Flexibility Value of Distributed Generation in Transmission Expansion Planning

Paúl Vásquez[1] and Fernando Olsina[2]
[1]*Consejo Nacional de Electricidad (CONELEC), Ecuador*
[2]*Institute of Electrical Energy (IEE), CONICET, Argentina*

1. Introduction

The efficiency of the classic planning methods for solving realistic problems largely relies on an accurate prediction of the future. Nevertheless, the presence of strategic uncertainties in current electricity markets has made prediction and even forecasting essentially futile. The new paradigm of decision-making involves two major deviations from the conventional planning approach. On one hand, the acceptation the fact the future is almost unpredictable. On the other hand, the application of solid risk management techniques turns to be indispensable.

In this chapter, a decision-making framework that properly handles strategic uncertainties is proposed and numerically illustrated for solving a realistic transmission expansion planning problem.

The key concept proposed in this chapter lies in systematically incorporating flexible options such as large investments postponement and investing in Distributed Generation, in foresight of possible undesired events that strategic uncertainties might unfold. Until now, the consideration of such flexible options has remained largely unexplored. The understanding of the readers is enhanced by means of applying the proposed framework in a numerical mining firm expansion capacity planning problem. The obtained results show that the proposed framework is able to find solutions with noticeably lower involved risks than those resulting from traditional expansion plans.

The remaining of this chapter is organized as follows. Section 2 is devoted to describe the main features of the transmission expansion problem and the opportunities for incorporating flexibility in transmission investments for managing long-term planning risks. The most salient characteristics of the several formulations proposed in the literature for solving the optimization problem are reviewed and discussed along Section 3. The several types of uncertain information that must be handled within the optimization problem are classified and analyzed in Section 4. The proposed framework for solving the stochastic optimization problem considering the value provided to expansion plans by flexible investment projects is presented in Section 5. In Section 6, an illustrative-numerical example based on an actual planning problem illustrates the applicability of the developed flexibility-based planning approach. Concluding remarks of Section 7 close this chapter.

2. The transmission expansion planning

Since the beginning of the power industry, steadily growing demand for electricity and generation commonly located distant from consumption centres have led to the need of planning for adapted transmission networks aiming at transport the electric energy from production sites towards consumption areas in an efficient manner. In the vertically integrated power industry, the responsibility for optimally driving the expansion of transmission networks has typically lied with a centralized planner.

During the last two decades, stimulating competition has been a way to increase the efficiency of utilities as well as to improve the overall performance of the liberalized electricity industry (Rudnick & Zolezzi, 2000; Gómez Expósito). Because of the large economies of scales, a unique transmission company is typically responsible for delivering the power generation to the load points. Under this paradigm, the transmission activity has special significance since it allows competition among market participants. In addition, the transmission infrastructure largely determines the economy and the reliability level that the power system can achieve. For this reasons, planning for efficient transmission expansions is a critical activity. With the aim of solving the transmission expansion planning problem (TEP), a great number of approaches have been devised (Latorre *et al.*, 2003; Lee *et al.*, 2006).

A classic TEP task entails determining *ex-ante* the location, capacity, and timing of transmission expansion projects in order to deliver maximal social welfare over the planning period while maintaining adequate reliability levels (Willis, 1997). Under this traditional perspective, the TEP problem can be mathematically formulated as a large scale, multi-period, non-linear, mixed-integer and constrained optimization problem. In practice, however, such a rigorous formulation is unfeasible to be solved. Planners typically solve the TEP problem under a very simplified framework, e.g. static (one-stage) formulations, where timing of decisions is not a decision variable (Latorre *et al.*, 2003).

2.1 The emerging new TEP problem

The improvement of computing technology with increasingly faster processors along with the option of solving the problem in a distributed computing environment has made possible to handle a bigger number of parameters and variables and even formulate the TEP as a multi-period optimization problem (Youssef, 2001; Braga & Saraiva, 2005). However, jointly with the above mentioned increasing competition brought by the deregulation, relevant aspects such as: the development of new small-scale generation technologies (Distributed Generation, DG), the improvement of power electronic devices (e.g. FACTS), the environmental concerns that makes more difficult to obtain new right-of-way for transmission lines, the lack of regulatory incentives to investing in transmission projects, among others, have increased considerably the dynamic of power markets, the number of variables and parameters to be considered, and the uncertainties involved. Accordingly, the TEP problem is now substantially more complex (Buygi, 2004; Neimane, 2001).

Under this perspective, *ad doc* adjustments of expansion plans or additional contingent investments made in order to mitigate the harmful economic consequences that unexpected events have demonstrated the limited practical efficiency of applying classic TEP models (Añó *et al.*, 2005). In fact, the substantial risks involved in planning decisions emphasize the need of developing practical methodological tools which allow for the assessment and the risk management.

2.2 Nature of transmission investments

Due to some singular characteristics, transmission investments exhibit a distinctive nature with respect to other related investment problems (Kirschen & Strbac, 2004; Dixit & Pindyck, 1994):

Capital intensive: because of the substantial economies of scale, large and infrequent transmission investments are often preferred, involving huge financial commitments.

One-step investments: a substantial fraction of total capital expenditures must be committed before the new transmission equipment can be commissioned.

Long recovering times: transmission lines, transformers, etc. are expected to be paid-off after several years or even decades.

Long-run uncertainties: transmission investments are vulnerable to unanticipated scenarios that can take place in the long-term future. Future demand, fuel costs, and generation investments are uncertain variables at the planning stage.

Low adaptability: transmission projects are typically unable to be adapted to circumstances that considerably differ from the planning conditions. An unadapted transmission system entails considerable loss of social welfare.

Irreversibility: once incurred, transmission investments are considered sunk costs. Indeed, it is very unlikely that transmission equipment can serve other purposes if conditions changes unfavourably. Under these circumstances the transmission equipment could not be sold off without assuming significant losses on its nominal value.

Postponability: In general, opportunities for investing in transmission equipment are not of the type “now or never”. Thus, it is valuable to leave the investment option open, i.e. wait for valuable, arriving information until uncertainties are partially resolved. Thus, transmission investment projects can be treated in the same way as a financial call option. The opportunity cost of losing the ability to defer a decision while looking for better information should be properly considered.

Due to the mentioned features, transmission network expansions traditionally respond to the demand growth by infrequently investing in large and efficient projects. Consequently, traditional solutions to the TEP inevitably entail two evident intrinsic weaknesses:

- Because only large projects are economically efficient, planners have a limited number of alternatives and consequently the solutions found provide low levels of adaptability to the demand growth, and
- To drive the expansion, enormous irreversible upfront efforts in capital and time are required.

The huge uncertainties of the problem interact with the irreversible nature of transmission investments for radically increasing the risk present in expansion decisions. Such interaction has been ignored in traditional models at the moment of evaluating expansion strategies. More recently, it has been recognized that conventional decision-making approaches usually leads to the wrong investment decisions (Dixit & Pindyck, 1994). Therefore, the interaction between uncertainties and the nature of transmission investments must be properly accounted for.

2.3 New available flexible options

Although the major negative concerns regarding classic TEP models have been analyzed, in this work potential positive aspects are also considered and exploited. In fact, available *technical and managerial embedded options* exhibit some desirable features such as: modularity, scalability, short lead times, high levels of reversibility, and smaller financial commitments. This option can be incorporated as novel decision choices that a planner has available for reducing the planning risks as well as for improving the quality of the found solutions.

In this sense, planners must rely on an expansion model able to capture all major complexities present in the TEP in order to properly manage the involved huge long-term uncertainties and deal with the problem of dimensionality.

The key underlying assumption of conventional probabilistic models is the passive planner's attitude regarding future unexpected circumstances. In fact, available choices for reacting to the several scenarios which could take place overtime are ignored during the planning process. However, in practice planners have the ability to adapt their investment strategies in response to undesired or unanticipated events.

Hence, planning for contingent scenarios by exploiting technical and managerial options embedded in transmission investment projects is a effective mean for satisfactorily dealing with the current TEP problem

2.4 The flexibility value of Distributed Generation

Distributed Generation is defined as a source of electric energy located very close to the demand (Ackerman *et al.*, 2001; Pepermans *et al.*, 2003). Usually, DG investments are neither more efficient nor more economic than conventional generation or transmission expansions, which still enjoy of significant economies of scale such. Nevertheless, important contributions of DG occur when: energy T&D costs are avoided, demand uses it for peak shaving, losses are reduced, network reliability is increased, or when it lead to investment deferral in T&D systems (Jenkins *et al.*, 2000; Willis & Scott, 2000; Brown *et al.*, 2001; Grijalva & Visnesky, 2005).

DG seems a plausible means of improving the traditional way of driving the expansion of the transmission systems. Delaying investments in T&D systems by investing in DG is one of the major motivations and research topics of this work (Brown *et al.*, 2001; Daly & Morrison, 2001; Vignolo & Zeballos, 2001; Dale, 2002; Vásquez & Olsina, 2007).

The fact of considering DG projects as new decision alternatives within the TEP, involves the incorporation of additional parameters such as investment and production costs of DG technologies, firm power, etc.

Based on the typical short lead times of DG projects and their lower irreversibility, the uncertainty present in DG project investment decisions and investment costs can be neglected. Provided that the DG technologies considered in this work are fuel-fired plants, the availability of the DG could be modelled by assessing only availability factors (Samper & Vargas, 2006).

3. State-of-art of the TEP optimization approaches

The successful development of an efficient and practical expansion model primarily depends on considering the following topics: the planner's objectives, the availability and quality of the information to be handled as well as the depth level at which the planner decides to face the problem. In this sense, a set of basic elements that the planner must consider and specify before mathematically formulating the problem are summarized in the Table 1.

Topic	Concern	Recommended Value	Symbol
Scales of time	Planning horizon	10 to 15 years	T
	Decision periods	≥ 1 year	p
	Sub-periods resolution	Weekly, monthly, seasonally	$subp$
	Demand duration curve	Peak, valley, mid-load	$P(t)$, $Q(t)$
Decision alternatives	Alternatives that planner has available for driving the expansion	Expansion strategy	S_k, S_f
		Large transmission projects	$D_k(p)$
		Defer transmission projects	$O_k(p)$
		Invest in DG projects	
		Type of alternative	[0,1,2,3..*n*]
		Investment decision timing	p
		Decision alternative location	$\overline{f}(bus)$
Objective function (C_k) components	Efficiency in investments, operative efficiency, reliability and technical feasibility	Investment costs	C_I, C_{IDG}
		Operative costs	C_G, C_{GDG}
		O&M costs	$C_{O\&M}$
		VOLL or EENS costs	C_{LOL}
		Active power losses costs	-
Constraints	Transmission expansion plans performance assessment subject to:	Power balance	$S_G + S_D = S_L$
		Voltage limits	$V_{j\,min}$, $V_{j\,max}$
		Generators capacity limits	$P_{i\,min}$, $P_{i\,max}$
		DG plants capacity limits	$DG_{i\,min}$, $DG_{i\,max}$
		Transmission lines power flow limits	F_l
		Budgetary constraints	-
Input parameters	Certain	Certain	$S(t)$
	Uncertain	Random	$X(t)$
		Truly uncertain	
		Fuzzy	-

Table 1. Basic elements to be defined before devising a TEP methodology

The current TEP problem can be described as the constant planners' dilemma of deciding on a sequential combination of large transmission projects and new available flexible options, which allows the planners to efficiently adapting their decisions to unexpected circumstances that may take place during the planning period.

Under this novel paradigm, TEP is a multi-period decision-making problem which entails determining *ex-ante* the right type, location, capacity, and timing of a set of available decision options in order to deliver a maximal expected social welfare as well as suitably reducing the existing risks over the planning period.

Probabilistic decision theory, i.e. the probabilistic choice paradigm, is well-known and has been extensively applied in several stochastic optimization problems. However, a probabilistic decision formulation within the TEP is an intractable task and its application has only been feasible when very strong simplifications are adopted by planners (Neimane, 2001). This work proposes a practical framework for treating the TEP. Even though a number of simplifications are still necessary, the main features of the new TEP problem are retained.

The analysis of the state-of-art of the TEP solutions approaches sets as a start point the classic stochastic optimization problem formulation. Under the assumption of inelastic demand behaviour, the optimization problem can be rigorously stated as follows:

$$\underset{S_{opt}\in\overline{S}_f}{opt}\left\{\mathrm{E}[OF|_S]\right\}=\underset{S_{opt}\in\overline{S}_f}{opt}\left\{\int_0^T\overbrace{\int\ldots\int_\Omega}^{i} OF(C)\,dF(C)\right\} \quad (1)$$

where, the performance measure of the optimization is the expected present value of the objective function E[*OF(C)*] evaluated over a planning horizon *T*, for a proposed expansion strategy *S*. $\overline{S_f}$ is the set of all feasible states of the network, *F(C)* is the distribution function of the expansion costs function $C(C_1,C_2,C_3,...,C_i)$. The planning period *T* usually only can take discrete values $t_0,t_1,t_2,t_3,...,t_p$, and Ω is the domain of existence of *C*(*X*,*S*). The expansion costs function depends on several uncertain input parameters $X\left(x_1(t),x_2(t),x_3(t),...,x_n(t)\right)$ which change over the time, as well as depending on the state of the network, which also varies over the time $S\left(s_1(t),s_2(t),s_3(t),...,s_d(t)\right)$. It is important to note that the problem is subject to a set of constraints, namely Kirchhoff's laws, upper and lower generation plants capacity limits, transmission lines capacity limits, upper and lower voltage and phase nodes limits, and budgetary constraints, among others, which are represented by means of equality and inequality equations. With these considerations, (1) can be rewritten as follows:

$$\underset{S_{opt}\in\overline{S}_f}{opt}\left\{\mathrm{E}[OF]\right\}=\underset{S_{opt}\in\overline{S}_f}{opt}\left\{\overbrace{\int\ldots\int_\Psi}^{n.(p+1)} OF\left[C(X,S)\right]d\Phi(X)\right\} \quad (2)$$

subject to:

$$P_A(X,S)+P_B(X,S)=P_L(X,S)$$
$$b_{1\min}\leq g_1(X,S)\leq b_{2\max}$$
$$b_{1\min}\leq g_2(X,S)\leq b_{2\max}$$
$$\vdots \qquad \vdots \qquad \vdots$$
$$b_{m\min}\leq g_m(X,S)\leq b_{m\max}$$

where $\Phi(X)$ is the $n(p+1)$-dimensional function of probability distributions of input parameters and Ψ is the domain of existence of the input parameters *X*.

Formulating $\Phi(X)$, which incorporates the information about the uncertainties that largely influence the solution, is a complex task as it involves determining probabilities and distribution functions of $n(p+1)$ uncertain parameters. However, the more difficult (and in some cases impossible) task is the formulation of the objective function *OF(C)*. In this sense the most common simplification considered by TEP models is $OF\left[C(X,S)\right]=C(X,S)$ and (2) can be rewritten as:

$$\min_{S_{opt}\in S_f}\left\{\mathrm{E}[C|_S]\right\}=\min_{S_{opt}\in S_f}\left\{\overbrace{\int\ldots\int_{\Psi}}^{n.(p+1)}C(X,S)d\Phi(X)\right\} \tag{3}$$

which implies that the objective function can be entirely described by the expansion costs function. In this case the planning problem is often reduced to the minimization of the expected total expansion costs. Although the complexity of the problem is greatly reduced, such a formulation does not take into account desires of the decision-maker for reducing risks present in the expansion decisions. Eventually, this risk neutral formulation may lead to wrong decisions.

On the other hand, considerable difficulties are related to the computational effort necessary for efficiently assess the multidimensional integral and for proposing the corresponding optimization procedure. The only method for dealing with (3) as strict as possible, given that the $n(p+1)$-dimensional integral must be solved, is applying Monte-Carlo simulation techniques for evaluating the attributes of the objective function.

There are $(n+d)(p+1)$ input parameters in the expansion costs function $C(x_{1,0},\ldots x_{n,0},\ldots,x_{n,p},\ldots s_{1,0},\ldots s_{d,p})$, from which $d(p+1)$ are decision variables. Assuming as I the number of available decision choices in each possible right-of-way d, the number of possible candidate solutions are $I^{d(p+1)}$. Additionally, by denoting as N the number of simulations that requires the Monte Carlo simulation, the number of simulations to be performed depends on the number of periods of time as $N(p+1)$. It is important to mention that N depends on the degree of confidence that the planner demands on the results. Under these considerations, the number of required computations for rigorously evaluating the multidimensional integral and therefore for finding the global optimum is $N(p+1)I^{d(p+1)}$. Unfortunately performing this task in a real multi-period TEP is not possible since the number of simulations dramatically increases with the result of multiplying the possible links and the time periods $d(p+1)$. Due to this fact, researchers have proposed diverse approaches in order to make the TEP feasible and, in some cases, to incorporate the desires of the decision-maker for reducing the planning risks. According to the reviewed literature such simplifications can be categorized as static, deterministic and non-deterministic formulations of the TEP.

3.1 Static formulation

When the planner demands on further simplifying a deterministic formulation, the intertemporal dependences and the dynamic nature of the TEP problem is not considered. Such a formulation is named static. This is a deterministic formulation that entails finding the optimal state of the network for a future fixed year. Consequently, the input parameters X do not change during the whole solving process. In this case, there are $n+d$ input parameters within the expansion costs function $C(x_1,x_2,\ldots,x_n,\ldots s_1,\ldots s_d)$ from which d are decision variables. Assuming as I the number of available decision choices in each possible right-of-way d, the number of possible solutions is I^d . For instance, in a small TEP problem with d = 11 and five decision choices on each right-of-way I = 5, the number of possible combinations is $5^{11} = 4.88 \cdot 10^7$.

3.2 Deterministic formulation

Deterministic models are nowadays widely used in practice for transmission network planning. This type of models assumes that all the input parameters and variables are known with complete certainty and, therefore, there is a unique and known scenario for the evolution of all input parameters. Consequently, there is no need to use probability distribution functions and the complexity of the optimization process is greatly reduced. Thus, deterministic formulation entails finding the optimal state of the network over a planning horizon T, given that the evolution of X along the time is known with certainty.

There are $(n+d)(p+1)$ input parameters inside the expansion costs function $C(x_{1,0},...x_{n,0},...,x_{n,p},...s_{1,0},...s_{d,p})$ from which $d(p+1)$ are decision variables. Assuming as I the number of available decision choices in each possible right-of-way d, the number of possible solutions to be evaluated for finding the global optimum is $I^{d(p+1)}$. For instance, in a small TEP problem with eleven possible new right-of-ways d = 11, five decision choices in each right-of-way I = 5, and only two decision periods p+1 = 2, the number of possible combinations are $5^{11.(1+1)} = 2.38 \cdot 10^{15}$.

In this work, the subject of optimization is the present value of the total expansion costs function C(X,S), evaluated along a planning horizon T, for a proposed expansion strategy S. C(X,S) is a non-linear function subject to a set of constraints, i.e. Kirchhoff's laws, generation plants capacity limits and transfer capacity of transmission lines, among others. Such constraints are represented by means of equality and inequality equations.

$$\min_{S_{opt} \in \bar{S}_f} \left\{ C|_S \right\} = \min_{S_{opt} \in \bar{S}_f} \left\{ C(X,S) \right\} \tag{4}$$

$$C(X,S) = \sum_{t=0}^{T} \left[\frac{C_I(X,S)}{(1+r)^t} + \frac{C_{Gen}(X,S)}{(1+r)^t} + \frac{C_{O\&M}(X,S)}{(1+r)^t} + \frac{C_{LoL}(X,S)}{(1+r)^t} \right] \tag{5}$$

subject to:

$$\begin{aligned} & P_A(X,S) + P_B(X,S) + \ldots + P_R(X,S) = P_L(X,S) \\ & b_{1\min} \le g_1(X,S) \le b_{2\max} \\ & b_{1\min} \le g_2(X,S) \le b_{2\max} \\ & \vdots \qquad \vdots \qquad \vdots \\ & b_{m\min} \le g_m(X,S) \le b_{m\max} \end{aligned}$$

where

$C_I(X,S)$: Investment costs of the new expansion decisions.

$C_{Gen}(X,S)$: Production costs of the different generations units.

$C_{O\&M}(X,S)$: Annual O&M costs of the transmission network elements.
$C_{LoL}(X,S)$: Loss of load annual costs.
r : Annual discount rate.

3.3 Non-deterministic formulation

Basically non-deterministic formulations of the TEP problem are able to consider the possible events which could take place in the future by taking into account the uncertainty present in the information. In this category, the TEP problem can be solved either by means of a stochastic optimization-based formulation, where the objective function is typically formulated in term of an expected value or by means of a decision-making framework, which encompasses a deterministic optimization plus a decision tree analysis. Unfolding uncertainties are incorporated as branches and decisions are made on the evaluation of the consequences of deciding on the different expansion alternatives. In this sense, the decision-making framework allows the planners to gain insight into the risks involved in each expansion choice and could even suggest new and improved alternatives.
The dimension of the search space for the different TEP formulations depends on the number of decision choices, the number of decision variables and the number of periods. Additionally, the degree of detail of the model describing the temporal evolution of the PES along the planning horizon, namely demand discretization, time resolution and extent of the planning horizon is another important aspect to take into account since the computational effort for evaluating each combination depends on it.
To reasonably accomplish the challenging task of solving the TEP problem from a non-deterministic perspective, require incorporating and modeling a variety of data of diverse nature. Moreover, due to the large problem size, which is clearly defined by its stochastic, multi-period, multi-criteria and combinatorial nature, substantial efforts are required in order to sustain the viability of the proposed models. In this sense, an adequate treatment of the different types of the information is one of the most important stages before formulating the non-deterministic TEP model.

4. Handling information within the TEP

The process of solving actual planning problems requires handling a large amount of information from which only a small fraction is known with complete certainty. In this section, the major uncertainties affecting the TEP and referred to as variables that affect the outcomes of decisions and which are not known at time of planning, are analyzed and categorized from a descriptive viewpoint. Excluded here are the uncertainties originated in the model's user, i.e. what is not captured by the model but desired by the user, as well as uncertainties originated in the model (i.e. the "right" model structure, modelling techniques and tools).

4.1 Uncertainties present in the TEP

Data about the current state of the network is much more accurate than forecasted data. Furthermore, uncertainties present in forecasted data are very diverse in nature (Neimane,

2001). Therefore, it is recognized the importance of categorizing the uncertain information to be incorporated within TEP models.
In this work, it is assumed that forecasts and characterization of the forecast uncertainty are provided to the planning activity. Instead, the attention of this research work is posed in categorizing all the information to be handled within the TEP and proposing a systematic methodology for properly incorporating uncertain information of various source and nature within the TEP model.

4.2 Certain Information

Certain data are those parameters which can be defined explicitly (Neimane, 2001). This category includes the present network configuration, electrical parameters of the network components, possible expansion choices and their electrical parameters capacity limits of transmission lines, nominal voltages and voltage limits.

4.3 Information subjetc to stochastic uncertainty

Uncertainty in data mostly appears due to the inevitable errors incurred when forecasts are performed. When it is possible to objectively assess the magnitude of such errors with a satisfactory degree of confidence, then the uncertainty is said to be of random nature (Buygi, 2004). The uncertainty of such variables can be adequately represented by means of probability distribution functions. Demand, fuel prices and hydrologic resources evolution are typical examples belonging to this category. In (Vásquez *et al.*, 2008) a well-founded means for modelling random uncertainties is extensively presented.

4.4 Uncertain non-random information

When it is not possible to estimate with a satisfactory degree of confidence the errors incurred when forecasts are performed, information is deemed to be of a non-random nature (Buygi, 2004). Uncertainties in this group are related to human processes (e.g. investors decisions, changes in regulation, planners and managers investment strategies, beliefs or subjective judgments). In fact, the future does not appear to be predictable through extrapolation of historical trends applied to the current environment (Clemons & Barnett, 2003). Thus, non-random uncertainties assessment is derived from decision-makers perception, experience, expertise and reasoning. Inside this group there are two types of uncertainties.
The first type belongs to a large amount of valuable information that only can be expressed in linguistic form, e.g. “satisfactory”, “considerable”, “large”, “small”, “efficient”, etc. Although this **vague information** has a very subjective nature and usually is based on expert judgment, it can be useful during the decision-making process. Fuzzy sets theory is a well-founded approach for modelling properly these kinds of uncertainties (Buygi, 2004).
The second type of non-random uncertain information is distinguished by holding uncertainties typical of dynamic environments that undergo severe and unexpected changes. This is the case with the TEP environment. According to the literature, these kinds of uncertainties are known as **strategic uncertainties** (Clemons & Barnett, 2003; Brañas et al., 2004; Detre et al., 2006). A specific feature of them is that they are gradually solved as new information arrives over time and, once enough information is known, the uncertainty is solved and disappears definitively (Dillon & Haimes, 1996; Clemons & Barnett, 2003).

Within the TEP problem, this uncertainty affects crucial events that could take place in the future, such as the generation expansion evolution or the delay on the expansion projects completion. Data with strategic uncertainties are considered the most important information to be handled within TEP since they are fundamental drivers of PES evolution and, therefore, of this decision-making problem. For further reading about this topic see (Detre *et al.*, 2006). On the other hand, within the PES planning environment, there are not much bibliographic references about modelling of strategic uncertainties in planning models. In (Neimane, 2001), this type of information has been designated as **truly uncertain information**[1]**.** Either discrete probability distribution functions or a scenarios technique are proposed for modelling information of this kind.

Taking into account the above mentioned, in this work it is proposed to model truly uncertain information by means of discrete probability distribution functions (PDF) where the probabilities assigned to the occurrence of different scenarios are assumed as known information. In this sense, a reasonable way for dealing with these two types of uncertainties is proposed in (Vásquez *et al.*, 2008).

5. The proposed flexibility-based TEP framework

The described TEP problem can be suitably faced by applying the decision tree technique, which basically consists in decomposing the whole problem into a number w of less complex sub-problems, each one concerned with solving a multi-period deterministic optimization as well as assessing the attributes of the expansion plans.

A sub-problem or complete path is represented by a number P of sequential discrete events. Such events are specified by the assumed discrete nature of strategic uncertainties. Under these conditions, each sub-problem handles only random uncertainties. Therefore, the different feasible expansion plans can be valued by applying a probabilistic analysis of the attributes of the objective function and decisions are made by applying a robustness-based risk management technique.

A master dynamic programming (DP) problem, by means of a backward induction of P sequential decisions, makes it possible to incorporate flexible options and, subsequently, rank the new flexible expansion strategies.

The entire proposed methodology, can be described as follows in five stages and illustrated in Fig. 1:

1. To decompose the TEP problem into w sub-problems.
2. To obtain a set of feasible expansion plans for each sub-problem w.
3. To assess the *OF* attributes of the different expansion plans for each path w.
4. To sequentially incorporate in the expansion plans, starting from the last decision period P, new flexible decisions for each path w.
5. To form flexible expansion strategies, by repeating 3 and 4 with backward induction until $P = 1$.

[1] This term refers to relevant non-random uncertain variables, which convey strategic information.

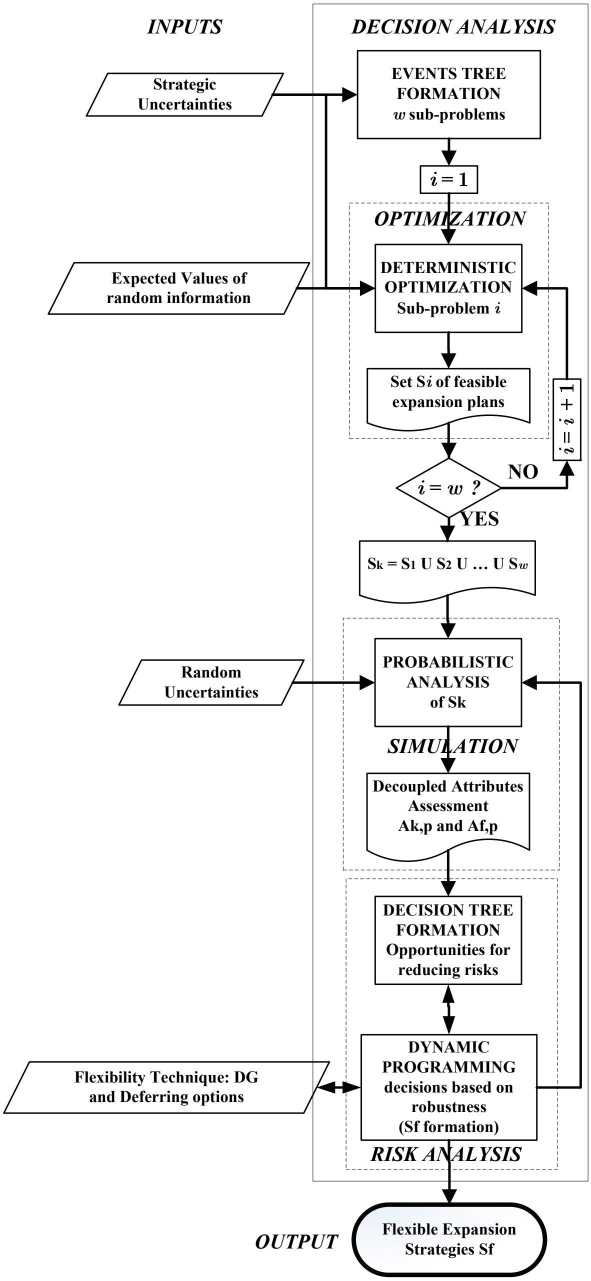

Fig. 1. Complete proposed framework for finding a flexible strategy

5.1 Decomposing the problem

The reason why optimization-based TEP models are inefficient is the presence of uncertainties. In fact, one of the most important concerns within the current TEP problem lies in suitably handling a large amount of uncertain information of diverse natures.
The traditional TEP formulations commonly reduce the future into an assumed probability-weighted certainty equivalent. This fact, in presence of strategic uncertainties implies averaging highly different scenarios. However, in practice equivalent scenarios will never take place since the future can unfold as either favourable or adverse. Therefore, stochastic optimization models formulated in terms of expected values are not suitable approaches for treating the TEP.
Event tree technique is a graphic tool that provides an effective structure for decomposing complex decision-making problems under the presence of uncertainties. The interested reader in decision tree analysis technique is further referred to Dillon & Haimes, 1996 and Majlender, 2003.

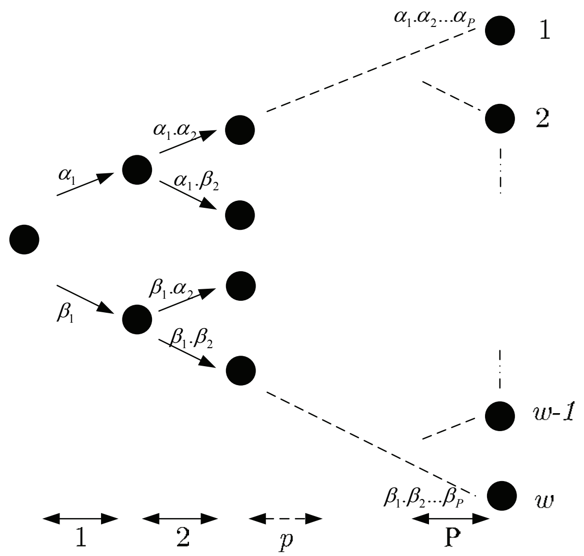

Fig. 2. Example of a binomial event tree

Fig. 2 depicts an example of a resulting events tree formed by assuming that the whole of the problem's strategic uncertainties can unfold into only two discrete scenarios. A complete event tree representing crucial states of the problem along the planning horizon allows getting insight about the diverse future circumstances, which candidate expansion plans should cope with.
Nodes of the event tree represent an explicit feasible scenario obtained as a result of combining all the possible discrete probability distributions of uncertain events along a discrete time *p*–decision periods. Each event is associated with composed occurrence probability which results from combining the discrete subjective probabilities assigned to the occurrence of a single uncertain event (α_p, β_p, …) and provided that the occurrence of such probabilities are independent of what happened in previous periods as shown in Fig. 2.

5.2 Obtaining a set of feasible expansion plans

The goal of this stage of the planning process lies in successfully reducing the dimension of the TEP by finding a set of feasible candidate expansion plans which fulfil fundamental constraints of the sub-problem. By reducing the search space, a rigorous economical and risk-based assessment of a reduced set of feasible expansion plans in subsequent stages turns practicable.

Under the scope of this work, it is assumed that the regulatory entity annually executes a centralized TEP task, in which a set of environmental, societal and political long-term energy policies must be achieved. In fact, the previous performance of environmental, societal and political feasibility assessments reduces the large number of decision alternatives to be considered by planners for searching candidate expansion plans for driving the expansion of the transmission grid. It is assumed that a number of possible transmission expansion alternatives have indentified. Despite this, the number of possible combinations of sequential decisions, i.e. the potential solutions, is still enormous. Since only a reduced number of combinations will meet the constraints of the TEP sub-problem, a technical efficiency-based assessment is a plausible means for reducing the search space and finding a set of technically feasible expansion plans.

The TEP sub-problems are formulated as a deterministic multi-period optimization and an evolutionary algorithm has been developed for properly solving such optimization problem (Vásquez, 2009)

Why is deterministic optimization the best choice?

The major foundations of this work for deciding on the deterministic choice lie in the nature of the TEP problem as well as in the problem decomposition proposed in the previous section. In fact, since only a reduced number of combinations will meet the TEP problem's constraints, and given that location, timing and type of the transmission expansion alternatives are discrete and limited in number, feasible candidate solutions are therefore also limited in number and noticeably different from one another. On the other hand, with the proposed decomposition of the TEP into sub-problems, strategic uncertainties have been removed temporarily. In this sense, the only presence of random information, which implies that uncertainties can be forecasted with a satisfactory degree of confidence, allows for a suitable technical assessment where the uncertain input variables are explicitly modelled by means of expected values.

5.3 Assessing the performance of expansion plans

The reduced number of candidate solutions allows a more detailed valuation of the expansion plans. This stage of the planning process entails performing a probabilistic technical-economical performance assessment of all the feasible expansion plans. The performance assessment of an expansion plan is achieved by accounting for a group of decoupled attributes of the objective function. Decoupled attributes A_k denote a measurement of the relative "goodness" of a specific transmission expansion plan S_k in every decision period p expressed by means of its probability distribution $F_{k,p}$. These p probability distribution functions represent the likelihood of the possible future values that the *OF* could acquire over time, characterizing the time-dependent risk profile of selecting the expansion plan S_k.

Stochastic simulation

Stochastic simulation techniques are applied for modelling the randomness of the objective function. In spite of the large computational effort demanded by Monte Carlo methods, the most significant advantage of the simulative approach over analytical probabilistic techniques is the accurate estimation of the tails of probability distribution $F_{k,p}$.

On the other hand, some planning engineers may worry about a possible conflict between the proposed deterministic optimization stage and the subsequent probabilistic and risk analysis stages. In fact, there is no conflict at all provided that all the feasible expansion plans have been found during the deterministic analysis stage. The probabilistic analysis stage is not intended to replace the deterministic TEP models, but to add better information on the merits of the expansion plan and its risk profile. This goal is achieved by assessing the time-decoupled attributes for every feasible expansion plan.

The total attributes of a specific expansion strategy S_k, A_k comprise all the information enclosed in the probability distributions $F_{k,p}$, which describe the possible future performance of S_k provided that all the problem uncertainties (random and strategic) have been taken into account during the simulative process (Neimane, 2001). If such resulting probability distribution function, defined in this work as F_1, can be fit to a Gaussian distribution, A_k can be expressed as follows:

$$\mathrm{A_k} = F_{1,k}\left(\bar{C}_k, \sigma_k\right) \tag{6}$$

where,

$\bar{C}_k = \dfrac{1}{N_k}\sum_{i=1}^{N} C_{k,i}$: *OF*'s Expected Value for S_k

$C_{k,i}$: *OF*'s value of the strategy S_k during the realization *i*. See Equation (5)

A_k : Total Attributes of the stratey S_k

$F_{1,k}$: *OF*'s Probability Distribution for strategy S_k

N_k : Number of realizations until achieve the required confidence in determining $\mathrm{F}_{1,k}$

σ_k : *OF*'s standard deviation for strategy S_k

Although an assessment of A_k provides the information about the performance of an expansion strategy, the planner is unable to visualize the risk evolution over time and the effects on the *OF*'s performance caused by the diverse type of uncertain variables. Nevertheless, having this information is a key issue for properly tackling the TEP. One of the major contributions of this work lies in successfully coping with these two concerns. In first place, Section 4.1 proposed to decompose the problem by applying the event tree technique. In second place, under the assumption that each node of the events tree represents one event unfolded by the combination of strategic uncertainties, a set of decoupled attributes where only random nature uncertainties are present needs to be evaluated. Under this perspective, by performing *w* Monte-Carlo realizations and then, by means of backward induction and considering the associated cumulative occurrence probabilities, the individual effects of the strategic uncertainties can properly be accounted for, from the last decision period until the first one. At the same time, the diverse time-

decoupled attributes of an expansion strategy F_p are assessed, step by step, until its total attributes F_1 are obtained.
At the end of this valuation process, F_1, which represents the total attributes of the analyzed expansion strategy, is obtained as follows:

$$\mathrm{F}_P\left(\bar{C}_P,\sigma_P\right)\Big|_{w_{P-1}} = \left[f_{P-1,j}\left(\bar{c}_{P-1,j},\nu_{P-1,j}\right) + \sum_{i=1}^{s_P} \alpha_{P,i}\cdot f_{P,i}\left(\bar{c}_{P,i},\nu_{P,i}\right) \right]\Bigg|_{w_{P-1}}$$

$$\mathrm{F}_{P-1}\left(\bar{C}_{P-1},\sigma_{P-1}\right)\Big|_{w_{P-2}} = \left[f_{P-2,k}\left(\bar{c}_{P-2,k},\nu_{P-2,k}\right) + \sum_{j=1}^{s_{P-1}} \alpha_{P-1,j}\cdot F_P\left(\bar{C}_P,\sigma_P\right) \right]\Bigg|_{w_{P-2}}$$

$$\vdots \qquad \qquad \vdots$$

$$\mathrm{F}_1\left(\bar{C}_1,\sigma_1\right) = A\left(\bar{C},\sigma\right) = f_{0,v}\left(\bar{c}_{0,v},\nu_{0,v}\right) + \sum_{k=1}^{s_1} \alpha_{1,u}\cdot F_{2,u}\left(\bar{C}_{2,u},\sigma_{2,u}\right) \tag{7}$$

where,

F_p : *OF*'s decoupled attributes during the period p

$\bar{C}_{p,s}$: *OF*'s Expected Present Value for event s during p

$\sigma_{p,s}$: *OF*'s standard deviation for event s during p

$\alpha_{p,s}$: Ocurrence Probability of event s during the decision period p

s_p : Number of feasible discrete events during p

$f_{p,s}$: Partial *OF*'s Probability Distribution for event s during p

$\bar{c}_{p,s}$: Partial *OF*'s Expected Value for event s during p

$\nu_{p,s}$: Partial *OF*'s standard deviation for event s during p

Fig. 3 graphically shows the increasing uncertainty of the objective over time. As planning horizon extends in time, the risk grows accordingly. Provided that the probabilistic properties of expansion attributes are reasonably described by a Gaussian probability distribution, blue dots correspond to the annual expected values of the expansion costs and the vertical black segments represent the annual standard deviations of the objective function.

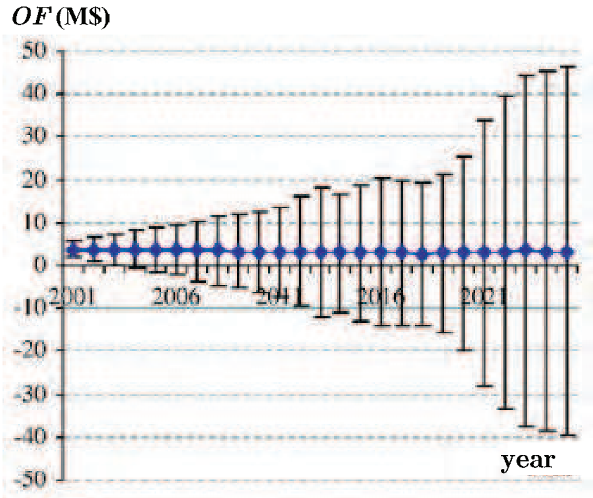

Fig. 3. Graphic representation of the time-decoupled attributes of an underlying asset

The idea of a decoupled assessment of the expansion plans' attributes can be rooted to the Bellman's Principle of Optimality since it allows applying dynamic programming for valuing the flexibility gained when embedded or contingent decision options are incorporated within the planning process (Dixit & Pindyck, 1994). In following sections, this process is explained in detail.

Ranking of expansion strategies and decision-making

Derived from the optimal portfolio selection theory, expansion plan attributes can be ranked based on their efficiency, by means of the Sharpe ratio r_{sharpe} (Nielsen & Vassalou, 2003). This index was proposed by Sharpe in 1966 as the ratio between the expected benefit and the risk, where risk is measured as a standard deviation of the benefit. According to static mean-variance portfolio theory, if investors face an exclusive choice among a number of alternatives, then they can unambiguously rank them on the basis of their robustness (Sharpe ratios). An expansion alternative with a higher Sharpe ratio will enable all investors to achieve a higher expected utility by accepted risk unit.

The inverse of r_{sharpe}, which is known as the coefficient of variation according to Ladoucette & Teugels (2004) and Feldman & Brown (2005) is a useful measure for comparing variability between positive distributions with different expected values. An alternative with a lower coefficient of variation will result in lower risk exposition per unit of expected benefit. In this work, the inverse of the r_{sharpe} will be used to measure the desirability of an expansion strategy.

In order to express in percentage the coefficient of variation, the use of a relative volatility, which is accounted for as the relation between the expected volatility of the underlying asset $\bar{\sigma}_k$ divided by the maximum expected volatility of all the evaluated strategies $\bar{\sigma}_{\max}$, is proposed. See (8).