other distributions are presented and each one of them has their own advantages [2]. The Weibull distribution is an example. This distribution, as well as the gamma and the lognormal, has an interesting property. These distributions have no specific characteristic shape. This means that they can be shaped to represent many distributions or to fit sets of experimental data. It can be achieved by varying its shaping parameters.

In [2], other approach to implement a non constant failure rate is presented. This approach is based on the construction of the cumulative failure distribution, $Q(t)$. As it was seen before, through the use of the exponential distribution, $Q(t)$ can be easily defined as:

$$Q(t) = 1 - \mathrm{e}^{-\lambda \mathrm{t}}, \tag{3.15}$$

where λ is the failure rate and t is the time variable. The problem is that the exponential distribution uses a constant failure rate. So, in order to develop the cumulative distribution according to a non constant failure rate, the following integral needs to be calculated:

$$Q(t) = 1 - e^{-\int_0^t \lambda(t)dt}\,. \tag{3.16}$$

Furthermore, data about the failure rate variation and about the time intervals will be necessary. This kind of information can be obtained by analyzing statistical data of other similar components. Therefore, through the equation 3.16, it is possible to construct a cumulative failure distribution.

After the construction of $Q(t)$, through the use of a non constant failure rate, it is possible to generate the time of operation, of each unit. In the previous section, it was explained how to generate these times using an exponential distribution. In this new approach, the procedure is totally different. So, in order to generate the life cycle of each generating unit, the following steps are crucial:

1. Use a pseudo-random number generator to provide an uniformly distributed number in a [0,1] range.

2. The uniformly distributed number is used to intersect the constructed $Q(t)$ curve. So, $Q(t) = \text{uniformly distributed number}$.

3. The time interval (t) that will result from this intersection will be the new time to failure of a specific component.

4. Repeat the process until all the generating units have their own time to failure.

Another consideration needs to be made about point number 2. $Q(t)$ is a discrete curve. So, a problem must be faced: how it is possible to match a uniformly distributed number with a discrete curve? To overcome this problem, an interpolation process was included in the Monte Carlo simulation.

Concluding, this is an approach that allows the introduction of a variable failure rate. This means that the infant mortality and the wear-out regions are included in this method.

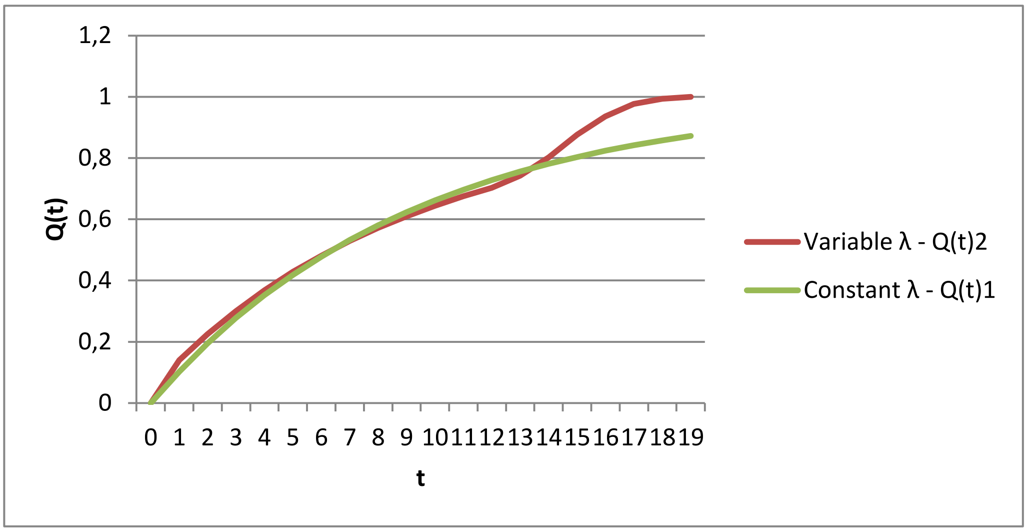


Figure 3.2 - $\boldsymbol{Q(t)_1}$ represents a cumulative distribution function developed according to a constant failure rate and, $\boldsymbol{Q(t)_2}$ represents the same curve, but developed according to a variable failure rate.

The λ data used to construct $Q(t)_2$ was obtained in [2]. Furthermore, all the figures presented, in this Chapter, that are related to a variable failure rate λ were based on data presented in [2]. In figure 3.2, important information can be withdrawn. Two curves are presented: $Q(t)_1$ according to a constant failure rate and $Q(t)_2$ according to a non constant failure rate. The procedure for the construction of these curves was presented before. It is crucial to understand why these two curves diverge from $t \geq 14$. The reason behind this fact is the inclusion of the wear-out period in λ. From $t \geq 14$, the probability of occur a failure in a certain component is higher, when λ is non constant. The inclusion of this idea in the Monte

Carlo algorithm will have consequences on the reliability indices. Figure 3.2 will also have interest for the inclusion of maintenance policies.

It's is possible to make an analogy between the use of a constant λ and an ideal maintenance case. If an ideal maintenance case could exist, the components would not get old. This means that the wear-out region would not exist. The use of a constant λ reflects this behavior. Thus, the use a constant failure rate can be compared to an ideal maintenance case. Unfortunately, perfection doesn´t exist in the maintenance field. On the other hand, the use of a non constant failure rate represents a real situation, in which the components get old with time. The implementation of an effective maintenance plan to this situation would have as consequence the approximation of $Q(t)_2$ to $Q(t)_1$. In other words, an efficient maintenance procedure can approximate a real situation to a hypothetical situation, in which the components stay forever in their useful life periods. The maintenance topic will be deeply studied in section 3.6.

Until now, the failure rate λ was the main focus of this section. It is also important to analyze the treatment that will be given to the repair rate. This rate will be treated as in a typical Monte Carlo process. So, the repair rate will be considered constant and, therefore, the exponential distribution will continue to be used.

3.3 - Assessing the reliability indices

For several times, in this thesis, the term "reliability indices" was mentioned. Ultimately, will be these indices that will measure the impact of the produced changes on the typical Monte Carlo process. The basic indices in a generating system adequacy assessment are:

- Loss of Load Expectation (LOLE);
- Loss of Energy Expectation (LOEE).
- Loss of Load Frequency (LOLF);
- Loss of Load Duration (LOLD);

In [1], the methodology to calculate these indices using Monte Carlo methods is presented.

The most widely used reliability index in generating capacity planning studies is the LOLE. This index is the average number of hours, days or weeks (it depends on the basis of the load model), in a given period (usually, one year), in which the hourly, daily or weekly load is expected to exceed the available generating capacity. Therefore, the LOLE index can be represented in different units: hours/year, days/year and weeks/year. Mathematically speaking, LOLE can be defined as follows:

$$LOLE = \sum_{i \in S} p_i \times T \,, \tag{3.17}$$

where p_i is the probability of system state i, S is the set of all system states associated with the loss of load and T is the given period. The LOLE index isn´t capable of indicating some characteristics related with the interruptions on supply. The severity, the frequency and the duration of the loss of load aren´t explained by this index.

Another well-known index is the loss of load probability (LOLP). This index can be obtained as follows:

$$LOLP = \frac{LOLE}{T}. \tag{3.18}$$

It's common practice, in reliability studies, the preference of the LOLE index, instead of LOLP. LOLP is an index that has no units, because it results from a sum of probabilities. For this reason, LOLE is a more understandable index.

The LOEE index is the expected energy not supplied by the generating system due to the lack of generating capacity to support the load demand. This index is able to provide information about the severity of this lack. Therefore, it is capable to analyze the impact of energy shortfalls. This kind of information isn´t provided by the other indices that were mentioned. In order to evaluate LOEE, it is necessary to know the area below the load curve. This area represents the annual energy that is required by the system. The next step is to compute, for each system state, the power not supplied (PNS). Finally, each PNS value is added in order to achieve the annual LOEE (MWh/year) index. Therefore, LOEE can be defined as follows:

$$LOEE = \sum_{i \in S} 8760 \times p_i \times C_i \ , \tag{3.19}$$

where p_i is the probability of system state i and S is the set of failure states. C_i represents the loss of load for system state i.

There is, still, another interesting index that can be defined: the energy index of reliability (EIR). This is a normalized index that results from a division between the energy that is actually supplied and the total energy demanded. It is an important index because it gives a measure about the capability of a power system to meet its annual demand energy.

$$EIR = 1 - \frac{LOEE}{E} \ , \tag{3.20}$$

where E (MWh/year) is the total energy demanded by a specifc power system.

The Frequency & Duration indices are an extension of LOLE and identify the expected frequency, during the evaluation period, of load curtailment occurrences and their expected durations. Therefore, these indices contain additional physical information, which makes them sensitive to additional generation system parameters. Although these indices are widely documented, they aren't much used in practice.

The concepts of frequency and duration are more important for the assessment of reliability in transmission or composite system. So, these two indices can be defined as follows:

$$LOLF = \sum_{i \epsilon S} (F_i - f_i) \ , \tag{3.21}$$

where, F_i is the total frequency of system state i and f_i is the part of F_i, which represents the frequency of system state i, when in this state there is no load curtailment. LOLF is calculated in occurrences/year.

The LOLD (hour/occurrence; day/occurrence; week/occurrence) index can be easily calculated through the knowledge of LOLF and LOLE indices.

$$LOLD = \frac{LOLE}{LOLF}\,. \tag{3.22}$$

Using Monte Carlo methods, the assessment of this type of indices becomes very simple. This is one of the advantages of Monte Carlo simulations over the enumeration or the population based methods (PB). However, this task is now easier to incorporate in these two methods (enumeration and PB) because of the F&D methods. The PB methods aren't object of study in this thesis, but more information about this subject can be found in [21], [22], [23] and [24].

3.4 - The generation and the load models in Monte Carlo methods

The general concepts that were, until now, presented in this thesis will be applied to a generating system. Beyond the state of the generating units, it is also necessary to know the state of the system load, in order to assess the reliability indices of generating system. Therefore, the data about the generation model isn´t enough to evaluate the reliability of a power system. The basic approach to evaluate the adequacy of a particular generation system is based on the three different models that are shown in figure 3.3.

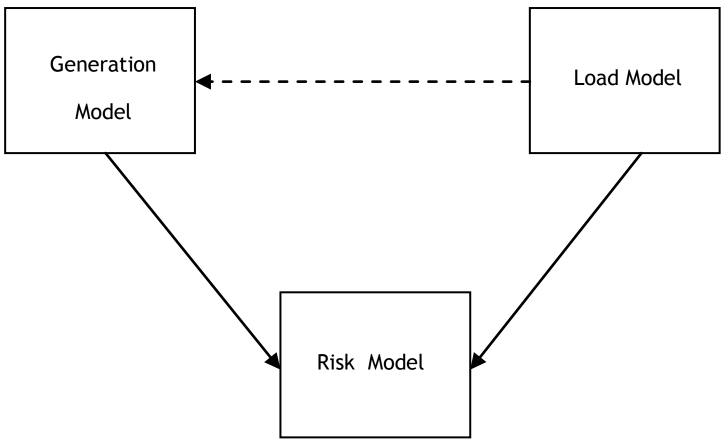


Figure 3.3 - Conceptual tasks in generating capacity reliability evaluation

Therefore, the generation and load models are combined to form the appropriate risk model. Thus, the evaluation of the reliability indices depends both on the generating units state as the system load state.

In the sequential approach, the load levels are enumerated in chronological order, in which they occur or are expected to occur. This can be on an annual basis or on any other continuous period. This load model can be used to represent the hourly, daily or weekly peaks. In the developed Monte Carlo process, the load model represents the hourly peak, giving 8760 individual peaks.

To sum up, the evaluation of the reliability of a generating system depends on the verification, for each state of the generating system, if the available capacity is enough or not to ensure the load model requirements.

3.5 - Stopping Criteria

The Monte Carlo simulations are statistical based methods. Therefore, it is possible to establish a certain degree of confidence. This means that the correct value of the index being estimated can be found in the correspondent interval of confidence. In the literature, one may find the use of degrees of confidence equal or higher than 95%. In this thesis, the degree of confidence used in the Monte Carlo simulation will be equal to 95%.

In the Monte Carlo processes, the value of the index estimate takes some time to get into the interval of confidence. Moreover, the index value doesn't have a steady growth. This fact can be observed in figure 3.4.

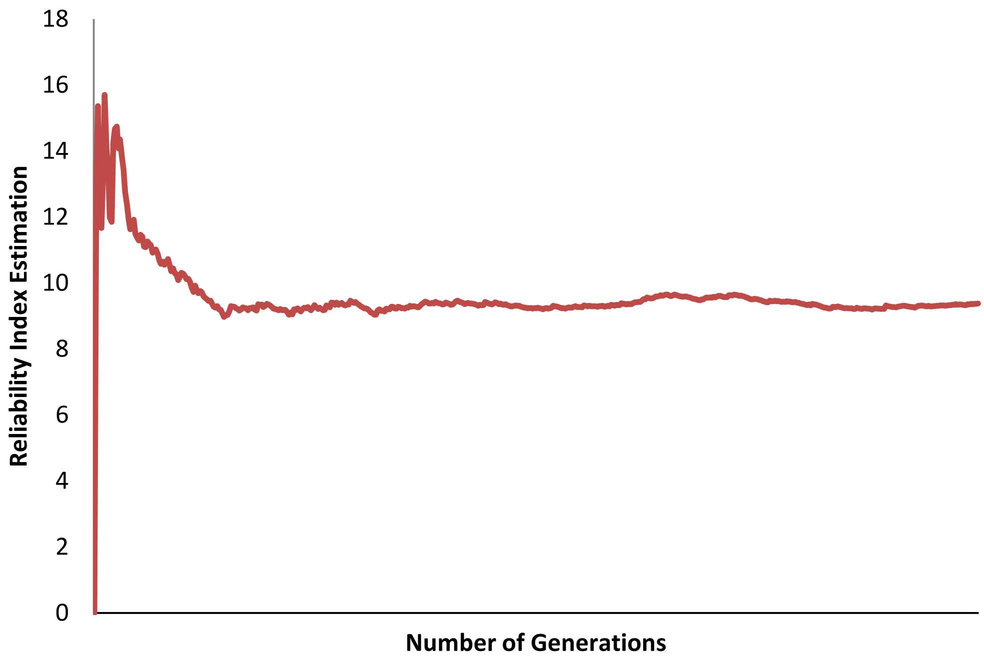


Figure 3.4 - Illustration of the formation of an estimate of a reliability index according to a Monte Carlo Process

In this figure, the increase of the number of generations doesn't have as consequence the growth of the reliability index estimate. This is a characteristic of Monte Carlo simulations. In PB methods, the reliability indices estimate has a different process of formation [25].

In this particular problem, the coefficient of variation $\boldsymbol{\beta}$ is updated at each simulated year. The convergence of the process depends on a pre-specified $\boldsymbol{\beta}$. This predetermined threshold is, in this thesis, equal to 5%.

$$\boldsymbol{\beta_{LOLE}} \leq \mathbf{5\%} \tag{3.23}$$

$$\boldsymbol{\beta_{LOLF}} \leq \mathbf{5\%} \tag{3.24}$$

$$\boldsymbol{\beta_{EENS}} \leq \mathbf{5\%} \tag{3.25}$$

Therefore, the addressed simulations will only stop when the convergence is reached for all these reliability indices.

3.6 - Inclusion of the maintenance techniques in the algorithm

In section 3.2 of this thesis, the first maintenance technique was presented: the reactive maintenance. Although the reactive policy is associated with the term "maintenance", there are no maintenance actions in this type of program. In other words, the repairs of the generating units only occur after they fail. For this reason, to add this kind of maintenance on the typical Monte Carlo process, no changes are needed.

As it was studied before, although the reactive maintenance is widely used, it has many disadvantages in a long term. On the other hand, the other two types of maintenance that will be discussed are based on active measures. These actions are taken during the operation of the generating units. As a consequence, new code parcels need to be developed, in order to introduce this new behavior on a typical Monte Carlo process. The inclusion of these two methods pretends to compare the time-driven programs with the condition-driven programs.

In a first phase, the main goal is to evaluate and analyze the positive effects of these maintenance programs. Therefore, the units won't be removed from service when maintenance actions are taken. So, the maintenance actions will not affect the capacity available for service. This task will be the object of study in section 3.7.

3.6.1 - Preventive maintenance inclusion

The inclusion of different maintenance policies is one of the main goals in this thesis. A well-structured maintenance plan, in which the goals are clearly defined, can lead to major improvements in the reliability of power systems. Furthermore, to achieve this goal, the collaboration with specialized staff is necessary. The developed Monte Carlo simulations will prove that these improvements are real.

The preventive maintenance can be defined as a time-driven process. So, this type of process is based on time schedules. The actual state of the generating units doesn't have any importance in the preventive policies.

In the theoretical plan, the maintenance actions have the main goal of extend the useful life period of the generating units. In other words, these policies pretend to delay the entry of these units in the wear-out period. It is important to remember that this period is characterized by an increasing failure rate.

In the simulation plan, some changes needs to be incorporated, in order to add the maintenance policies. First, in the preventive maintenance, it is necessary to establish the maintenance schedule. As it was already discussed, this type of maintenance is known for the periodic maintenance actions. Actually, is important to remind that some of these actions would be dispensable, if the state of the components were analyzed. This particularity needs to be implemented in the Monte Carlo simulation.

In order to understand the process of implementing this maintenance policy, it is necessary to examine the algorithm presented in Section 3.2 from the beginning. Through that algorithm, it is easy to realize that the whole process of simulation depends on the failure rate λ. The construction of the cumulative function $Q(t)$ and the generation of the time of operation of each component, depend on λ. It is, therefore, by manipulating the failure rates, that the expected effect of maintenance can be incorporated. Thus, whenever a new operation time is generated (as explained in section 3.2), it is necessary to check the maintenance schedule. If the lifetime of a given component is equal to one of the scheduled maintenances, maintenance actions will take place. This will involve changes in the failure rate of this component.

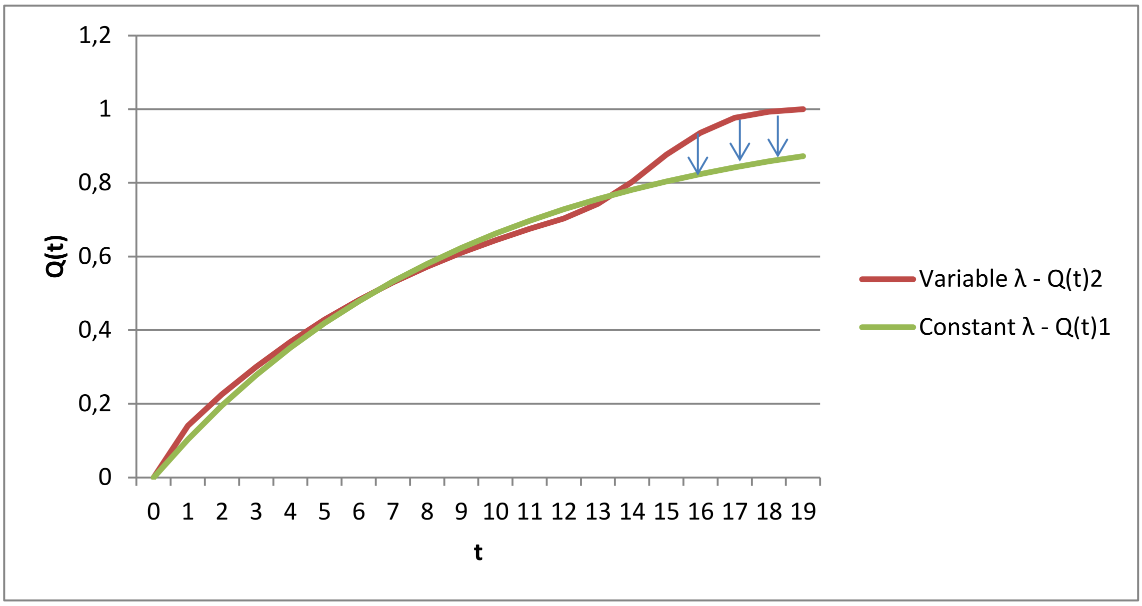


Figure 3.5 - Expected effect of preventive maintenance in $Q(t)_2$ curve: the preventive maintenance can approach a real situation ($Q(t)_2$) to an ideal maintenance case ($Q(t)_1$).

The way these changes occur is another important question. The fact that a given component receives periodic maintenance actions, will lead to an extension of his useful life period. In figure 3.6, a comparison between the failure rates of two components is made: one of them has periodical maintenance actions and the other one follows the reactive maintenance methodology.

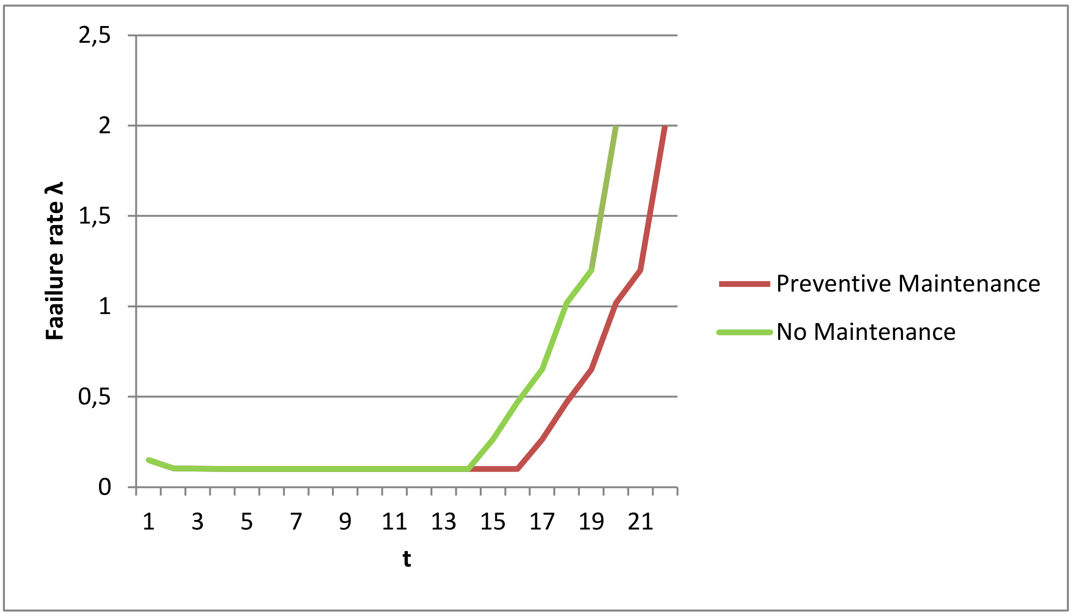


Figure 3.6 - Effect of preventive maintenance actions upon the failure rate λ: the extension of the useful life period.

In figure 3.6, it is possible to clearly verify the effect of maintenance actions upon the λ of the generating units.

Considering the algorithm presented in section 3.2, it is easy to realize that the changes produced on λ have as consequence the recalculation of the $Q(t)$ curve. Only through this new curve, the generation of the times of operation of each unit will include the effect of maintenance.

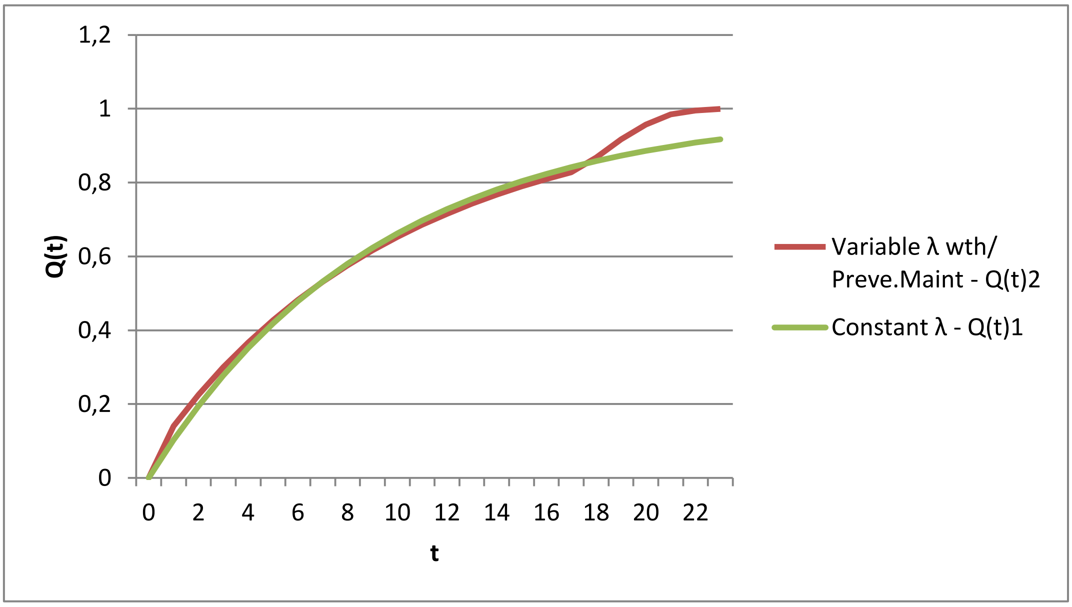


Figure 3.7 - Effect of preventive maintenance actions upon Q(t) curve: $\boldsymbol{Q}(\boldsymbol{t})_2$ diverge from $\boldsymbol{Q}(\boldsymbol{t})_1$ in a later stage of the generating unit life.

where $Q(t)_1$ represents the situation of an ideal maintenance case and $Q(t)_2$ represents a situation, in which a preventive maintenance plan is applied. This figure allows to observe something very important. The periodical maintenance actions had the expected effect on the cumulative curve: $Q(t)_1$ is now closer to $Q(t)_2$. In other words, a real situation (variable λ) is now closer to a hypothetical situation (constant λ) known for the ideal maintenance case. Therefore, the generating units enter on the wear-out period, in a later stage of their lives $(t \geq 18)$. Obviously, this fact will have clear effects on the reliability indices. The extension of the useful life periods of the generating units, will lead to less failures during their lives. Therefore, the variations on the reliability indices will correspond to this effect.

It is, still, important to mention one more aspect. The magnitude of the extension of the useful life periods gives a measure of the effectiveness of these maintenance plans. As it was seen before, the preventive maintenance isn't the more effective maintenance policy, since it does not evaluate the current state of components. For this reason, the increase of the useful life period, in this type of maintenance, will correspond to only one period of time, at each scheduled maintenance. In figure 3.6, this effect is presented.
After introducing the preventive maintenance basic ideas, now the steps of this methodology are explained in detail. This algorithm is based on a set of different approaches that were studied during this thesis. The most important can be found in [2] and [6].

1. Initialize the reliability characteristics of the generating units:

    - λ - failure rates;
    - $MTTR$;
    - Number of units;
    - Capacity of each unit.

2. Initialize the power system load curve.

3. Initialize the random number generator and other variables as:

    - Maximum number of years of the simulation process;
    - β threshold: $\beta_{max} = 5\%$.

4. For each generating unit, generate a time of operation according to the algorithm presented in section 3.2.

DO

5. Identify the lowest simulated time. The corresponding component will be called F.

6. Update the system load for this particular moment.

7. State evaluation. According to the current state of each component, the load curtailment is calculated.

8. Update the reliability indices accumulators.

9. Simulate a new operating or repair time to the component F. The type of simulated time depends on the previous state of the component F.

   9.1. If component F was in operational mode, a repair time will be generated. As it was studied before, the generation of a repair time will follow an exponential distribution.

   9.2. If component F was in repair mode, an operation time will be generated, according to the algorithm presented in section 3.2.

9.2.1. If the lifetime of component F is equal to one of the pre-defined moments of the scheduled maintenances, λ must be updated.

9.2.2. Update the $Q(t)$ curve.

10. Update the components F state and its lifetime.

11. Evaluate the lifetime of the system. Tests if the system has already completed one year and make the necessary updates, including the update of the coefficient of variation β.

Until the maximum generation criteria. $\boldsymbol{\beta_{max}} = \mathbf{5}\%$.

12. Compute the following reliability indices:

    - LOLP;
    - EPNS;
    - LOLD.

13. Compute the probability distributions of LOLE, EENS and LOLF.

In the next Chapter, the effects of the preventive maintenance will be clearly observable. In the next section, a different maintenance plan will be studied: the predictive maintenance.

3.6.2 - Predictive maintenance inclusion

Unlike the preventive policies, predictive maintenance isn't a time-driven program. Instead, this type of maintenance program depends on the actual state of the generating units. Therefore, the analysis of the degradation state of these units is a crucial stage of this type of maintenance. By performing these tests, it is possible to avoid the existence of unnecessary maintenance actions.

Predictive and preventive maintenance programs have the same main goal: to extend the useful life period of the generating units. The difference between them lies on the moments in which the maintenance actions occur. On the one hand, preventive maintenance actions are performed according to a maintenance schedule. On the other hand, predictive maintenance operations are performed, when a given component enters its last stage of life: the wear-out period. Furthermore, a predictive maintenance program requires a higher investment. For example, sensors are needed to check the degradation state of the generating units and a specialized team is necessary to deal with this type of maintenance.

The implementation of the predictive maintenance will also lead to some changes on the Monte Carlo algorithm. In first place, instead of defining the maintenance schedule, it is necessary to define the moment when the failure rate λ, of each generating unit, starts to increase (wear-out period). Therefore, whenever a new time of operation is generated for a given unit, it is necessary to check its lifetime. In other words, it is necessary to verify if this unit already entered in its wear-out period. Maintenance actions will be the consequence to a positive answer to this question. Thanks to these maintenance actions, the useful life of the generating units will be extended. Therefore, the main goal of the predictive maintenance can be defined as follows: whenever the failure rate λ, of a given unit starts to increase, bring this λ, through the maintenance actions, to its useful life period.

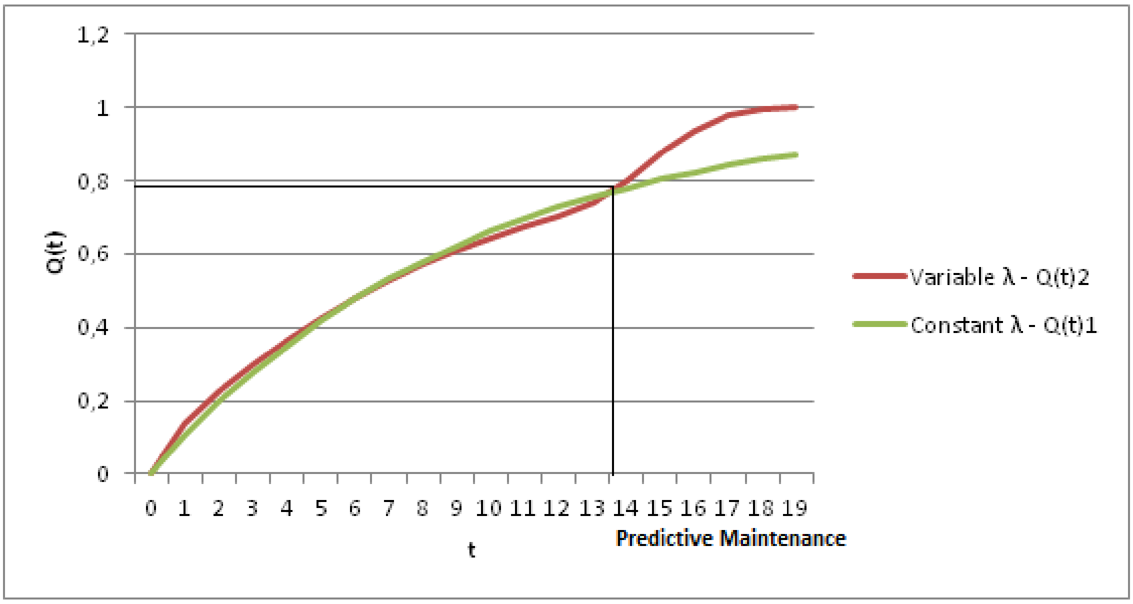


Figure 3.8 – Illustration of the moment, in which the generating unit enters on the wear-out period and, therefore, of the moment, in which the predictive maintenance actions start to occur.

Figure 3.8 shows an example of a curve Q(t), for a given generating unit, that was constructed according to the algorithm presented in section 3.2. This figure shows, clearly, the moment when this unit starts to enter on its wear-out period ($t \geq 14$). Therefore, maintenance operations should be performed when $t \geq 14$.

The consequences of the predictive maintenance for the failure rate λ can be observed in the following figure.

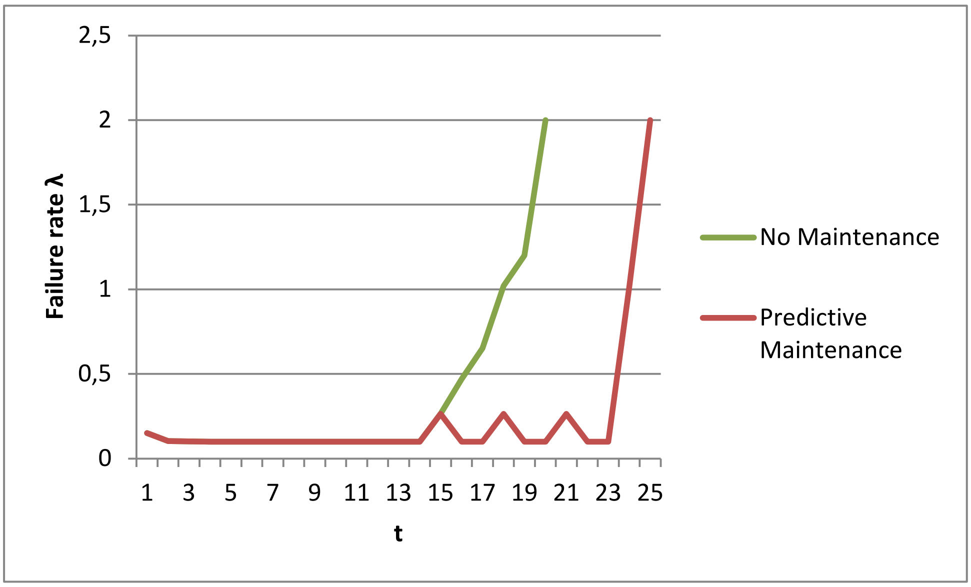


Figure 3.9 - Effect of predictive maintenance actions upon the failure rate $\boldsymbol{\lambda}$: the extension of the useful life period.

As it was discussed before, whenever λ increases, maintenance actions are taken in order to bring λ to its useful life period. The following step is the recalculation of the $Q(t)$ curve.

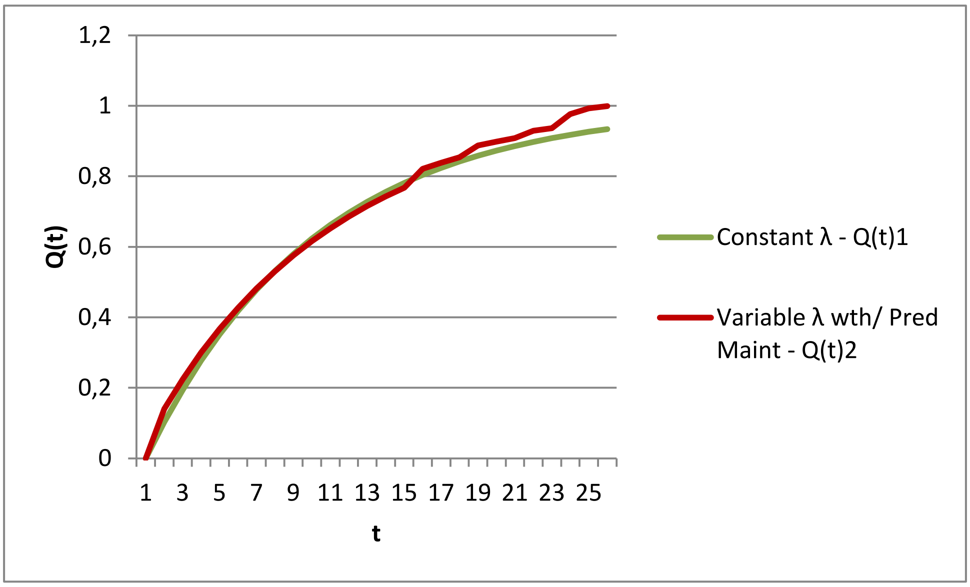


Figure 3.10 - Effect of predictive maintenance actions upon the Q(t) curve: $\boldsymbol{Q(t)_2}$ diverge from $\boldsymbol{Q(t)_1}$ in a later stage of the generating unit life.

Figure 3.10 establishes a comparison between the two types of maintenance that were studied. The main idea to withdraw is the following one: with a predictive maintenance process, the generating units enter on their wear-out periods in a later stage of their lives. Once more, this type of maintenance also had the expected effect on $Q(t)$: a real situation, in which the λ is variable, is now closer to a hypothetical situation, in which λ isn't constant. Considering the above points, is expected that the predictive maintenance will lead to better reliability indices than the preventive maintenance.

It is still important to discuss the subject of the magnitude of the useful life period extension. It was possible to realize, in this Chapter, that the predictive maintenance constitutes a more effective plan. For this reason, the increase of the useful life period, in this type of maintenance, will correspond to two periods of time, at each maintenance procedure.

It is now time to clarify, in terms of algorithm, the differences between the two types of maintenance. The algorithm presented in section 3.6.1 for the preventive maintenance is very similar to the algorithm that will include the predictive policies. The only difference between these two algorithms is related to the maintenance moments. Therefore, the step 9.2.1 of the algorithm presented in section 3.6.1 can be defined as follows:

9.2.1. If the lifetime of component F is equal or superior to the moment, in which λ starts to increase, maintenance actions will be performed. λ is updated.

After the introduction of these two different maintenance policies and their algorithms, it is now time to study other approach. This approach will consider the case, in which the generating units are removed from service for maintenance actions. This new particularity will have interesting consequences in the reliability indices.

3.7 - Maintenance policies : a new approach

In this new approach, an important particularity is added: the generation units will be removed from service for the maintenance actions. Therefore, during the maintenance periods, the available generating capacity will decrease. As it is possible to observe in figure 3.11, the generating units will assume a new state during the maintenance actions.

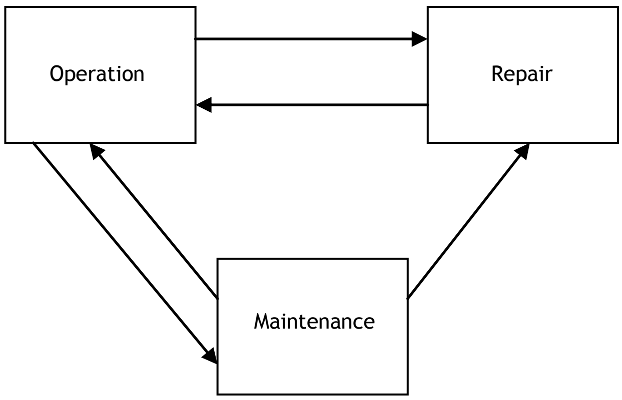


Figure 3.11 - New state model of the generating units: the maintenance state is, now, included.

In figure 3.11, the new state model of a power system is presented. The maintenance state is now included. This diagram is valid for the two maintenance programs that were studied. Now, some explanations about this diagram will be presented:

1. When a given generating unit is in repair mode (R), it will be repaired and, then, starts a new operation period (Operation Mode-O). Therefore, the maintenance actions will occur only, after, an operation period.

2. A generating unit, after a maintenance period, return to its childhood period. Most of the units surpass this period without any problems and, therefore, they evolve to the useful life period. The problem is that, sometimes, deficient procedures can occur. In this case, the generating units will return to their childhood periods, but, before entering in the useful life period, they will fail. So, in order to simplify this approach, it was decided that after a maintenance procedure, the generating units will evolve to one of the following two states: operation mode or repair mode. The major part of the generating units will evolve to the operation mode, representing the generating units that won't have problems during the childhood period. A small part of the generating units will evolve to the repair mode, representing the generating units that will fail before the useful life period.

In order to implement the analyzed situation in 2, a new probabilistic concept needs to be established. Thus, after a maintenance period, it is necessary to generate an uniformly distributed number in a [0,1] range (rand()). If $rand() \geq 0.9$, the generating unit will start a new repair period. If $rand() < 0.9$, the generating unit will start a new operation period. With this methodology, the small amount of cases, in which deficient maintenance procedures occur, are included.

Considering the above points, it is easy to conclude that the transitions for the maintenance state are based on deterministic criteria. All the other transitions are based on probabilistic criteria. This new approach will have as consequence an increase on the reliability indices.

The main question, now, is to realize how this new particularity will affect the different types of maintenance. This question will be answered through the comparison between the durations of each type of maintenance. On the one hand, the degradation state of the generating units in the preventive maintenances isn´t always severe. Therefore, this type of maintenance is usually faster. On the other hand, predictive maintenance actions are performed when the degradation state of the generating units is already in an advanced stage. Thus, predictive maintenance takes longer and is more careful.

Considering the above points, it´s obvious that, in the predictive maintenance, the generating units will be removed from service for longer periods of time. Therefore, this new approach will have higher influence in the predictive maintenance.

3.8 - Conclusions

In this Chapter, the main lines of a typical sequential Monte Carlo, applied to a reliability problem, were presented. Furthermore, it was through this first approach, that all the others algorithms were developed. This typical approach follows the methodology presented in [1] and [6]. Some other specific issues were presented in this Chapter, as for example, the reliability indices. These issues had in consideration the addressed problem: the generating capacity adequacy assessment.

The first concern in this Chapter was to develop a more realistic algorithm. Therefore, following the methodology presented in [2], a non constant failure rate λ was adopted. With this new approach, the wear-out period of the generating units started to be studied. The next step was the inclusion, in the algorithm, of the two types of maintenance: preventive and predictive maintenance. Theoretically, the predictive maintenance showed more advantages. Despite these advantages, the observation of the reliability indices, when the generating units are removed from service, will be very interesting.

The following Chapter is devoted to apply the models and concepts that were already studied. Moreover, the results of the several developed simulations will be analyzed and conclusions will be drawn.

Chapter 4

Solving the problem with sequential Monte Carlo

In this Chapter, the main results of the proposed methodologies will be presented. Through these results, the evaluation of the impact of the different types of maintenance, in a power system, will be made.

In Chapter 3, a new approach was developed. Instead of consider a constant failure rate λ, all the bathtub curve that was studied in the previous Chapters, was implemented. This fact will allow to observe the effect of the infant mortality and wear-out periods upon the generating units reliability. Since, most of reliability studies, uses a constant failure rate, the analysis of these results will be very interesting. This new approach can be accomplished by the inclusion of new code modules in the typical Monte Carlo algorithm. As it was seen before, these new modules are based on the development of the cumulative distribution function $Q(t)$. The developed algorithm will, also, allow the introduction of two different aspects in the maintenance procedures. In a first approach, the generating units won't be removed from service for maintenance actions. Then, according to a more realistic situation, the generating units will be removed from service for maintenance procedures.

In first place, the power system which will have its reliability evaluated will be presented. Furthermore, the performances of each developed algorithm will be object of analysis. The comparison between these performances will allow answering to a set of important questions: Which is the impact of the inclusion of a non constant failure rate λ? How the maintenance policies affect the reliability of a power system? Which is the best maintenance procedure? When the generating units are out of service for maintenance actions, the reliability indices are affected? In which generating units, maintenance actions should occur? For last, but not least, a cost-effective analysis will be made, in order to analyze the advantages and disadvantages of the studied maintenance policies.

All the results that will be presented were obtained with a MATLAB application developed for this purpose.

4.1 - Institute of Electric and Electronic Engineers Reliability Test System 79

In order to evaluate the adequacy of the generating capacity, the IEEE RTS-79 [26] was the chosen power system. Therefore, the proposed methodologies will be tested in this power system. The need of a standardized power system to test and compare results from different reliability approaches, led to the development of this and other standardized systems. These power systems are characterized for having a standardized database. In IEEE RTS-79, a lot of information and data are described, as for example, transmission network data. In the addressed problem, only two types of data are needed: the generation data and the load model.

The IEEE RTS-79 generation system is composed for 32 units. However, there are only 9 different types of generating units. For this reason, the 32 units can be clustered into 9 groups, in the Monte Carlo algorithms.

The system load model can represent the hourly, daily or weekly load peaks. The hourly basis will be used in the developed methodologies. The annual load peak, in IEEE RTS-79, is 2850 MW. The unit parameters used in the assessment of IEEE RTS-79 can be found in Annex A.

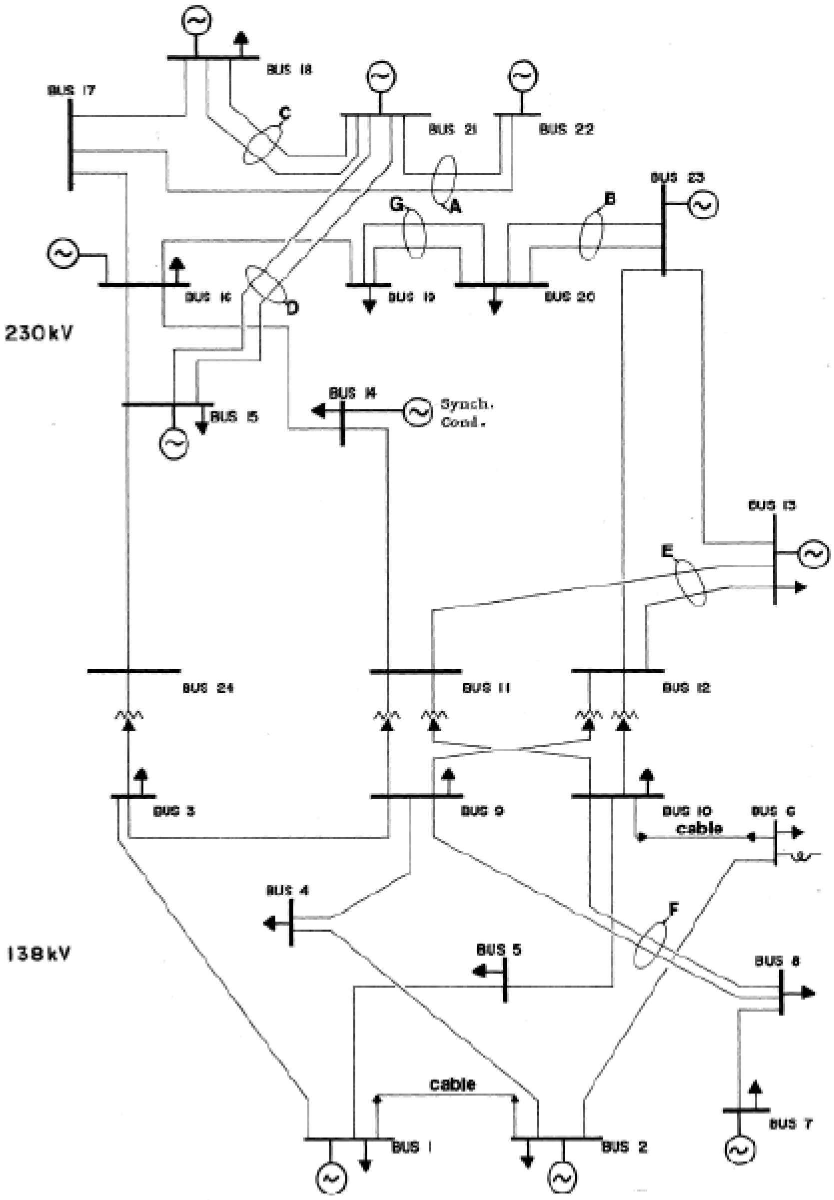


Figure 4.1 - Topology of the IEEE RTS – 76 [26]

In order to have a good basis for comparison with the developed methodologies, the following table will show the exact values of the most important reliability indices. These indices were obtained according to an hourly load model from [27] with analytical calculation.

Table 4.1 - IEEE RTS -76 generating capacity adequacy reliability indices

Adequacy reliability indices	
LOLE (hour/year)	9.394179
LOLF (occurrence/year)	2.019717
LOLD (hour/occurrence)	4.651236
LOEE (MWh/year)	1176.3

4.2 - Evaluation of the Monte Carlo performance with a constant failure rate λ

As it was seen in the previous Chapter, the development of a typical Monte Carlo algorithm was the first step taken in this thesis. This algorithm is based on one particularity: the failure rates λ of the generating units are constant and, therefore, an exponential distribution is followed. The figures and tables that will be presented in this section will have more interest, when compared to the results of the other methodologies. Anyway, it is important to perform some analysis and observations. After all, this algorithm is the basis of all working.

First, the reliability indices and their probabilities distributions will be shown:

Table 4.2 – Adequacy reliability indices of a Monte Carlo simulation according to a constant failure rate λ

Adequacy reliability indices	
LOLE (hour/year)	9.3755
LOLF (occurrence/year)	1.9992
LOLD (hour/occurrence)	4.6896
EENS (MWh/year)	1180.9

These results were very important for the development of this thesis. They allowed to validate the followed methodology. As it is possible to observe, these results are similar to the ones presented in the last section, which were calculated through analytical methods. So, this proves that the algorithm was well constructed. It is also important to mention that these results were obtained according to a variation coefficient $\beta = 5\%$. Moreover, these results constitute the ideal maintenance case. Therefore, preventive or predictive maintenance actions won't lead to better results. As it was said before, this situation implies that the generating units don't get older. Obviously, this is a hypothetical situation, since the generating units suffer a degradation process during their lives.

Now, a comparison between the analytical results and the Monte Carlo results is going to be made.

Table 4.3 - Comparison of results from analytical (ANA) and Monte Carlo (MC) methods, including the limits for the confidence interval.

	Adequacy reliability index LOLE				
ANA	LOLE (hour/year)	9.394179			
MC	β (%)	2.50	3	5	10
	No.Simulated Years	10000	5632	2590	465
	No.States	91984887	64231116	23822700	4276784
	LOLE (hour/year)	9.3586	9.2728	9.3755	9.2601
	$[LOLE \times (1 - 1.96\beta)]$	8.90	8.7276	8.456701	7.4451
	$[LOLE \times (1 + 1.96\beta)]$	9.8172	9.8180	10.294299	11.075

This table presents some important information. First, the reliability index EENS was computed through the Monte Carlo simulations, according to different variation coefficients β. Furthermore, in rows 5 and 6, the limits for the confidence interval at 95% confidence level are presented. Other interesting particularity is the increasing number of states with the decrease of the variation coefficient β. As it was studied in Chapter 2, the computational effort is considerably affected by the desired degree of confidence.

Figure 4.2 will show the evolution of estimated LOLE with the number of states visited.

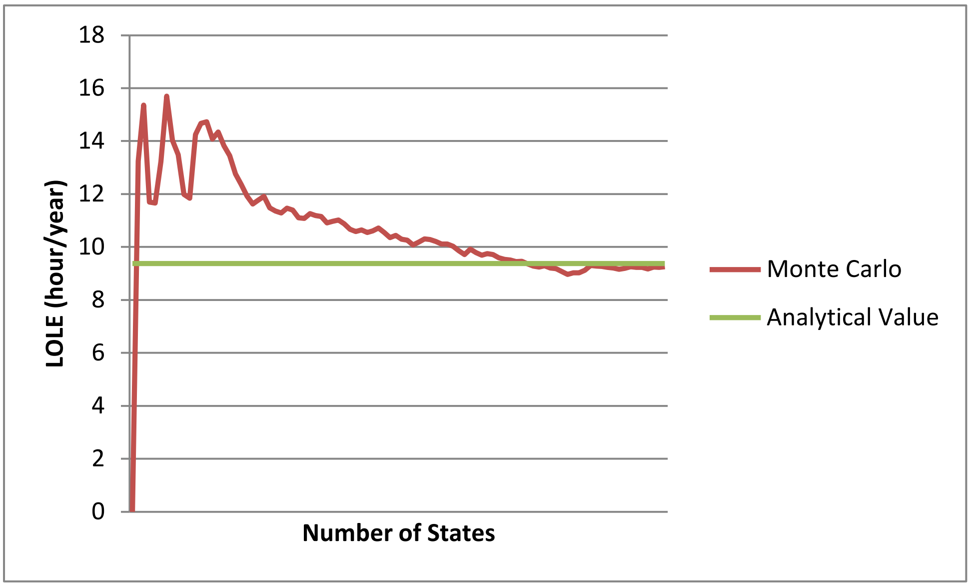


Figure 4.2 - Evolution of estimated LOLE (y-axis) with the number of states visited (x-axis): MC results (curve oscillating around the real value) vs Analytical approach

Figure 4.2 shows that the "Monte Carlo curve" oscillates around the analytical value, until the maximum of the variation coefficient $\beta_{max} = 5\%$.

The analysis of the probability distributions of the reliability indices is another very important source of information. It allows us to obtain a risk measure. The value of the reliability indices only gives us the mean value of their distributions. In other words, the values of the reliability indices don't give information about the dispersion of the results.

LOLE	Relative Frequency (%)
5,3801	76,37065637
11,1404	11,81467181
19,7007	4,980694981
31,3360	3,32046332
42,1513	1,891891892
53,1816	0,656370656
65,9418	0,463320463
83,7021	0,308880309
91,4624	0,077220077
110,2227	0,077220077
133,9830	0
146,7433	0
159,5035	0,038610039

EENS	Relative Frequency (%)
2070,994	91,93050193
4956,742	5,173745174
10814,57	1,621621622
15140,4	0,617760618
19466,23	0,308880309
23792,05	0,231660232
28117,88	0
32443,71	0,077220077
36769,54	0
41095,37	0
45421,19	0
49747,02	0
54072,85	0,038610039

LOLF	Relative Frequency(%)
0,730769	58,996139
1,823077	11,35135135
2,479846	15,05791506
4,195385	4,131274131
5,576923	5,019305019
7,098462	1,544401544
8,5	1,853281853
9,961538	0,540540541
12,42308	0,810810811
13,88862	0,193050193
15,34615	0,154440154
16,89769	0,154440154
18,86923	0,193050193

Figure 4.3 - Probability distributions of the studied reliability indices

Figure 4.3 shows the probability distribution of the studied reliability indices. To understand the importance of this figure, let's take as example the mean value of LOLE: $LOLE = 9.3755\ h/ano$. Only with this information, we wouldn't know how this value was obtained. Now, two different ways to obtain this LOLE will be presented:

a) Load curtailment during 9.3755 h, every single year of the simulation process;

b) Load curtailment during 24282.545h in only one of the years of the simulation process;

It is important to note that the LOLE dispersion is much more significative in case b), although both cases have the same mean value. The relative frequency of no load curtailment, in case b), is equal to 0.9996 and, in case a), equal to 0. All these results were obtained considering a number of simulated years equal to 2590 ($\beta = 5\%$). Concluding, figure 4.3 allows to understand the way how the reliability indices were obtained.

In this thesis, all the comparisons between the different approaches will be based on the cumulative distribution function $Q(t)$. Therefore, figure 4.4 will present the $Q(t)$ curve according to a constant failure rate.

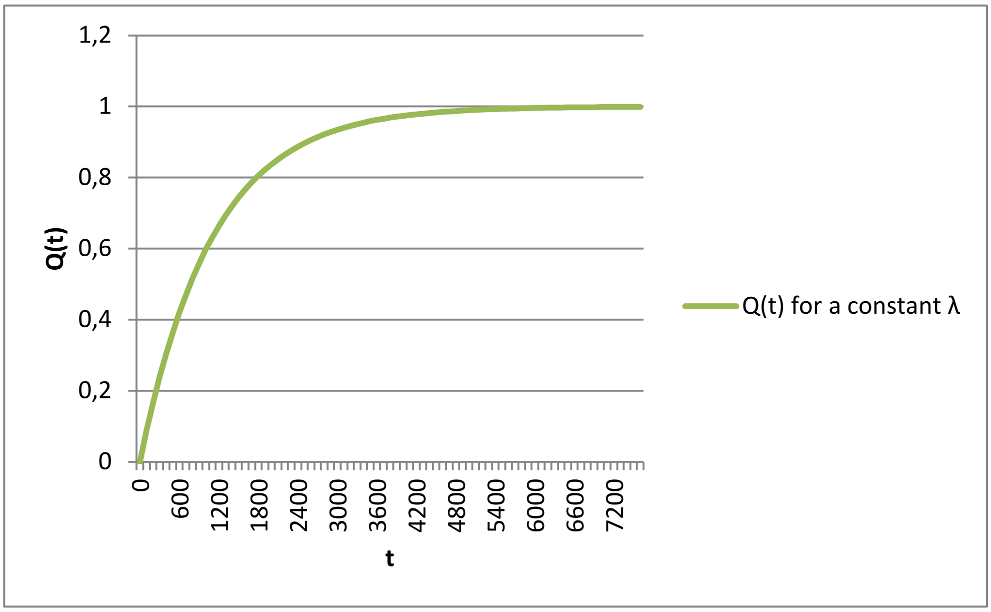


Figure 4.4 - Cumulative distribution function $\boldsymbol{Q(t)}$ of a generating unit with a constant failure rate $\boldsymbol{\lambda}$

Figure 4.4 shows that the probability of fail of this generating unit after $t = 7000h$ is equal to 1. This means that this generating unit, after 7000h, already has failed. As it was said before, this situation illustrates the ideal maintenance case. Thus, in the following approaches, it is expected that the generating units will fail in an earlier stage of their lives. It also important to remember that this Q(t) curve was developed according to an exponential distribution: $Q(t) = 1 - \exp(-\lambda t)$. The data of the generating unit used to develop this Q(t) curve can be found in Annex A. This generating unit is a nuclear unit and was chosen as the example to show the changes that will be produced in the Monte Carlo algorithm.

4.3 - Evaluation of the Monte Carlo performance with a non constant failure rate $\boldsymbol{\lambda}$

In this section, the results of the improvements produced in the Monte Carlo algorithm will be analyzed. Theoretically, the difference between this new approach and the typical method is very simple: the constant failure rate $\boldsymbol{\lambda}$ is replaced for a variable failure rate $\boldsymbol{\lambda}$. In the other hand, in practice, the changes produced in the Monte Carlo algorithm are several. As it was studied in Chapter 3, instead of following an exponential distribution, the cumulative distribution function $\boldsymbol{Q(t)}$ needs to be developed through the calculation of an integral. With these improvements, we intend to create a more realistic situation. This situation is presented in the following figure:

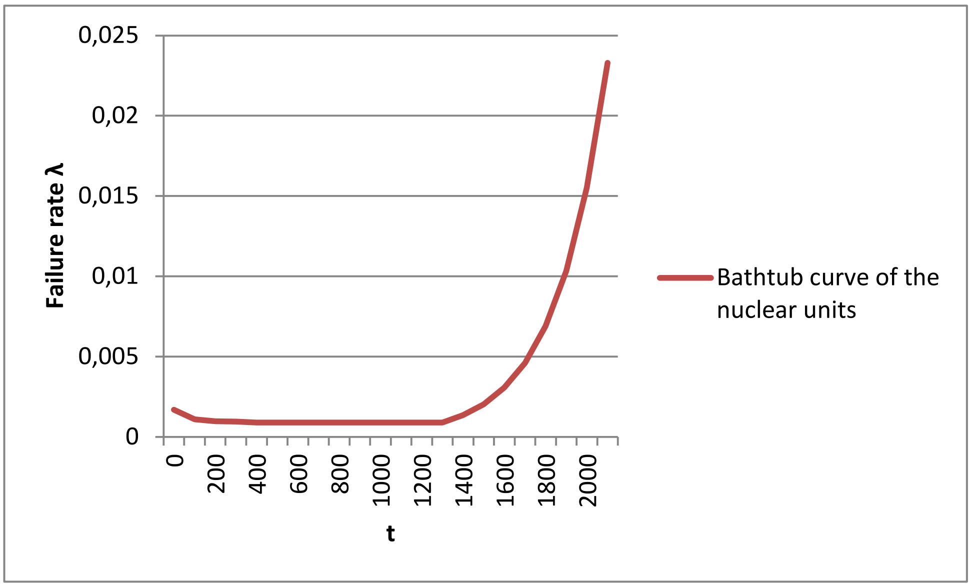


Figure 4.5 - Bathtub curve that will be implemented in the Monte Carlo algorithm, instead of a constant failure rate

Figure 4.5 shows the "bathtub curve" of the nuclear units. In Annex B, the data of this curve can be inspected. This figure shows that, in this new approach, the infant mortality and wear-out periods are included. Therefore, a real situation is presented, in which the nuclear units have debugging problems at the beginning of their lives and, in which the degradation process with the elapse of time is clearly visible.

According to the algorithm presented in section 3.2, the changes produced on the failure rate λ have as consequence the recalculation of the Q(t) curve. The new Q(t) curve is presented in the following figure:

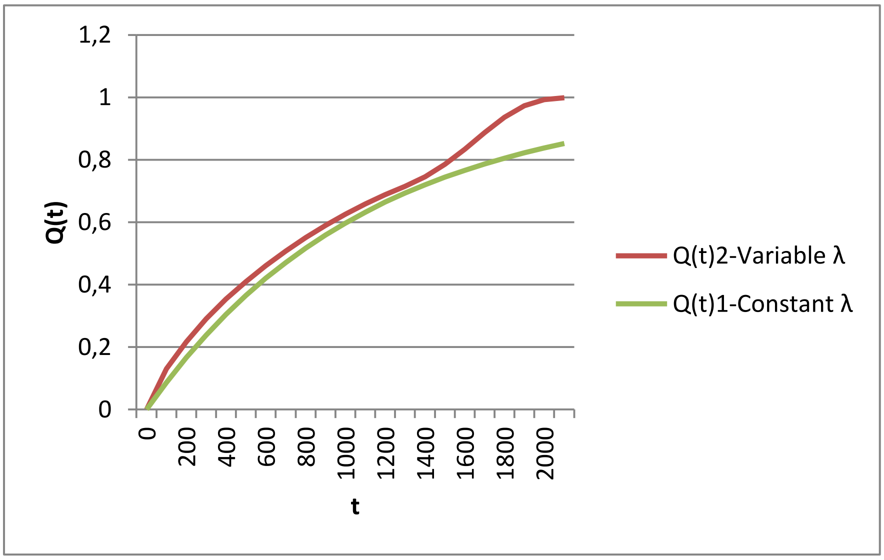


Figure 4.6 - Two Q(t) curves for the nuclear units: $\boldsymbol{Q(t)_1}$ according to a constant $\boldsymbol{\lambda}$ and $\boldsymbol{Q(t)_2}$ according to the bathtub curve presented in figure 4.5.

The data of this curve is also presented in Annex B. Figure 4.6 shows a comparison between two Q(t) curves: one is constructed according to a constant failure rate $\boldsymbol{\lambda}$ and the other one is developed according to a variable failure rate λ. The main feature to withdraw from this figure is the divergence shown by the curves from $t \geq 1400h$. The explanation of this divergence is the inclusion of the wear-out period in $Q(t)_2$. From $t \geq 1400h$, the probability of failure, $Q(t)$, of this generating unit is much higher, when the failure rate isn't constant. This is a normal consequence of the introduction of the wear-out period, which is characterized for an increasing failure rate. The next figure will show more clearly the differences between these two curves:

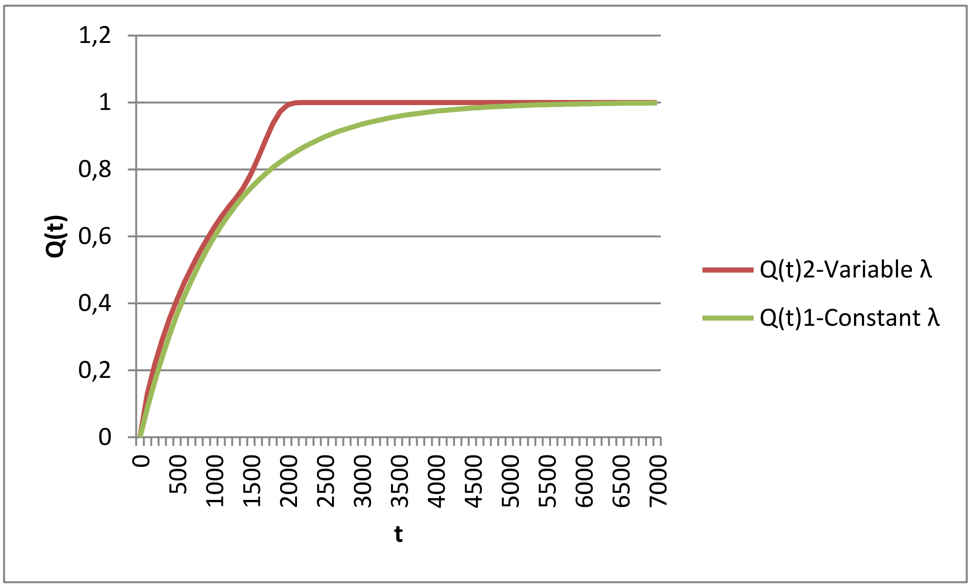


Figure 4.7 - Two Q(t) curves showing the moment when this generating unit fails. Q(t)=1 means that this generating unit already have failed.

After analyze this image, the following conclusions can be withdrawn:

- With a non constant failure rate λ, when $t = 2100h$, the generating unit already has failed;

- With a constant failure rate λ, this moment happens in a later phase. Precisely when $t = 7000h$;

It is also important to mention that this is a comparison between a reactive maintenance plan and an ideal maintenance case. As it was studied before, reactive maintenance is a type of maintenance program, in which maintenance action aren't taken. In other words, the generating units are repaired only in case of failure. Therefore, the use of a non constant failure rate can be considered a case of reactive maintenance.

The next goal, in this thesis, is to approach the two curves presented in figures 4.6 and 4.7, through the implementation of maintenance policies. Before that, it is now the moment to analyze some more results.

Table 4.4 - Adequacy reliability indices of a Monte Carlo simulation according to a non constant failure rate λ

Adequacy reliability indices	
LOLE (hour/year)	11.196
LOLF (occurrence/year)	2.3256
LOLD (hour/occurrence)	4.8144
EENS (MWh/year)	1486.1

These results were obtained according to a coefficient of variation $\beta = 5\%$. As it was expected, these reliability indices are higher, when compared to the ones obtained for a constant failure rate λ. The inclusion of the degradation process led to an increase in the number of failures of the generating units. Therefore, the increase of the reliability indices illustrates this consequence. Moreover, these indices are more realistic, since they are the result of a real situation.

4.4 - Evaluation of the Monte Carlo performance with maintenance activities

In this section, the maintenance policies will be introduced in the problem of the assessment of the reliability of IEEE RTS – 76. Therefore, according to the type of maintenance program, different results are expected.

Both preventive and predictive maintenance have the same goal: extend the useful life period of the generating units. In other words, their goal is to delay the entrance on the wear-out period. Obviously, this will lead to certain impacts on the reliability indices. By extending the useful life of the generating units, they will fail less and, therefore, the reliability indices will decrease. This fact constitutes an advantage for customers and suppliers.

In the past decades, several maintenance programs were developed. Some of them had great success. In the previous Chapter, two of the most widely used maintenance programs were described. Now, it is time to verify if the theory matches with practice. In the one hand, the preventive maintenance is based on a schedule, which means that there aren't concerns about the generating units state. In the other hand, the predictive maintenance is based on the degradation state of the generating units. The advantages and disadvantages of each one of these maintenance programs were already studied and discussed.

It's now time to answer to a simple question: which one of these methods is the most effective?

4.4.1 Evaluation of the Monte Carlo performance with a preventive maintenance program

As it was said for several times in this thesis, preventive maintenance is characterized for scheduled maintenance actions. Therefore, the first task was the definition of this schedule in order to implement it in the developed Monte Carlo algorithm. This definition depends on some characteristics of the generating units, as for example, the MTTF. Furthermore, each generating unit has their own characteristics. For this reason, it was decided to apply the maintenance program only to one of the types of the generating units. By choosing units with higher capacity, the effect of maintenance upon the reliability indices is clearer. Therefore, the nuclear units were the chosen ones. According to the characteristics of the nuclear units, which can be inspected on Annex A, the maintenance actions will occur at each $400h$. Thanks to these maintenance actions, the useful life of the nuclear units will be extended, as it is possible to observe in the following figure:

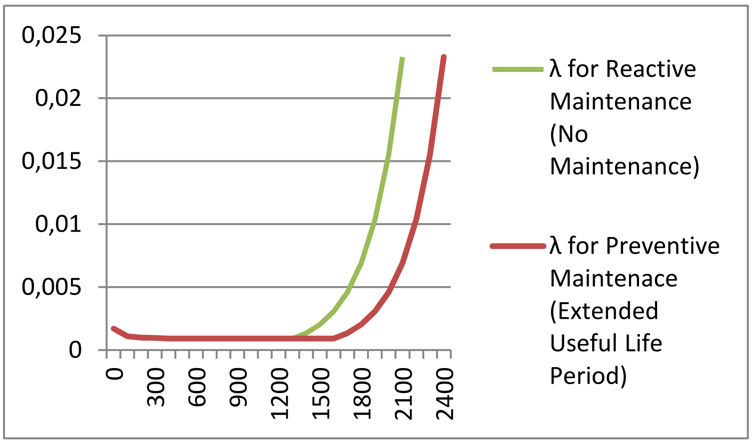
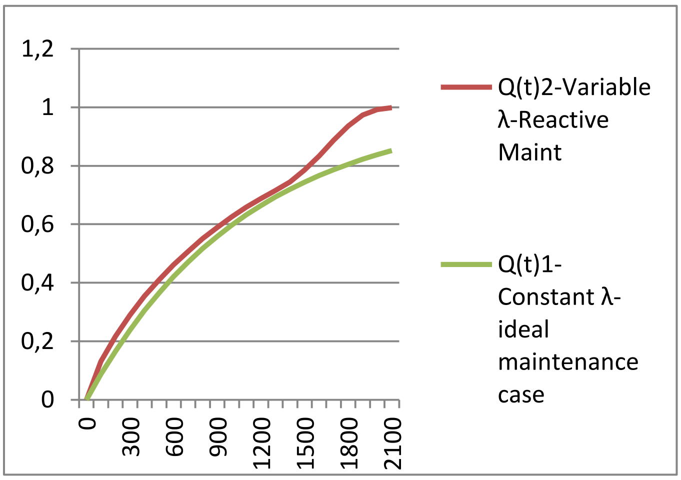


Figure 4.8 - Extended useful life period of the nuclear unit, after a preventive maintenance procedure

Then, as it was discussed, the Q(t) curve needs to be recalculated. Therefore, the new Q(t) curve will include the effect caused by the useful life extension. The following figures present some interesting aspects that need to be analyzed:



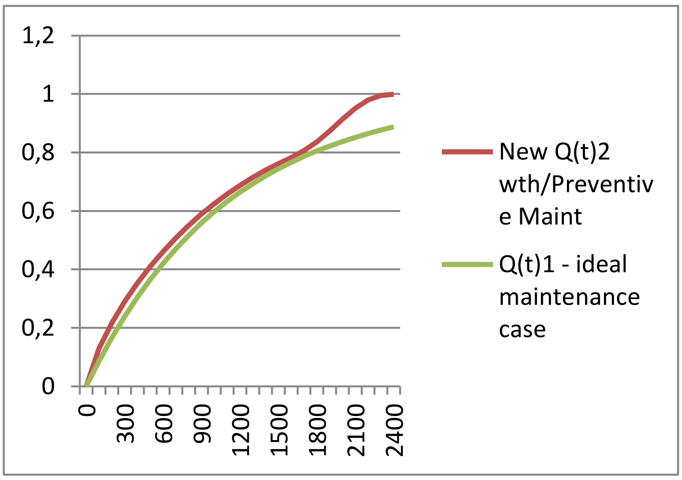


Figure 4.9 - Figure on the left: Q(t)2 curve enters soon in the wear-out period;
Figure on the right: The preventive maintenance plan delays the entrance on the wear-out period

In these figures, the effect of preventive maintenance is clearly observable. In the figure on the left, $Q(t)_2$ represents the cumulative curve of the nuclear units, in which maintenance actions aren't taken. In the figure on the right, $Q(t)_2$ represents the same curve, but including the scheduled maintenances. In fact, the main points to withdraw are the following:

- When maintenance actions aren't taken, these generating units enter on their wear-out periods after $t = 1400h$;

- When preventive maintenance is applied, these generating units enter on their wear-out periods after $t = 1700h$;

So, the changes produced on the Q(t) curve are beneficial for the reliability of the power systems. By introducing the maintenance actions, the failure rate λ of the nuclear units starts to increase in a later stage of their lives. The data of this new Q(t) curve and the data of the extended failure rate λ can be found in Annex C.

Ultimately, the reliability indices can measure the effects produced by the maintenance policies. The following results represent the mean values of the studied reliability indices, after applying the preventive maintenance plan:

Table 4.5 - Adequacy reliability indices of a Monte Carlo simulation, after the implementation of the preventive maintenance

Adequacy reliability indices	
LOLE (hour/year)	10.882
LOLF (occurrence/year)	2.2621
LOLD (hour/occurrence)	4.8107
EENS (MWh/year)	1406.2

After analyzing these results, it is possible to conclude that the preventive maintenance plan had the expected effect: the reliability indices are, now, lower when compared to the ones presented in section 4.3 (reactive maintenance). Thus, the decrease of the loss of load expectation, the decrease of the expected energy not supplied and the decrease of the loss of load frequency are the consequences of an extended useful life period, which implies a reduction on the number of failures of these generating units. On the other hand, by comparing these results with the ones obtained in section 4.2 (ideal maintenance case), these are much higher. This fact was already expected since now we're treating a real situation, in which the failure rate λ is not constant.

4.4.2 Evaluation of the Monte Carlo performance with a predictive maintenance program

In this section, the results of a different type of maintenance will be analyzed. As it was seen before, in the predictive maintenance programs, the maintenance actions depend on the actual state of the generating units. In other words, the maintenance actions will take place, only when the degradation state of the generating units starts to increase. Therefore, the first step to take is to identify the moment when the generating units enter on their wear-out periods. This moment is different for each generating unit and depends on their failure rates $\boldsymbol{\lambda}$. So, in order to establish a comparison between the two studied maintenance types, the predictive maintenance will be applied on the nuclear units.

As it was seen before, after $t = 1400h$, $Q(t)_1$ and $Q(t)_2$ start to diverge. This is exactly the moment when the nuclear units enter on their wear-out period. Therefore, always that these units enter on their wear-out period, maintenance actions will be taken.

The predictive maintenance policy has exactly the same final goal that the preventive maintenance policy: the extension of the useful life period of the generating units. The difference between these two maintenance types lies on the moments, in which the maintenance actions occur. This fact leads us to another important specification: the main goal is the same, but the mode how it processes is very different.

In figure 4.10, the effect of predictive maintenance upon the failure rate $\boldsymbol{\lambda}$ of the nuclear units can be observed:

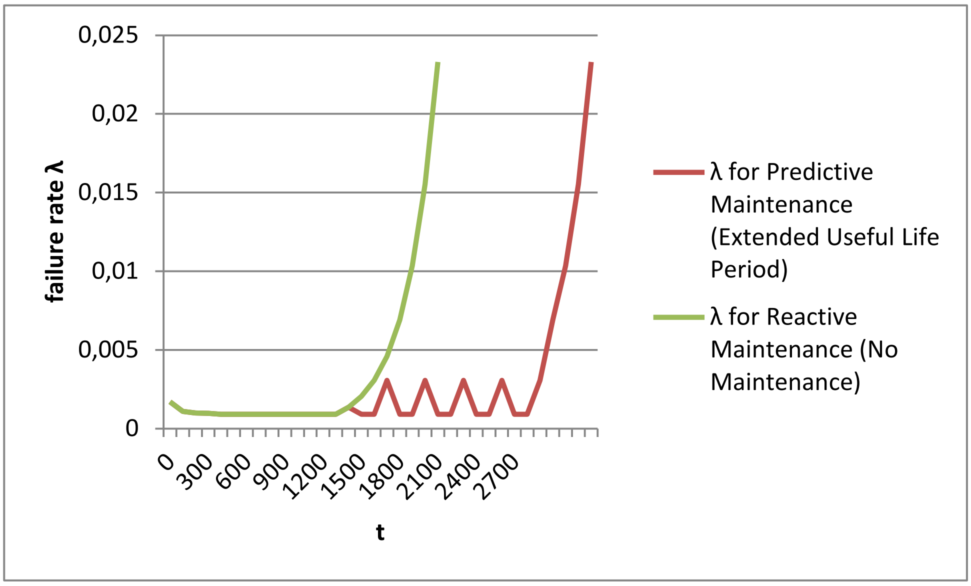


Figure 4.10 - Extended useful life period of the nuclear unit, after a predictive maintenance procedure

The ups/downs of the failure rate λ in figure 4.10, reflect the type of maintenance that was applied. Whenever λ increases, maintenance actions are taken in order to bring λ to its useful life period. Thus, the existence of unnecessary maintenance actions is avoided.

The produced changes on λ led to the reconstruction of the Q(t) curve. The following figure will show this new curve:

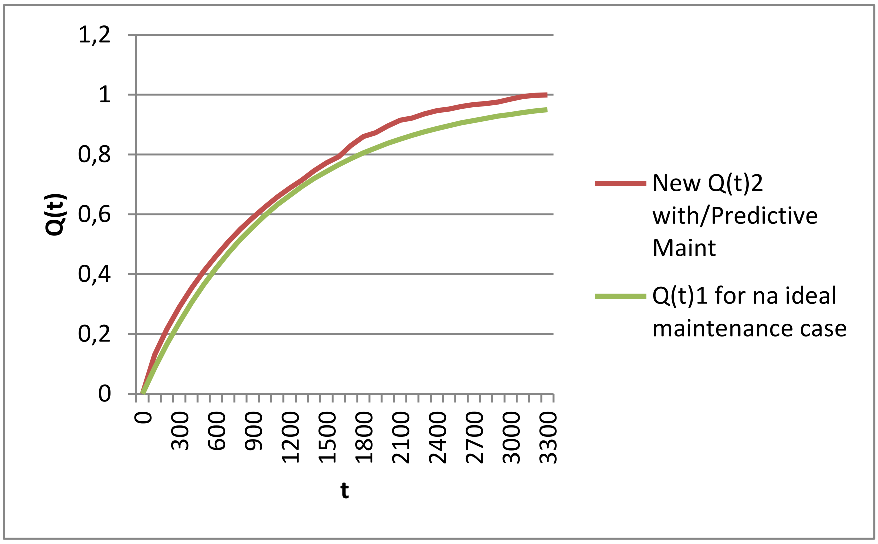


Figure 4.11 - Effect of predictive maintenance actions upon Q(t) curve, delaying the entrance on the wear-out period

As it was expected, thanks to the predictive maintenance plan, the nuclear units enter on their wear-out period in a later stage of their lives (after $t = 2900h$). By comparing this figure with figure 4.9 (preventive and reactive maintenance), the advantages of predictive maintenance are clearly recognizable. In fact, the main conclusions to withdraw from this comparison are the following:

- With a predictive maintenance plan, the nuclear units enter on their wear-out period $1200h$ later, when compared with the preventive policies.

- With a predictive maintenance plan, the nuclear units enter on their wear-out period $1500h$ later, when compared with the reactive policies.

The data concerning the failure rate λ and the Q(t) curve, according to the predictive actions, can be found in Annex D.

It is known that predictive maintenance is an effective and efficient type of maintenance. However, the differences for the studies that use a constant failure rate are, still, very clear.

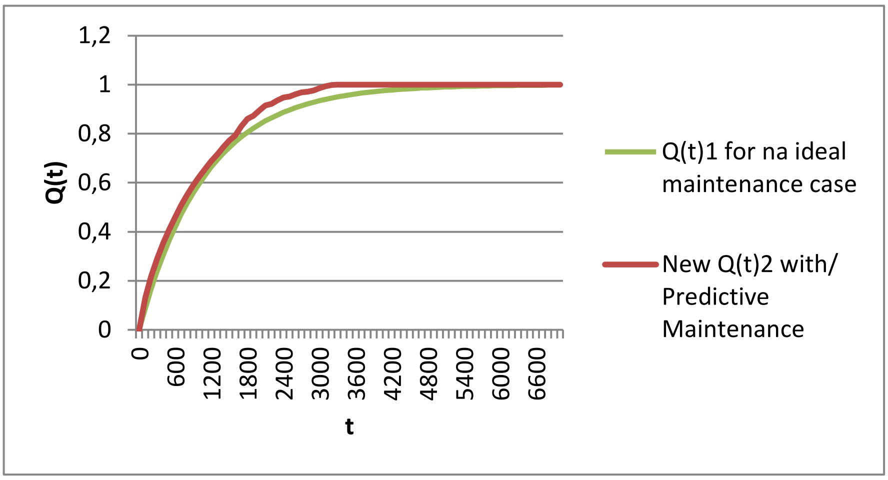


Figure 4.12- Two Q(t) curves showing the moment when this generating unit fails. Q(t)=1 means that this generating unit already have failed.

Despite include the predictive maintenance, figure 4.12 shows that the nuclear units have already failed after $t = 3500h$. Once more, it is proved that the use of a constant failure rate is a hypothetical situation.

In order to conclude the analysis of this new approach, there is one question that we need to answer: Which is the more efficient and effective maintenance plan?

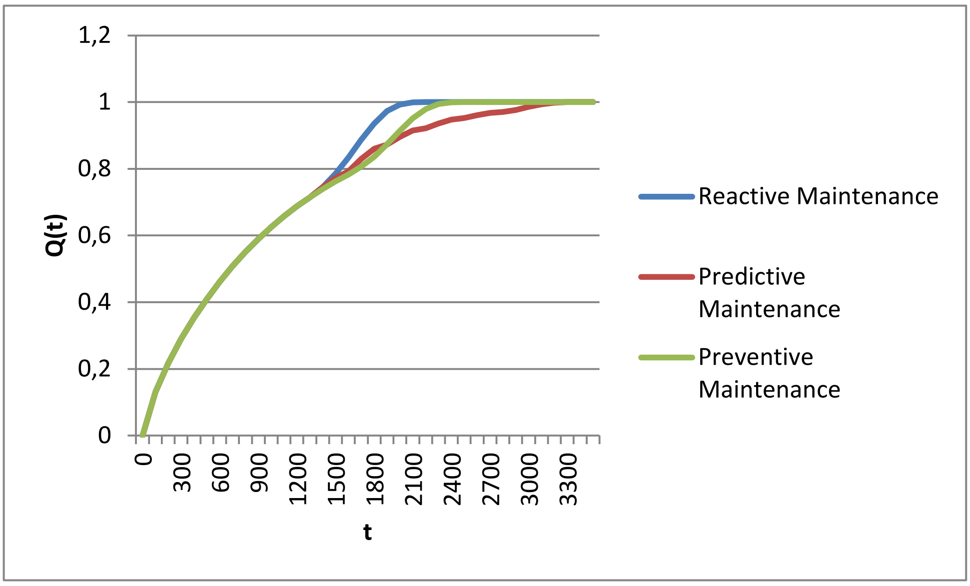


Figure 4.13 - Comparison between three different types of maintenance programs: The predictive maintenance allows a later entrance on the wear-out period.

Figure 4.13 shows that the implementation of a predictive maintenance leads to a bigger extension of the useful life period of the nuclear units. Therefore, apparently, predictive maintenance is the most effective policy. But, for now, is difficult to give a proper answer to this question, since the generating units aren't removed from service for the maintenance actions. This particularity will be introduced in the next section.

For last, but not least, the reliability indices for a predictive maintenance are presented:

Table 4.6 - Adequacy reliability indices of a Monte Carlo simulation, after the implementation of the predictive maintenance

Adequacy reliability indices	
LOLE (hour/year)	10.486
LOLF (occurrence/year)	2.1897
LOLD (hour/occurrence)	4.7892
EENS (MWh/year)	1379.1

Table 4.6 shows that the reliability indices decrease regarding to the ones obtained for a preventive maintenance plan. This was already expected, since the predictive maintenance is based on a continuous inspection of the generating units state.

4.5 - Removing the generating units from service for maintenance actions

Until now, the generation units weren't removed from service for maintenance actions. In other words, the maintenance actions were considered an instantaneous process. Despite being an unrealistic approach, it was an important first step in order to reach the main goal. Moreover, this first approach already allowed us to develop the major part of the algorithm and to evaluate the positive effects of maintenance. Despite the merits of this first approach, one more step needs to be taken.

In the previous Chapter, a different approach to introduce the maintenance policies was studied. This new approach is based on the introduction of a new state on the life of the generating units – the maintenance state. This new state will be characterized by a new particularity: the generation units will be removed from service, during the maintenance actions. Therefore, the maintenance actions will no longer be an instantaneous process. The problem lies on the consequences that this new approach brings: if the generating units are removed from service for maintenance actions, the available generating capacity will decrease in those periods. Thus, a loss of load will be associated with the maintenance state and its magnitude will depend on the duration of the maintenance processes. So, it seems obvious that the type of maintenance that takes longer will be the most affected by this new approach.

After these explanations, it is the moment to answer to the following question: which maintenance policy is the most expensive in terms of time? To this particular problem, the following sentence fits perfectly: "Time is money". On the one hand, the preventive maintenance can be compared to a routine exam. Therefore, the preventive maintenance is a faster process with no bigger concerns. Usually, the preventive maintenance doesn't include a check-up of the system in order to detect possible defects. This type of maintenance is systematized. On the other hand, the predictive maintenance can be compared to a more serious exam. In this type of maintenance, the actual state of the units needs to be analyzed, the defects need to be detected and solutions need to be developed. As it was studied before, the predictive actions occur when the degradation state of the generating units starts to increase. Therefore, predictive maintenance is a more complex, more exhaustive and more complete process. For all these reasons, it is easy to understand that predictive actions have longer durations.

Considering the above points, it was defined that the nuclear units will be removed from service, during 1 hour, for preventive actions and, during 24h for predictive processes. The results of these changes can be analyzed in the following tables:

Table 4.7 - Adequacy reliability indices of a Monte Carlo simulation: the units are out of service for the maintenance actions

Adequacy reliability indices/Predictive M	
LOLE (hour/year)	11.022
LOLF (occurrence/year)	2.2841
LOLD (hour/occurrence)	4.8255
EENS (MWh/year)	1431.7

Adequacy reliability indices/Preventive M	
LOLE (hour/year)	10.932
LOLF (occurrence/year)	2.2688
LOLD (hour/occurrence)	4.8184
EENS (MWh/year)	1415.7

The reliability indices that result from this new approach are particularly interesting. As it was expected, these indices increase when compared to the ones obtained on the previous approach, in which the nuclear units weren't removed from service for the maintenance actions. Furthermore, another interesting aspect can be analyzed. The predictive maintenance that was presented as a more effective maintenance program is now, according to the reliability indices, the worst type of maintenance (excluding the reactive maintenance). This fact doesn't invalidate all that was said about the two types of maintenance. The explanation of these new results lies on the higher duration of the predictive actions.

In the next section, a cost-efficiency analysis will be performed in order to try to find the best maintenance procedure.

The analysis of this new state doesn't end here. As it was studied in the previous Chapter, after a maintenance process, the generating units return to their initial period of life. This period is known as the infant mortality period and is characterized by a decreasing failure rate λ. Then, during this period, the generating units can evolve to one of the following modes:

- Usually, after a maintenance process, the generating units are in perfect conditions. Therefore, after returning to their initial period of life, they evolve to their useful life period;

- Sometimes, due to deficient maintenance actions, the generating units fail during their infant mortality period. So, these units don't evolve to the useful life period. First, they need to be repaired.

In order to simplify the implementation of this new aspect in the Monte Carlo algorithm, it was decided that the generating units which fail during" the infant mortality period" evolve directly to the repair mode. In other words, we're forgetting the passage of these units in the infant mortality period, since the duration of this passage is very short.

As it was decided in the previous Chapter:

- 10% of the generating units, after a maintenance procedure, will fail before entering their useful life period. They evolve directly to the repair mode;

- 90% of the generating units, after a maintenance procedure, evolve without problems to their useful life period (operational mode);

The results presented in tables 4.7 e 4.8 were already affected by this new aspect.

Now, it is time to analyze another issue presented in the last Chapter: the qualification of the maintenance staff. Tests were made considering that a more qualified maintenance team could increase the percentage of generating units that after a maintenance procedure evolve to their useful life periods to the 95%.The results are presented in the following table:

Table 4.8- Adequacy reliability indices of a Monte Carlo simulation: the probability of a unit doesn't fail, after a maintenance, is now bigger.

Adequacy reliability indices/Predictive M	
LOLE (hour/year)	11.001
LOLF (occurrence/year)	2.2811
LOLD (hour/occurrence)	4.8226
EENS (MWh/year)	1429

Adequacy reliability indices/Preventive M	
LOLE (hour/year)	10.910
LOLF (occurrence/year)	2.2655
LOLD (hour/occurrence)	4.8157
EENS (MWh/year)	1412.8

As it was expected, this increase led to the decrease of the reliability indices.

4.6 - Cost-efficiency analysis

One of the most interesting and important aspects of this thesis will be now introduced. The main goal of this section is to perform a comparison between the cost and the efficiency of each one of the studied maintenance types. In order to achieve this goal, two types of data are necessary: the costs of each maintenance type and the number of maintenances that each maintenance program implies. Through the Monte Carlo algorithm analyzed in section 3.6, the number of maintenances of each maintenance program was obtained. On the other hand, the costs of each type of maintenance were obtained through [28].

Table 4.9 - Number of maintenances of each type during the simulation process.

Number of Maintenances	
Preventive M.	10782
Predictive M.	5388

Table 4.10 shows that the number of maintenance actions is superior when a preventive maintenance plan is used. This was already expected, since the preventive maintenance doesn't analyze the degradation state of the generating units.

Table 4.10 – Prices of each type of maintenance

Maintenance Prices (cents/action/kW)	
Preventive M.	1.65
Predictive M.	2

Table 4.11 shows that predictive maintenance is a more expensive type of maintenance program. As it was seen before, the predictive policies are based on more sophisticated actions and on more qualified staff.

By combining these two types of data, it is easy to figure out that predictive maintenance is more profitable. However, up until now, the analysis was only focused on the costs associated with maintenance. Now, it is necessary to analyze the impact of these maintenance programs in terms of reliability.

Table 4.7 showed that predictive maintenance leads to worse reliability indices. This fact is the consequence of the higher duration of the predictive maintenances. Therefore, it is now more difficult to understand which maintenance type is the best. On the one hand, predictive maintenance is more profitable, but, on the other hand, it leads to worse reliability indices. Obviously, the choose of the best maintenance program depends on the supplier:

- If the supplier has a small budget, he will probably choose a predictive maintenance program;

- If the supplier doesn't have concerns about the budget, he will probably choose a preventive maintenance plan in order to provide a better service to the clients;

According to the presented data, it seems that preventive maintenance appears as the best maintenance plan. The difference between the maintenance costs is small, but the improvements on the service provided to the clients are significant (better reliability indices) when a preventive maintenance plan is applied.

As it was studied in the previous section, the predictive maintenance has one crucial problem: the generating units spend too much time in the predictive maintenance actions. Therefore, the reliability indices, in this type of maintenance, are worse than in preventive maintenance. This problem can be surpassed through a more qualified maintenance staff. Thus, the predictive maintenance actions would consume a less amount of time.

Several tests were made and the results are presented in the following tables:

Table 4.11- Adequacy reliability indices of a Monte Carlo simulation: a more qualified maintenance team

Adequacy reliability indices/Predictive M	
LOLE (hour/year)	10.876
LOLF (occurrence/year)	2.2632
LOLD (hour/occurrence)	4.8050
EENS (MWh/year)	1409.2

Adequacy reliability indices/Preventive M	
LOLE (hour/year)	10.910
LOLF (occurrence/year)	2.2655
LOLD (hour/occurrence)	4.8157
EENS (MWh/year)	1412.8

Table 4.11 shows the reliability indices, considering that the duration of the predictive maintenance is now equal to $16h$. Therefore, with these new conditions, predictive maintenance would be the best maintenance process. On the one hand, is a cheaper process and, on the other hand, it leads to better reliability indices.

4.7 – Conclusions

In this Chapter, the main results of the work developed in thesis were presented. Through these results, we can withdraw several important conclusions. First, it was proved that the inclusion of the real variation of the failure rate λ has a significant impact upon the reliability indices. Although this new approach is more complex, it allows to include the impact of the natural process of degradation of electrical components. Therefore, with this new approach, it's possible to understand the moments when maintenance actions should occur.

Through the results obtained in this Chapter, it was possible to figure out that the inclusion of the maintenance policies allowed to extend the useful life period of the nuclear units. Furthermore, the predictive maintenance was responsible for a higher increase of the useful life period. However, it was also showed that predictive maintenance has one significant problem: the duration of the maintenance actions when compared to preventive maintenance. This means that, during the predictive maintenance, the units were out of service for long periods. Obviously, this fact had a great impact upon the reliability indices. Therefore, the preventive maintenance appeared as a better maintenance process in terms of reliability. However, we decided to perform some more tests. Thanks to these tests, it was possible to figure out that the decrease of duration of the predictive maintenances led to a very significant decrease of the reliability indices. Therefore, it was concluded that he solution to achieve a more effective and efficient predictive maintenance is the improvement of the quality of the maintenance staff. In these tests, predictive maintenance appeared as the best maintenance procedure.

Chapter 5

Conclusions and future work

In Chapter 1, the guidelines and the main goals of this thesis were presented. Now, it is time to verify if those goals were achieved or not. Therefore, this Chapter will be focused on the main conclusions of the produced work. Furthermore, some guidelines to continue and improve this work will be described.

5.1 - Objectives achieved

In this thesis, a new method to assess power systems reliability was presented. As it was studied, this method is based on a typical sequential Monte Carlo algorithm. However, some modifications were produced on it. Furthermore, the study of the influence of the maintenance policies upon the power systems reliability was another important part of this thesis.

In Chapter 2, the traditional methods to solve reliability problems were introduced. Despite the specification of some characteristics of these methods, the main objective of this introduction was the establishment of a starting point, in order to introduce the new methodologies for evaluating power systems reliability. Moreover, the main characteristics of three different maintenance types were described in this Chapter. Therefore, the main methodologies presented on the literature of power systems reliability were analyzed in Chapter 2. This fact leaded us to a very important conclusion: in most of reliability studies, the components follow a constant failure rate λ. Thus, the childhood period and the wear-out period aren't considered in these studies. So, these facts leaded us to analyze the effect of these two periods (bathtub curve) upon the power systems reliability.

The first step taken in this thesis was the development of a new Monte Carlo algorithm with some modification on the failure rate λ of the generating units. In theory, these modifications seem slight changes, but, in practice, several improvements on the typical algorithm were produced. As it was studied, the use of a constant failure rate simplifies the algorithm, since the simulation of the life cycle of the components is based on an exponential distribution. In this new approach, the simulation of the life cycle depends on the construction of the $\boldsymbol{Q}(\boldsymbol{t})$ curve. Therefore, this modification, per se, was a new application of the Monte Carlo methods, constituting an additional contribution for the actual state of the art.

After the validation of this new method, a new particularity needed to be studied: the introduction of different maintenance policies. The main goal in this approach was to analyze the advantages and disadvantages of the proposed maintenance programs. To accomplish this, two main philosophies were developed. In a first approach, the generating units weren't removed from service for the maintenance actions. Then, in a more complex approach, the generating units were removed from service for the maintenance activities. As it was studied, in this last approach, some new interesting aspects were introduced: the probability of failure after a maintenance procedure and the importance of the quality of the maintenance staff in order to decrease this probability. For last, the impact of the quality of the maintenance staff for the decrease of the duration of the predictive actions was object of study.

The results presented in Chapter 4 allowed us to withdraw several important conclusions. In first place, by using a constant failure rate $\boldsymbol{\lambda}$, most of studies are far from reality. This was proved by the higher reliability indices, shown in Chapter 4, when a variable failure rate $\boldsymbol{\lambda}$ was applied. This means that the infant mortality period and the wear-out period have a significant impact on the components lives and, therefore, this is reflected on the reliability indices. To sum up, the inclusion of the degradation process of a component is very important if we want to analyze a real situation.

The inclusion of the maintenance procedures brought some more important conclusions. In a first approach, the predictive maintenance appeared as the best maintenance procedure. This was already expected, since the predictive actions are based on the actual state of the generating units. In a more complex approach, the big problem of the predictive maintenance was discovered: the duration of the predictive actions. The high duration of the predictive activities had as consequence a significant increase of the reliability indices. Therefore, in this approach, the preventive maintenance appeared as the best maintenance process. Despite these results, it was decided to perform some more tests. Thus, it was assumed that a more qualified maintenance team could decrease the duration of the predictive maintenance procedures. Through these new tests, it was concluded that with a well trained maintenance team, the predictive maintenance can be the best maintenance procedure.

For last, but not least, the cost-efficiency analysis allowed to pre, once more, that with a lower duration of the predictive maintenance, this maintenance type would have more advantages.

To sum up, it was proved that a more realistic Monte Carlo algorithm can be developed in order to evaluate the reliability of power systems.

5.2 - Future work

The results of the work developed in this thesis may be the inspiration for other research studies. Thus, a list of some improvements that can be added to this work is, now, presented:

- Apply the developed method to a multi-objective evolutionary particle swarm optimization (MEPSO). Therefore, the developed Monte Carlo algorithm would be one of the objective functions. Another objective function related to the maintenance costs would need to be developed. The main objective would be to find the Pareto Front of this problem. More of this subject can be found in [29],[30] and [31];

- This MEPSO application would be incredibly heavy in terms of computational effort because, for each new state of the search space, the developed Monte Carlo would need to be run. So, another idea is to develop a method that allows to run the developed Monte Carlo only one time, for one of the states of the search space. The other states would be visited through the application of inverse functions to the visited state;

- Apply to the developed method an importance sampling technique in order to achieve a higher convergence speed;

- Apply the developed method to a distribution system. This new approach would be very interesting for some aspects, as for example, the redundancy between components of a distribution system. Obviously, in this approach, an optimal power flow (OPF) would need to be developed;

- Apply to the developed method other maintenance policies, as for example, the reliability centered maintenance (RCM) and compare with the results obtained in this thesis. More of this subject can be found in [20]

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Annex A - IEEE RTS-76

The evaluation of the IEEE RTS-76 generating capacity is based on the following parameters:

Unit	Unit size (MW)	MTTF (hour)	MTTR (hour)	FOR
1	12	2940	60	0.020
2	12	2940	60	0.020
3	12	2940	60	0.020
4	12	2940	60	0.020
5	12	2940	60	0.020
6	20	450	50	0.100
7	20	450	50	0.100
8	20	450	50	0.100
9	20	450	50	0.100
10	50	1980	20	0.010
11	50	1980	20	0.010
12	50	1980	20	0.010
13	50	1980	20	0.010
14	50	1980	20	0.010
15	50	1980	20	0.010
16	76	1960	40	0.020
17	76	1960	40	0.020
18	76	1960	40	0.020
19	76	1960	40	0.020
20	100	1200	50	0.040
21	100	1200	50	0.040
22	100	1200	50	0.040
23	155	960	40	0.040
24	155	960	40	0.040
25	155	960	40	0.040
26	155	960	40	0.040
27	197	950	50	0.050
28	197	950	50	0.050
29	197	950	50	0.050
30	350	1150	100	0.080
31	400	1100	150	0.120
32	400	1100	150	0.120

Figure A1 - Reliability data of the units of IEEE RTS-76 [26].

The hourly load model of the IEEE RTS-79 is calculated according to the following figures. As it was already said, the annual peak load is 2850 MW.

Week	Peak Load	Week	Peak Load
1	86.2	27	75.5
2	90	28	81.6
3	87.8	29	80.1
4	83.4	30	88
5	88	31	72.2
6	84.1	32	77.6
7	83.2	33	80
8	80.6	34	72.9
9	74	35	72.6
10	73.7	36	70.5
11	71.5	37	78
12	72.7	38	69.5
13	70.4	39	72.4
14	75	40	72.4
15	72.1	41	74.3
16	80	42	74.4
17	75.4	43	80
18	83.7	44	88.1
19	87	45	88.5
20	88	46	90.9
21	85.6	47	94
22	81.1	48	89
23	90	49	94.2
24	88.7	50	97
25	89.6	51	100
26	86.1	52	95.2

Figure A2 - Weekly Peak Load in Percent of Annual Peak [26].

Day	Peak Load
Monday	93
Tuesday	100
Wednesday	98
Thursday	96
Friday	94
Saturday	77
Sunday	75

Figure A3 - Daily Peak Load in Percent of Weekly Peak [26].

Hour	Winter Weeks Weeks 1-8 & 44-52		Summer Weeks 18-30		Spring/Fall Weeks 9-17 & 31-43	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
12 pm -1 am	67	78	64	74	63	75
1 am -2 am	63	72	60	70	62	73
2 am -3 am	60	68	58	66	60	69
3 am -4 am	59	66	56	65	58	66
4 am -5 am	59	64	56	64	59	65
5 am -6 am	60	65	58	62	65	65
6 am -7 am	74	66	64	62	72	68
7 am -8 am	86	70	76	66	85	74
8 am -9 am	95	80	87	81	95	83
9 am -10 am	96	88	95	86	99	89
10 am -11 am	96	90	99	91	100	92
11 - Noon	95	91	100	93	99	94
Noon - 1 pm	95	90	99	93	93	91
1 pm - 2 pm	95	88	100	92	92	90
2 pm - 3 pm	93	87	100	91	90	90
3 pm - 4 pm	94	87	97	91	88	86
4 pm - 5 pm	99	91	96	92	90	85
5 pm - 6 pm	100	100	96	94	92	88
6 pm - 7 pm	100	99	93	95	96	92
7 pm - 8 pm	96	97	92	95	98	100
8 pm - 9 pm	91	94	92	100	96	97
9 pm - 10 pm	83	92	93	93	90	95
10 pm - 11 pm	73	87	87	88	80	90
11 pm - 12 pm	63	81	72	80	70	85

Figure A4 - Hourly Peak Load in Percent of Daily Peak [26].

Annex B – Data of the bathtub and Q(t) curves

This annex presents the modified data of the nuclear units of IEEE RTS-76. In order to implement a new approach, the constant failure rate λ was replaced for a variable failure rate λ. This new data is presented in the following table:

Table B1 – Data of the variable λ that was implemented in the nuclear units of IEEE RTS-76.

T(hours)	λ variable(failures/hour)
0	0,0017
100	0,0011
200	0,00099
300	0,00097
400	0,000909091
500	0,000909091
600	0,000909091
700	0,000909091
800	0,000909091
900	0,000909091
1000	0,000909091
1100	0,000909091
1200	0,000909091
1300	0,000909091
1400	0,001363636
1500	0,002045455
1600	0,003068182
1700	0,004602273
1800	0,0069034091
1900	0,010355114
2000	0,01553267
2100	0,023299006
2200	0,034948509
2300	0,052422763

As it was explained in this thesis, after change the failure rate λ, the Q(t) curve was recalculated. The data of this new curve is presented in the following table:

Table B2 - Data of the new Q(t) function according to a variable failure rate λ.

T (hours)	Q(t)
0	0
100	0,130642
200	0,216904
300	0,290007
400	0,353676
500	0,409841
600	0,461126
700	0,507953
800	0,550712
900	0,589755
1000	0,625405
1100	0,657957
1200	0,68768
1300	0,71482
1400	0,745454
1500	0,785346
1600	0,833774
1700	0,886724
1800	0,936277
1900	0,973114
2000	0,992631
2100	0,998943
2200	0,999943
2300	0,999999

Annex C - The effect of preventive maintenance

Preventive maintenance has the main goal of extend the useful life period of the generating units. Therefore, after the implementation of a preventive plan, the failure rate λ and the Q(t) curve will be different. The following tables will show these changes.

Table C1 - Failure rate λ, after a preventive maintenance plan

T(hours)	λ(failures/hour)
0	0,0017
100	0,0011
200	0,00099
300	0,00097
400	0,000909091
500	0,000909091
600	0,000909091
700	0,000909091
800	0,000909091
900	0,000909091
1000	0,000909091
1100	0,000909091
1200	0,000909091
1300	0,000909091
1400	0,000909091
1500	0,000909091
1600	0,000909091
1700	0,001363636
1800	0,002045455
1900	0,003068182
2000	0,004602273
2100	0,0069034091
2200	0,010355114
2300	0,01553267
2400	0,023299006
2500	0,034948509

Table C2 - Data of the new Q(t) curve, after a preventive maintenance procedure.

T(hours)	$Q(t)$
0	0
100	0,130642
200	0,216904
300	0,290007
400	0,353676
500	0,409841
600	0,461126
700	0,507953
800	0,550712
900	0,589755
1000	0,625405
1100	0,657957
1200	0,68768
1300	0,71482
1400	0,739602
1500	0,762231
1600	0,782893
1700	0,806214
1800	0,836584
1900	0,873452
2000	0,913763
2100	0,951488
2200	0,979532
2300	0,99439
2400	0,999195
2500	1

Annex D - The effect of predictive maintenance

Table D1 - Failure rate λ, after a predictive maintenance plan

T (hours)	λ(failures/hour)
0	0,0017
100	0,0011
200	0,00099
300	0,00097
400	0,000909091
500	0,000909091
600	0,000909091
700	0,000909091
800	0,000909091
900	0,000909091
1000	0,000909091
1100	0,000909091
1200	0,000909091
1300	0,000909091
1400	0,001363636
1500	0,000909091
1600	0,000909091
1700	0,003068182
1800	0,000909091
1900	0,000909091
2000	0,003068182
2100	0,000909091
2200	0,000909091
2300	0,003068182
2400	0,000909091
2500	0,000909091
2600	0,003068182
2700	0,000909091
2800	0,000909091
2900	0,003068182
3000	0,006903409
3100	0,010355114
3200	0,01553267
3300	0,023299006
3400	0,023299006
3500	0,023299006

Table D2 - New Q(t) curve, after a predictive maintenance procedure

T(hours)	Q(t)
0	0
100	0,130642
200	0,216904
300	0,290007
400	0,353676
500	0,409841
600	0,461126
700	0,507953
800	0,550712
900	0,589755
1000	0,625405
1100	0,657957
1200	0,68768
1300	0,71482
1400	0,745454
1500	0,772796
1600	0,79254
1700	0,829953
1800	0,860619
1900	0,872731
2000	0,895683
2100	0,914495
2200	0,921925
2300	0,936005
2400	0,947546
2500	0,952104
2600	0,960742
2700	0,967821
2800	0,970618
2900	0,975916
3000	0,985372
3100	0,993828
3200	0,998308
3300	0,999757
3400	0,999976
3500	0,999998

Predictive maintenance has the main goal of extend the useful life period of the generating units. Therefore, after the implementation of a predictive plan, the failure rate λ and the Q(t) curve will be different. The previous tables have shown these changes.

Annex E - Article for submission

As consequence of the results obtained through the developed strategy in this thesis, it was decided to write a paper, in which the main achievements and ideas of such strategy are presented. In this Annex, a brief and general presentation of the main topics that are focused in the referred paper will be made. The article will be submitted for a journal or conference for Power Systems.

Definition of maintenance policies in power systems with a sequential Monte Carlo

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***Abstract* — This paper reports an application of a simulation method to power systems reliability. The Monte Carlo methods are, nowadays, the most widely used method for the estimation of reliability indices. The work reported in this paper shows that most of reliability studies that use Monte Carlo simulations are based on hypothetical situations: the use of a constant failure rate λ. This paper demonstrates a new application that is able to include the typical variation of the failure rate λ of electrical components and, moreover, is able introduce different maintenance policies. The results obtained with the Monte Carlo applications are compared with each other and with a typical Monte Carlo process.**

***Index Terms* — Failure rate, maintenance, Monte Carlo, reliability**

I. INTRODUCTION

MONTE CARLO simulations remain the standard method to compute estimates of reliability indices in Power Systems. These simulations are divided in two approaches: the chronological and the non chronological.

One of the goals of this paper is the inclusion of different types of maintenance policies in the life cycle of a Power System. Sometimes, maintenances are based on the elapse of time and, for this reason, this paper presents a chronological simulation.

However, most of reliability studies that present a chronological approach, use an exponential distribution to generate the life cycle of the components of a Power System. The use of this approach simplifies a lot the generation of the life cycles. The problem of this approach lies on the consequence of the use of an exponential distribution. To use such distribution, the failure rate λ of the components needs to be constant. In Power Systems, this assumption isn't true. The failure rate λ of electrical components suffers an evolution during their lives. The well-known bathtub curve illustrates this evolution. Therefore, this paper presents a new approach that allows to include the bathtub curve in order to achieve a realistic situation in the Power Systems reliability evaluations.

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This paper also includes the analysis of the introduction of three different maintenance policies: reactive maintenance, preventive maintenance and predictive maintenance. The goal of these approaches is to delay the natural process of degradation of the electrical components. In other words, the introduction of the maintenance policies helps to delay the entrance on the wear-out period.

All the processes presented in this paper are based on the construction of the cumulative distribution function $Q(t)$. The analysis of this curve is very interesting, since it allows to understand the differences between the developed approaches and the typical method. The following figure shows this aspects:

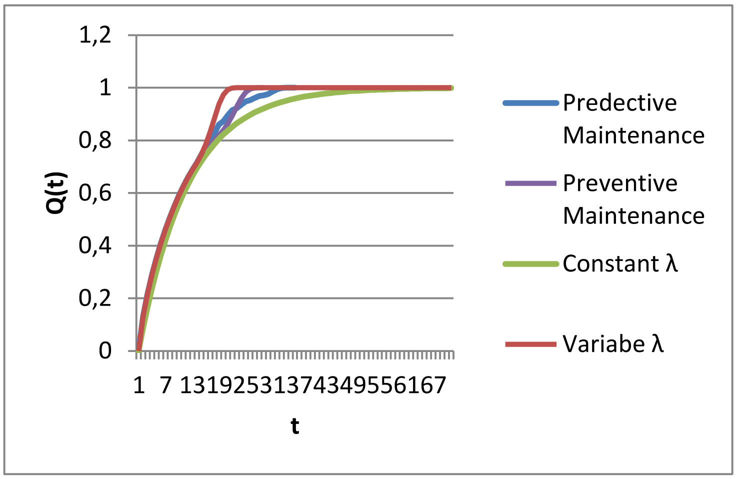

Fig. 1. Comparison between the followed approaches and the typical Monte Carlo method

Through the analysis of this figure, the following conclusions can be withdrawn. The green curve represents the widely used approach: the use of constant failure rate λ. Therefore, this curve can be compared to an ideal maintenance case, in which the components don't get older. The red curve represents the followed methodology, in which the bathtub curve is applied. It is possible to observe that these two curves diverge in a certain moment. This moment represents the beginning of the wear-out period. The other two curves are related with two different types of maintenance actions. By observing this figure, is clear that these actions delay the entrance in the wear-out period.

This paper presents new results confirming that a more realistic approach, in the assessment of Power Systems reliability can be obtained.