Investment Decisions in Distribution Networks Under Uncertainty With Distributed Generation—Part I: Model Formulation

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***Abstract*—Investment in distributed generation (DG) is an attractive distribution planning option for adding flexibility to an expansion plan, mainly by deferring network reinforcements. In this first part of a two-part paper, a risk-based optimization approach is proposed to model a multistage distribution expansion planning problem that takes DG into account as a flexible option to temporarily defer large network investments. Five features of the installation of DG related to location, size, type, operation and timing are all optimized. The evolutionary particle swarm optimization (EPSO) method is applied to solve this mixed integer nonlinear problem. A return-per-risk index is proposed to assess expansion investments. This index achieves an efficient synergy between the expected return and the risk of investments by performing Monte Carlo simulations. In turn, the flexibility of network investment deferral is assessed through a real option valuation. Finally, in order to quantify the investment deferral benefit, the expected return from a traditional expansion plan (without DG) is compared to the return obtained from a flexible expansion plan (with DG). In the companion paper, the proposed approach is tested on a typical Latin American distribution network; implementation aspects and analysis of numerical results are presented.**

***Index Terms*—Distributed generation, distribution planning, EPSO, expansion decisions, real options, risk analysis.**

NOMENCLATURE

A. Acronyms

BEP	Best-compromise expansion plan.
CHP	Combined heat and power (cogeneration).
D/S	Distribution substation.
DG	Distributed generation.
EPSO	Evolutionary particle swarm optimization.
FEP	Flexible expansion plan.
GBM	Geometric Brownian motion.
ICE	Internal combustion engine.
LSM	Least-squares Monte Carlo.
MT	Micro-turbine.
O&M	Operation and maintenance.
OF	Objective function.
PBR	Performance-based regulations.
T&D	Transmission and distribution.
VAD	Value-added distribution (in its Spanish acronym).

B. Variables

C_{ADG}	Additional variable cost of DG.
$C_{ENSxCapa.}$	Cost of ENS by capacity constraints.
$C_{ENSxRelia.}$	ENS penalty cost for reliability.
C_{ESLQ}	Penalty cost for poor quality.
CF	Cash flow.
C_{INV}	Investment cost of an expansion alternative.
C_{LOSS}	Cost of energy losses.
$C_{O\&M}$	Incremental O&M cost due to investments.
Dp	Peak power demand per node.
Ep	Electricity price in the wholesale market.
$Ep*$	Expected value of long run equilibrium.
ENS	Energy not supplied.
$ESLQ$	Energy supplied with low quality.
I_{Lj}	Current per line.
$I_{Max.Lj}$	Maximum capacity of line.
$\Delta I_{Exce.j}$	Current that exceeds the capacity of line.
Inc	Incomes (due to the established VAD).
NPV	Net present value.
OV^*	Optimal option value.
P_{Dem}	Total power demand.
$P_{Iny.D/S}$	Power injection from D/S.
P_{Loss}	Total power losses.
$P_{Max.T}$	Maximum capacity of D/S.
$\Delta P_{Exce.T}$	Power which exceeds the D/S capacity.
ROV	Real option valuation.

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RRI	Return-per-risk index.
SP	Strike price.

C. Parameters

M	Number of Monte Carlo simulations.
r	Discount rate.
rf	Risk free rate.
T	Analysis period.
α	Mean reverting rate.
ε	Normally distributed random variable N(0,1).
μ	Growth rate or drift (pu).
σ	Standard deviation or volatility (pu).

D. Indices

i	Monte Carlo simulation.
j	Line of the distribution network.
t	Sub-period of time (a year).

I. Introduction

When performance-based regulations (PBR) are introduced into the electricity distribution sector, the risk of investment decisions is assumed by the utility [1]. Thus, determining efficient and well-timed investments for a distribution expansion task, under the significant uncertainties of many planning parameters, is a major challenge.

When considering the distribution expansion planning problem, utilities must optimize their investment decisions in order to fulfill efficiency and quality requirements, while taking into account all present uncertainties. Moreover, the techno-economic feasibility of distributed generation (DG) should be evaluated as an attractive option for deferring distribution network investments, and thereby improving both the efficiency and the quality of service [2]–[4]. In USA regulation, for instance, some rules are in place according to which utilities are allowed to situate DG at strategic locations on the grid in order to defer network upgrade costs [4], [5]. Currently, the regulatory frameworks of three Latin American countries (Panama, Costa Rica, and Nicaragua) allow utilities to invest in DG and operate its own generators. In Argentina, some special programs (such as "Energy Delivery") have been instrumented to overcome the lack of investment in recent years, deferring reinforcements in generation, transmission and distribution (T&D) networks. These programs have aimed to install DG plants (largely diesel generators) close to high demand areas, mainly for supplying energy at peak load periods.

DG comprises generation plants, characterized by its reduced size, that are connected directly to the distribution network or on the customer side of the meter [6]. Generally, DG can be used for different operations, such as backup power, peak power, base-load power, and cogeneration (CHP). DG includes fossil-fuel technologies (e.g., microturbines, internal combustion engines) and renewable energy sources (e.g., solar, wind). The proper location of DG may bring about various benefits such as: losses reduction, voltage control, higher power quality, peak shaving, T&D capacity release, and deferring T&D network reinforcements [2], [4], [7]–[11].

In addition, there are some economic benefits of DG for the end-users, such as a lower electricity bill, especially for gas-fired technologies. This is especially valid in regions where the so-called "spark spread", that is, the difference between the local electricity rates and the gas prices, is high [10]. For example, New York [10] and Bolivia, in USA and Latin America, respectively, are regions with a relatively high "spark spread" where the use of microturbines to produce electricity locally is very attractive, mainly for peaking generation and CHP applications.

DG plants ownership by utilities is a key aspect to be examined; it can provide many benefits for utilities, which can choose where to place DG plants and control its operating pattern [4], mainly in regions with a high "spark spread". If only private generators are allowed, utilities may resort to planning methodologies for evaluating any additional credit that might be offered to private investors who decide to place DG plants in appropriate locations of the network [8].

A. Problem Statement

The problem of distribution network expansion planning consists in determining the type, capacity, siting, and timing of the installation of new equipment. This optimization problem is very complex, as it is a non-convex mixed integer nonlinear problem. The methods used to solve this problem can be divided into two categories: methods of mathematical programming and heuristic methods [12]–[15].

Various approaches have been proposed in recent decades for solving expansion planning problems. For example, among the mathematical programming methods, the most widely used include nonlinear programming [9], mixed integer programming [16], dynamic programming [17], and branch-and-bound algorithms [14]. Heuristic methods are, for example, branch-exchange algorithms [18], genetic algorithms [19], the ant colony [20], simulated annealing [21], and tabu search [22]. Recently, a comprehensive learning particle swarm optimization was proposed in [23]; balanced genetic algorithm and heuristic optimization algorithm are applied to a green-field planning in [15] and [24], respectively.

The methods of mathematical programming provide the optimum solution corresponding to a given set of equations. They have mathematically proved to find an optimal solution. There is a difficulty with these methods which arises when representing the non-convexity of the expansion planning problem; due to the combinatory nature of this problem, these methods are mostly able to solve small problems with a simple description [19], [24]. Even a numerical solution requires overwhelming computational effort, which increases exponentially as the size of the problem increases (curse of dimensionality). The heuristic methods allow to tackle real-sized problems and might, in some cases, produce better solutions; although they are subject to stochastic errors because of the algorithms involved [15]. However, these last methods gained attention because they can work in a straightforward fashion with nonlinear constraints and objective functions, while it is also easy to introduce aspects such as reliability and uncertainties [14]. Another advantage is that the objective function does not have to be continuous or even differentiable; thus, they are more flexible in dealing with complex problems [25], [26].

In addition to optimization methods, other techniques are required if the expansion planning problem takes place under uncertainties, which are mainly related to demand growth. For this, probabilistic and fuzzy approaches have been proposed [15], [27]–[29]. While traditional models in expansion planning concentrate their analysis on solutions to the problem, the modern risk analysis paradigm is primarily concerned with investment decisions [19], [30]. Even though uncertainties are greater in the long-term [19], [31], investment decisions should be focused in the short-term, and investments should be flexible (or adaptable), according to the future behavior of the system [28].

Regarding the inclusion of DG as an investment option, in recent years research efforts have been focused on the assessment of the investment deferral [4], [10], [11], [32].

This work presents a risk-based optimization approach for modeling a multistage distribution expansion planning problem under uncertainty and considering DG plants as flexible expansion options. The resulting problem is solved by a heuristic method, namely evolutionary particle swarm optimization (EPSO). DG plants are mainly proposed to temporarily defer large network investments. Thus, some DG technologies are required, which can be strategically installed on the network during a given period (2–5 years), until the deferred investment will be justified; then the DG should be uninstalled and re-installed in another location of the network. Fossil-fuel technologies are the ones best suited to meet these requirements.

The approach is focused on assessing short-term expansion plans of a current distribution grid, framed within long-term planning, at both sub-transmission and primary distribution networks, from the point of view of a utility, under the specific PBR framework of Latin America. The considered uncertainties are mainly related to the demand growth, the installation time of a new big load, and the electricity price (for assessing the energy losses). A return-per-risk index (RRI) that measures risk-adjusted returns for comparing investment alternatives is proposed to assess expansion investments. In turn, the flexibility of deferring a large investment (with DG of lower cost and reversible investment) is valuated economically by means of real option techniques. In addition, the impact of DG on energy losses, voltage and reliability is assessed. The type of DG technology to be installed, location, size (units up to 5 MW), operation (for base-load, peak or backup generation), and timing of the DG are optimized. In the second part of this two-part paper [33], further practical aspects and an analysis of numerical results are presented.

The four main contributions of this work for the particular regulation context of Latin America are: implementing real options valuation to quantify the investment deferral benefit of DG; using the proposed RRI to assess investments under uncertainty; jointly optimizing type, location, size, operation and timing of DG; and using the EPSO algorithm in order to solve the optimization problem.

This paper is organized as follows. The Latin American context (regarding PBR, DG, utility's benefit, expansion planning, and investment decisions) is briefly explained in Section II. Section III describes real options valuation for assessing the flexibility of network investment deferral. Section IV presents the proposed risk-based approach to support the expansion investment decisions, describing the RRI, the mathematical formulation of the expansion problem and the optimization process. Finally, the conclusions are presented in Section V.

II. Expansion Investment Decisions

A. Utilities in Latin America

In most European countries there are two separated activities at the supply-distribution level: distribution network and retailing, while in Latin American countries these activities are combined within the traditional distribution system, which is operated and exploited by a single utility.

Within the PBR framework, the benchmarks with which a utility in Latin America should operate and manage its service are established ex-ante for a tariff period, through the VAD (value-added distribution, in its Spanish acronym for "*Valor Agregado de Distribución*") [1]. The end-user tariff is the sum of VAD and a pass-through cost of energy and power purchase in the wholesale electricity market. The most widely-used tariff scheme is Price-Cap, followed by Yardstick Competition with a cap on the tariff.

The main features of this regulation scheme are:

- The VAD ($/kW) is set ex-ante, based on concepts of efficiency (PBR). It is a mandatory value applied for a full tariff period, generally of 4–5 years.
- The VAD recognizes a percentage of energy losses, which is only a reference. Regulation recognizes that percentage to the utility as a fixed-standard in the pass-through of purchased energy. A bigger deviation would be an additional cost to the utility and vice versa.
- Failure to comply with quality of service terms (voltage and reliability) involves financial penalties to the utility. These are determined based on values of energy supplied with low quality ($ESLQ$) and energy not supplied (ENS), which are associated with each end user.

From the utility point of view, an important issue is to establish a model with the purpose of maximizing economic benefit. This model is primarily intended to help decide what investments should be made in the short term, for which the major regulatory rules are known. Although the VAD is pre-fixed for that period, the associated standard performance indicators are indicative but not mandatory. The utility can then adjust the established VAD according to its risk profile in order to maximize its profit. For example, it may decide not to comply with the loss standards, which involves additional costs. However, the utility may be able to defer some investments and offset these costs. Similarly, the compliance level to the quality of service could be speculated upon; it is known that it can never be absolutely satisfied. Thus, the economic benefit of the utility will depend largely on the real investment decisions to be taken that, in the Latin American context, could be affected by two main uncertainties: demand growth and electricity price in the wholesale market. Both uncertainties can affect the incomes and expenditures of the utility. For example, if the short-term demand is lower than the forecasted one, incomes will be negatively affected; or when energy losses (which are assessed at the wholesale electricity price) exceed the recognized standard, expenditures will increase. The maximum benefit will depend on the trade-off reached, considering the impact of these parameters and their associated uncertainties.

In this context, the benefit of the utility is set by (1):

$$Benefit = \sum Incomes - \begin{pmatrix} Investment\ Costs + O\&M\ Costs \\ +Losses\ Costs + Penalty\ Costs \\ for\ poor\ quality\ of\ service \end{pmatrix}. \quad (1)$$

B. Expansion Planning and Investment Decisions

The expansion of distribution networks require that investments be made in a discrete way and at a relatively significant cost. Therefore, for optimal adaptation of the network to demand, the investment must be decided in due time and form.

In the Latin American context, a hierarchical planning of the network expansion is performed, in which "expansion planning" is the first stage. This stage aims to define conceptually the large investment projects and their approximate timing, from the structural point of view. It has a horizon of long-term evaluation (10–15 years). The results of this first stage define the inputs that set the benchmark plan for a second stage of "investment decisions" associated with the short term (4–5 years, matching the tariff period). As part of this second stage, the characteristics of large investment projects and their timing are adjusted in detail every year. In addition, there is competition with alternative projects with lower investment costs, which even though they do not replace the first ones, they do modify their timing in favor of gaining some additional financial profit for the utility. This investment decision stage has also a long-term horizon, but contemplates giving special attention and consideration to the short-term period, since in it, the VAD (the tariff) is known with certainty and the utility can thus better estimate the income and the financial aspects associated with it. The objective function, in this stage, must synergistically evaluate the expected benefit of investment and its associated risk.

This work focuses on short-term investment decisions, while simultaneously considering the long-term reference plans. In this context, the utility ought to optimize the "trade-off" among the investments to be made, the costs of energy losses, and the costs from poor quality of service.

C. Distributed Generation in Latin America

According to the stricter requirements for using the DG when installing, uninstalling and reinstalling it in different strategic locations of the network, it should be able to work with three fossil-fuel technologies: diesel and gas internal combustion engine (ICE), and gas micro-turbine (MT). These technologies are chosen primarily for their wide dissemination across the world, their lower installation costs (when compared to other emerging technologies), their commercial availability, and the relative easiness with which they can be located. In addition, they are also chosen because they can provide incremental peaking capacity and could enhance local area reliability and power quality [34], [35]. This last aspect should be considered if the distribution system allows properly isolated operations of DG by providing grid ancillary services such as frequency and voltage support, in "smart microgrids", for example (as in recent projects [36]–[40]).

In a previous study conducted by the same authors [41], the cost of both installation and generation of the three above-mentioned DG technologies are evaluated. Table I shows the main technical characteristics and costs associated with the technologies in question. The costs in Table I show that gas ICE is the best alternative for base-load and peak generation. Thus, for backup use, ICEs are the most economically favorable, considering end-user oil prices between 0.65–0.95 US$/L and natural gas from 2.5–20 US$/MMBtu.

TABLE I
MAIN CHARACTERISTICS OF THE DG TECHNOLOGIES ANALYZED

	Gas Micro-Turbines	Internal Combustion	
		Gas ICE	Diesel ICE
Range of Power Rating (typical)	30-250 kW	30 kW-5 MW	20 kW-5 MW
Electrical Eficiency (%)	25-32	30-42	30-45
Equipment Lifetime (years)	10-15	15-20	15-20
Capital Costs (US$/kW)	900-1200	250-700	200-500
Generation Costs for application:			
Base-load power (US$/MWh)	47-350	32-285	132-302
Peak power (US$/MWh)	93-660	48-530	145-455
Backup power (US$/MWh)	251-7287	90-5808	182-3720

III. Flexibility Valuation in Distribution Investments

In order to mitigate the risk in expansion investment decisions, especially regarding the uncertainties in demand growth, the utility has the option of investing in robust or flexible plans. Robust ones can withstand unforeseen situations, without any change (insensitivity to the system parameters) [42]. Flexible plans allow making adjustments with lower initial investment costs, until some uncertainties are solved [43].

In distribution investment, an expansion plan that uses traditional capital-intensive investment alternatives (e.g., HV lines, HV/MV substations) can be considered a robust plan. This is mainly because, when assessing an investment of this type, it is evaluated considering the expected demand in the long term; therefore, these investments are technically tailored when they are made (robust investment). However, if an almost continually growing demand can be met with smaller investments, such as for instance investing in DG, this can be defined as a flexible expansion plan.

A. Real Options

Flexibility is an attribute related to investment decisions which adds value to a project. Real option techniques allow to evaluate the flexibility that DG may give to expansion planning [44]. Real option valuation (ROV) starts from the net present value (NPV) of a project without flexibility. Starting with (2), the value of flexibility (the ROV) is the difference between a flexible plan and a robust one. The investment required to implement a flexible plan is called "strike or exercise price (SP)", and the time to undertake such flexible investment is called "maturity date":

$$ROV = NPV_{flexible} - NPV_{traditional\ or\ robust}. \quad (2)$$

From the traditional point of view, the higher the level of uncertainty, the lower the economic value of the investment. From the viewpoint of the strategic management of uncertainty, an

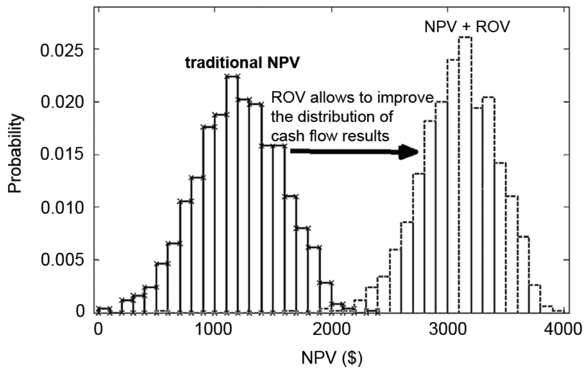

Fig. 1. Uncertainty can increase value.

increased uncertainty can produce a superior economic value if the "decision makers" are able to identify and use their options in order to flexibly respond to unforeseen developments (see Fig. 1) [45]. Under this approach, the risk of undesirable outcomes is limited, since the investor does not make the investment if market conditions are unfavorable for the project. It allows improvement of the distribution of future cash flow results in search of extraordinary profits.

Real options can be classified according to the flexibility that they give to the owner into these categories:

- Option to defer: it represents the right to postpone an investment for a period of time.
- Option to abandon: if market conditions are not as expected, it allows ending activities and selling assets.
- Option to expand or contract: it allows alteration of the size of operations if market conditions change.
- Option to switch: flexibility in the event that other project or technology may be more economical in the future.

In turn, these options can be combined together into a portfolio of options, which can be classified as:

- Independent options: when the exercising of an option does not influence the decision to exercise the other.
- Compound options: this portfolio includes options about other options. A typical example of this kind of sequential options is the right to expand capacity of a line, which is originated precisely when the initial investment option of such a line is exercised.
- Mutually exclusive options: when the exercise of an option eliminates the opportunity of execution of the remainder.

B. Option Pricing

The ROV is based on financial option pricing theory. There are three general solution methods: differential equations (e.g., Black-Scholes model), dynamic programming (e.g., binomial trees) and simulation models [44]. This paper proposes using the least-squares Monte Carlo (LSM) simulation method developed by Longstaff-Schwartz [46]. It combines the Monte Carlo simulation with dynamic programming, using least squares linear regression in order to determine the optimal stopping time in the decision-making process. Recently, Gamba [47] has presented a model that extends the LSM approach, decomposing a portfolio of multiple real options into simple hierarchical sets of individual options for assessing compound options.

The optimal option value (OV^*) of a flexible investment portfolio is estimated by finding the optimal exercise timing of the flexibility options. At a generic time "t", the model will estimate the NPV of the investment portfolio considering the uncertain variables under two possible scenarios: investing now or holding on the investment option until the next period; these scenarios represent the value of exercising an option and the continuation value of that option, respectively (3). This optimal relationship extends the classic NPV rule. The extended rule states: "*At year t, the decision-maker should not invest in the investment project (wait for at least one year) unless the NPV of the investment portfolio is greater than the continuation value.*" Once an individual option is exercised, future exercising opportunities for that option disappear. This optimization process is multi-period and dynamic, from the maturity date (T) until $t = 1$. Note that OV_t^* is the optimal NPV at year t; so in year 1 it ends up being the $NPV_{flexible}$:

$$OV_t^* = Max\left[\underbrace{(NPV_t - SP_t)}_{Exercising\,Value\,(EV)};\quad \underbrace{\frac{OV_{t+1}^*}{(1+rf)}}_{Continuation\,Value\,(CV)}\right]. \tag{3}$$

Fig. 2 shows an example of the application of (3). In this example, an independent option to defer is valuated by means of Monte Carlo simulations. The flexibility of deferring a large network investment (a traditional expansion plan without DG) by an option of investing in DG (of lower cost) is valuated. The cost of the DG investment is the SP (strike price) of this option. In Fig. 2, three generic simulations (i, m and M) and two time-periods are presented. In each simulation, the OV_T^* is the maximum value between the continuation value (CV) and the exercising value (EV) of the defer option at maturity time T; that is, the NPV of continuing with the traditional plan (without DG) and the NPV of investing in DG minus the SP, respectively. Later, from the "T" period to the previous "t" period, the OV_t^* is valuated with (3), where at time t the CV is the respective OV_{t+1}^* discounted at the risk-free rate (rf). Just like financial options, real options are valuated in a risk-neutral world at the "rf" were the investor's attitude to risk needs not be considered [44], [45]. In the companion paper [33], further details of this evaluation procedure are presented.

It should be noted that the main objective of ROV is to decide which investments should be made at the present time. From the next year onwards, the expansion plans will be re-evaluated based according to the future behavior of the system and the best-compromise investment decisions will be made.

IV. Model Description

This section presents the proposed risk-based approach for supporting expansion investment decisions, which is based on re-evaluating and re-formulating expansion alternatives on the basis of four features: long-term expansion planning results; evolution of the input parameters in the short term; consideration of its uncertainties; and the VAD. These alternatives compete among themselves from the technical and economic viewpoint. Each alternative is evaluated through an objective function which considers incomes and expenditures and that determines expected benefits with its associated risk.

In order to assess each alternative, the method of discounted cash flow is used by means of Monte Carlo simulations. The result is an expected NPV (return), the variability of which is a

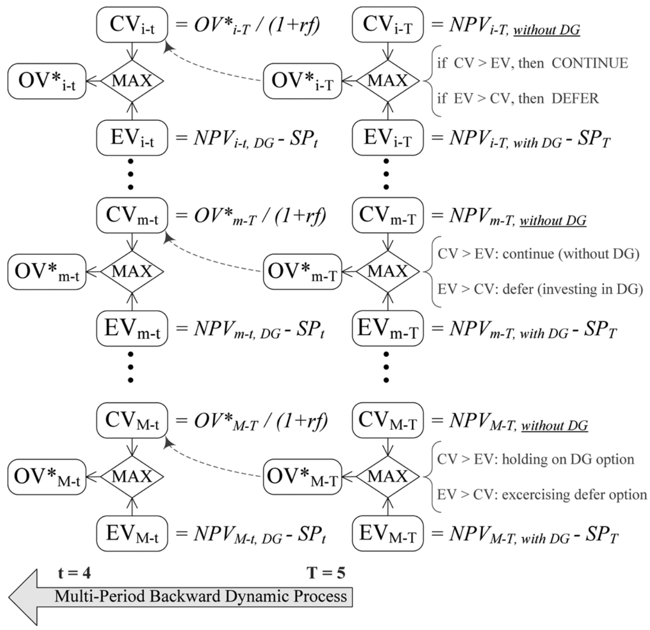

Fig. 2. Real option valuation.

measure of risk (computed by the standard deviation of NPV). In order to compare the expansion alternatives, an index which can assess the expected investment profitability per unit of risk taken within the optimization process is proposed.

As a working hypothesis, the tariff period begins at the same time the study begins, which is why it is assumed that the utility has a five-year investment program.

Therefore, the proposed index for investment assessment under uncertainty, the mathematical formulation that models the expansion problem and the outline of the proposed risk-based optimization approach are all presented below.

A. Return Per Unit of Risk

In economics and finance, risk can be defined as the probability that the real return on an investment differs from the expected return [48]. Risk includes both negative values (downside risk), lower than expected, and positive values (upside risk) [49].

A premise of investment portfolio theory states that in order to compare two assets (investment alternatives); both must have the same risk level. However, in practice it is difficult to find two assets with similar risk. Thus, the concept of an efficient investment portfolio arises, which is defined as one that has the highest expected return for a given level of risk. In this sense, it is a common practice to use risk-adjusted returns measures, such as the ratios of Sharpe [50] and Sortino [51].

The Sharpe ratio is a measure of the excess return (or risk premium) per unit of risk; where the risk is the variability of returns and is represented through the standard deviation of returns [48]. According to statistical mean-variance portfolio theory, an asset with a greater Sharpe ratio gives more returns for the same risk. This under the assumption that the returns are fairly normally distributed, i.e., the skewness of the return distribution's is zero or close to zero (returns are relatively evenly distributed on both sides of the mean). In turn, the Sortino ratio is a modification of the Sharpe which takes into account only those returns falling below a user-specified target, or required rate of return or even a

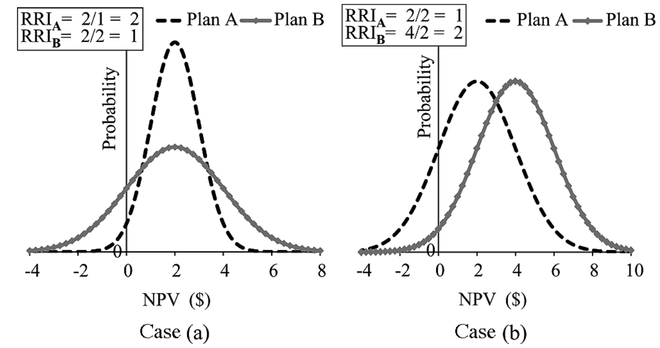

Fig. 3. Examples of project evaluation using the RRI.

required value-at-risk; where the risk is represented as the target semi-deviation (equal to the square root of the target semi-variance).

In this work, an index (the RRI) for assessing each expansion alternative in the optimization process similar to the Sharpe ratio is proposed, but it works for assessing real investments (tangible). This RRI is proposed in order to normalize the expected returns per unit of risk and, then, to properly compare the investment alternatives. The RRI is described by (4) as the expected return on the investment alternative $(E[NPV_{simulated}])$ per unit of risk $(\sigma[NPV_{simulated}])$. It is assumed that the skewness of the return distribution's is close to zero; otherwise, another index, such as the Sortino ratio, should be used. In practice, the RRI is an additional measure that complements, for example, the information given by the traditional NPV or by other risk measures such as the value-at-risk or the cash-flow-at-risk (which are usually focused on the risk of loss and the hedging risk):

$$RRI = f\left(NPV_{simulated} = \sum_{i=1}^{M} NPV_i\right) = \frac{E\left[NPV_{simulated}\right]}{\sigma\left[NPV_{simulated}\right]}. \tag{4}$$

The NPV is a cash flow (CF) function of each expansion alternative to be calculated according to (5) [48]:

$$NPV_i = \sum_{t=1}^{T} CF_{i,t} \cdot (1+r)^{-t} \mid CF_{i,t} = \left(Incomes_{i,t} - TotalCosts_{i,t}\right). \tag{5}$$

Fig. 3 presents two cases of investment assessment with different NPV probability distributions. In case (a), the proposed RRI means that for equal expected NPV (equal returns) the least risky investment project should be chosen (Plan A); whereas in case (b), for equal investment risks, the project with the greatest expected value of NPV should be selected (Plan B).

B. Additional Cost of Generation

The purpose is remunerating the utility for the energy that it generates through its own DG at the same price it is purchased in the wholesale market. This is based on the fact that, on the one hand, Latin American regulations do not allow the utility to transfer to the end user the cost overruns of the energy produced

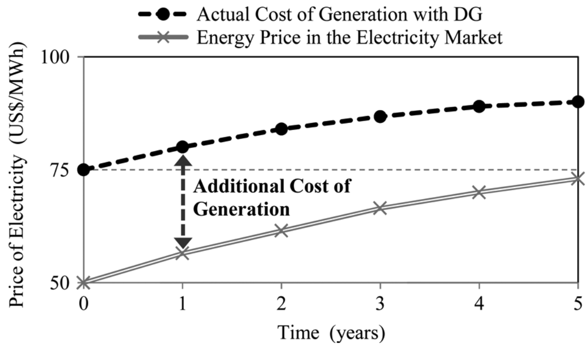

Fig. 4. Additional variable cost of DG.

by DG and, on the other hand, such cost overruns are assumed by the utility, since it uses DG to improve its own business. In general, generation costs of DG are higher than wholesale electricity prices. Therefore, when evaluating a DG investment alternative, the additional cost of generation that should be considered is the economic evaluation of the difference between the actual cost of generation with DG and the energy purchase price in the wholesale market (see Fig. 4).

C. Modeling Parameter Uncertainty

Regarding the expansion planning problem, three main uncertain parameters have been modeled with stochastic models in this work: demand growth, the installation time of a new big load, and the electricity price in the wholesale market.

Based on (1), regarding the profits of a utility, the demand impacts on incomes and expenditures. Incomes are a function of the established VAD that is paid to the utility through the tariff based on power and energy demand per month (or per year). In turn, power flows in the network are a function of load demand. This determines the energy losses, the voltage levels, and the current (or power flow) in the lines and the transformers of distribution substations (D/S). This affects directly the cost of energy losses (C_{LOSS}), the penalty cost for poor quality (C_{ESLQ}), and the ENS cost for capacity constraints $(C_{ENSxCapa.})$; and indirectly the ENS penalty cost for reliability $(C_{ENSxRelia.})$ and the additional variable cost of DG (C_{ADG}).

In this research, when performing Monte Carlo simulations, demand growth is assumed to be governed by a geometric Brownian motion (GBM) [52]. This is assumed mainly because the behavior of demand projection over time can usually be described by Brownian motion processes. However, another stochastic process can be used depending on the probabilistic input data available. For a time interval (Δt), the variation dynamics of a GBM satisfies the stochastic differential (6); where is the vector of a Wiener process. In addition, the likelihood that a big load demand in the future can be installed on the network is considered, using jumps in demand within the GBM:

$$\Delta Dp_{i,t} = \mu \cdot Dp_{i,t-1} \cdot \Delta t + \sigma \cdot \varepsilon \sqrt{\Delta t}. \tag{6}$$

The projection of electricity prices determines the value of energy losses costs (C_{LOSS}) and the magnitude of additional variable costs of DG (C_{ADG}). Electricity markets are highly developed and their behavior over time can be described by a stochastic mean reverting process, since, despite its variations in the short term, prices tend to conform to a long-term average [53]. In the present research, electricity prices are modeled by a geometric Brownian mean reverting process (7):

$$\Delta Ep_{i,t} = \alpha \cdot (Ep* - Ep_{i,t-1}) \cdot \Delta t + \sigma \cdot \varepsilon \sqrt{\Delta t}. \tag{7}$$

D. Mathematical Formulation of Investment Decisions

This expansion problem is governed by the stochastic processes that model the input parameters with uncertainty (8), performed by "M" Monte Carlo simulations during a given analysis period "T". The objective function is maximizing the RRI (9), which is a function of the NPV (10) and (11), and the constraints are represented by (12) to (15):

$$\sum_{i=1}^{M} \sum_{t=1}^{T} \begin{cases} Dp_{i,t} = Dp_{i,t-1} + \Delta Dp_{i,t} \\ Ep_{i,t} = Ep_{i,t-1} + \Delta Ep_{i,t} \end{cases} \tag{8}$$

$$Objective\ Function\colon\ Maximize\ RRI \tag{9}$$

$$RRI = f\left(\sum_{i=1}^{M} NPV_i\right) \tag{10}$$

$$NPV_i = \sum_{t=1}^{T} \frac{Inc_{i,t} - \begin{pmatrix} C_{INV} + C_{O\&M} + C_{ADG} + \\ C_{LOSS} + C_{ESQL} + \\ C_{ENSx\mathrm{Relia.}} + C_{ENSxCapa.} \end{pmatrix}_{i,t}}{(1+r)^t} \tag{11}$$

$$Subject\ to:$$

$$Line\ capacity_{i,t}\colon\ I_{Lj_{i,t}} = I_{Max.Lj_{i,t}} + \Delta I_{Exce.j_{i,t}} \tag{12}$$

$$D/S\ capacity_{i,t}\colon\ P_{Iny.D/S_{i,t}} = P_{Max.T_{i,t}} + \Delta P_{Exce.T_{i,t}} \tag{13}$$

$$Power\ balance_{i,t}\colon\ P_{Dem_{i,t}} + P_{Loss_{i,t}} = P_{Iny.D/S_{i,t}} \tag{14}$$

$$Power\ flow\ equations_{i,t}. \tag{15}$$

In this formulation, income (Inc) takes into account the VAD that is based on the demand per year, minus the ENS for both reliability and capacity of lines and D/S;C_{INV} and $C_{O\&M}$ are the investment and its incremental O&M costs for each expansion alternative assessed; the costs $C_{ENSxCapa}$ consider the ENS by capacity constraints in both lines and D/S; the current that exceeds the capacity of line "j" $(\Delta I_{Exce.j})$ is then used to compute the ENS by capacity of lines; the maximum power of $D/S(P_{Max.T})$ is set out by the power rating of transformers; the power that exceeds the D/S capacity $(\Delta P_{Exce.T})$ is used to compute the ENS by capacity of D/S; with power losses (P_{Loss}), energy losses can be calculated. Allowed voltage levels and reliability indexes are not part of the hard constraints, but are considered as variables to be optimized within the same OF. This means that the model states the extent up to which it is convenient to fulfill all the requirements for quality of service fixed by the regulation. Each expansion alternative to be assessed within the optimization process is a discrete variable to the problem; and the power flow equations—(15)—have implicit non-integer and nonlinear variables.

E. Approach for Supporting Expansion Investment Decisions

The proposed approach is a comprehensive optimization model of expansion alternatives to support investment deci-

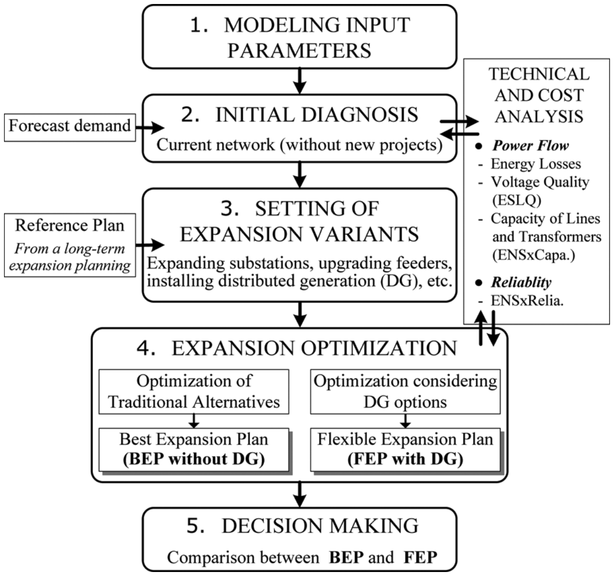

Fig. 5. Flowchart of the proposed approach.

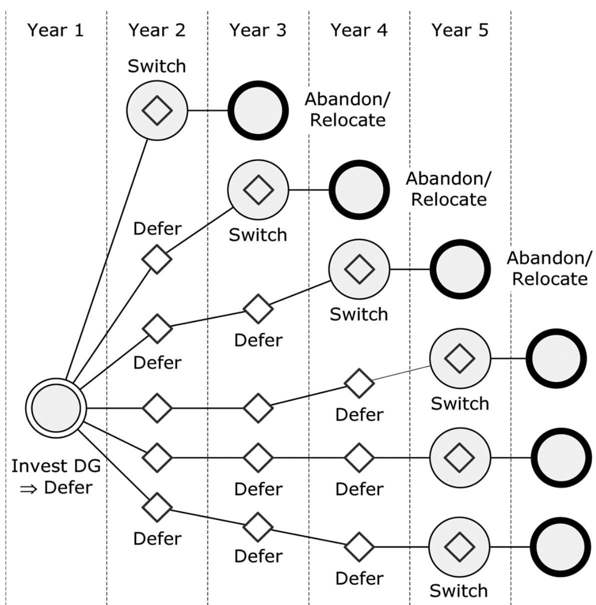

Fig. 6. Real options for deferring, switching, and abandoning the DG.

sions. Fig. 5 shows the general flowchart of the approach, which consists of five stages, as detailed below.

Regarding the "Technical and Cost Analysis", this model uses an algorithm of balanced nonlinear power flow calculation to assess the costs of energy losses and $ESLQ$ penalties (voltage quality) as well as ENS for capacity. Moreover, an algorithm of reliability assessment is employed to evaluate the ENS for reliability. In the companion paper [33], the application aspects of these algorithms are presented.

1) Modeling Input Parameters: The network and all input parameters involved in the expansion process are mathematically modeled using two ways: deterministic and stochastic. Some of the deterministic parameters are: current network data to be analyzed, demand characteristics (types of customers, typical load curves), reliability parameters, analysis period, and so on. The stochastic parameters are: demand growth, the installation time of a new big load, and the electricity prices.

2) Initial Diagnosis Network: This stage aims to identify the main problem that the current network may have when confronted with growing demand. For this purpose, several studies have been conducted, using the network without new projects, in order to identify areas with significant capacity problems and/or high voltage drops and/or low reliability, which might prevent supplying growing demand in due time and manner. This diagnosis involves short-term planning, as opposed to the expansion planning, which is viewed from a network perspective in the long term. It is defined as an initial step, since possible solutions can be set out by prioritizing and taking full advantage of the current network. These early solutions, which address local problems, are coined in this work as expansion variants.

3) Setting Network Expansion Variants: When some problem areas are identified in the previous stage, the planning engineer sets out possible expansion variants in order to address them. A local solution could be using temporary or low budget projects. Furthermore, some of the large investment projects, which are the result of an expansion planning, could be employed. These include a wide network area, as well as a permanent one and one of higher future possibilities.

At this step, traditional variants in distribution expansion are suggested, but the possibility of installing DG is also considered. Among traditional variants, new projects for MV lines are considered, such as: upgrading existing feeders and installing capacitor banks on MV busbars of D/S and feeders. Among long-term plans, expanding the D/S is taken into account, as well as building or upgrading HV sub-transmission lines. Among the DG investment variants, the type of technology to be installed (gas MT, gas and diesel ICE), location, size, and operation (for base-load, peak or backup generation) are considered.

These variants provide a basis for a later development of multiple alternative solutions, which would compete with each other. An alternative constitutes a potential expansion plan for the period under study.

4) Expansion Optimization: From the combination of the suggested variants, the optimization of expansion alternatives with and without DG is performed, maximizing the RRI (9). An expansion alternative is the combination of both expansion variants (what and where to invest) and investment timing (when to invest). Here, the expansion optimization is divided into two processes, one that poses traditional alternatives in distribution expansion, and another one that considers DG investment alternatives. From the first process, the best-compromise expansion plan (BEP) is obtained, which is called "BEP without DG". Then again, the second process is based on the previous one and raises real options for installing DG in order to defer large investments (of capital-intensive). From the BEP without DG, real compound options for deferring, switching and abandoning are identified, as shown in Fig. 6. That is, first the installation of DG is proposed in order to defer a large investment, and then the DG investment is switched for the investment which was deferred, abandoning or relocating the DG elsewhere on the network. The location, sizing, type, operation and investment timing in DG is optimized. As a result, a flexible expansion plan (FEP) is obtained which is coined "FEP with DG".

In this proposed context, "abandoning or relocating" the DG means that an installed DG unit can be uninstalled at any time and/or reinstalled elsewhere in the network to provide an advantageous and helpful expansion strategy. In fact, the major advantage of the DG proposed in this work is this strategy, based on the flexibility of temporarily deferring a large investment (with DG of lower cost). For that, the DG technologies chosen (gas MT, gas and diesel ICE) have the characteristic of being "mobile", i.e., they can be relocated (reinstalled) with relative easiness. Even if the DG cannot be relocated, it would be abandoned when performing the deferred investment. That is, the DG would be sold for a salvage value in a secondary market. From a practical point of view, for example, if there was the possibility of installing a big load demand on a network's feeder, with some likelihood of installing it within one to three years, it would be required from the utility a large investment for expanding a D/S in order to supply that big demand. Thus, the utility can choose to make a lower investment, installing DG, deferring that large investment and waiting for when the big demand will be already installed and only then performing the deferred expansion investment. Later, the DG unit would be available for re-use (reinstallation) elsewhere in the network (assuming that it has a lifetime of 10 to 20 years), maybe with a similar aim of deferring some other network reinforcement until it is economically justified.

Mathematically, the optimal solution of the expansion problem is equivalent to finding the investment decision vector (expansion plan) which maximizes the proposed RRI. This mixed integer nonlinear problem is a complex task due to its combinatorial explosion. For example, if one wishes to scan only 10 variants, considering an analysis period of 5 years for each investment and taking into account also the possibility of not performing them, more than 60 million alternatives (6^{10} alternatives) should be assessed. Therefore, the EPSO algorithm should be used to solve this problem.

The heuristic evolutionary EPSO algorithm has been applied with notable success in several complex power system problems, introducing attractive features such as self-adaptation of the algorithm parameters, robustness, fast convergence and low sensitivity to parameter initialization [54], [55]. In the second part of this paper [33], further implementation details of this optimization process, of its convergence characteristics, and computing times associated with the results, are shown.

5) Investment Decision Making: Finally, the fifth stage consists of a comparison between the BEP without DG and the FEP with DG, and how this comparison determines the decision of which expansion plan should be chosen. From this comparison the "added value of DG" is also obtained, thus properly assessing the impact of DG on power losses and quality of service, which, furthermore, makes it possible to consider the flexibility that DG provides to the expansion planning.

V. Conclusions

The characteristics and regulatory frameworks in Latin American countries and also the significant growth in demand about 3%–6% per year, would lead to have uncertainty in the deadlines projects of T&D (transmission and distribution) expansion investments. In this context, utilities have the option of temporarily installing DG at strategic locations on the network to defer T&D network reinforcements.

In this sense, this paper has addressed the problem of short-term investment decisions in distribution expansion under uncertainty, taking into account the expansion plans that determine long-term large investments. The four main contributions of this work are: implementing real options valuation to quantify the investment deferral benefit of DG; using the proposed RRI (index of return-per-risk) to assess expansion investments under uncertainty; jointly optimizing type, location, size, operation and timing of DG; and using the EPSO method in order to solve the expansion planning problem.

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