Electrical Power and Energy Systems 104 (2019) 724–733

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Risk assessment in planning high penetrations of solar photovoltaic installations in distribution systems

Mauricio E. Samper[a,*], Fathalla A. Eldali[b], Siddharth Suryanarayanan[b]

[a] Institute of Electric Energy, CONICET – UNSJ, San Juan, Argentina
[b] Colorado State University, Fort Collins, CO 80523, USA

ARTICLE INFO

Keywords:
Distributed energy resources
Energy storage
Power system planning
Renewable energy integration
Risk analysis

ABSTRACT

The stochastic nature of several renewable energy resources adds a layer of complexity to the planning of the distribution networks. Distributed energy storage is a potential solution for buffering the intermittent supply of energy from such stochastic resources and increasing reliability. This paper quantifies the benefit of investing in battery energy storage systems (BESS) along with relatively high solar photovoltaic (PV) penetrations to defer capital-intensive investments in distribution system assets. Uncertainties in the load growth and the solar PV generation are considered in the assessment of risk by using modified risk-adjusted cost ratios. Furthermore, the size and allocation of BESS in the network system are optimized by applying a heuristic algorithm. The results are demonstrated via simulations on a typical Latin American distribution network. Simulation results indicate that the flexibility of BESS for distribution planning lies in closely accommodating the growth demand and distributed PV integration.

1. Introduction

Battery energy storage systems (BESS) are integrated with distribution networks to help buffer the stochastic energy generated by renewable energy resources (RER) such as solar photovoltaics (PV). The combination of RER and BESS holds the potential for deferring capital investment on electricity grid assets by performing peak-shaving, peak-shifting, and minimizing the financial risk that limits investments in delivery networks expansion [1–3].

There is a correlation between the selections of the size and the location of energy storage systems (ESS). In the literature, several studies focused on finding the optimal choice of energy storage technologies and their dispatch profiles in order to improve supply reliability or to shave and shift the peak demand [4–6]. The work in [7] presents a heuristic planning tool using genetic algorithm (GA) to make the decision of sizing and allocating ESS in the distribution network. This intents to help the distribution system operator (DSO) to solve the problem of operating voltage rise due to high penetration of solar PV systems. The study shows that single-phase residential distributed energy storage might be more financially viable than the three-phase aggregated energy storage at the head of the feeder or at the substation.

Reference [8] proposes an optimal sizing of a hybrid energy system technique with RER independent of BESS. It calculates the net present value (NPV) to compare against the transmission line extension plans to ensure cost-effectiveness. The paper uses response surface methodology to optimize and ensure break-even of the hybrid system and its location in comparison with transmission line extension. It is worth mentioning that the paper considers the stochasticity of the input variables when solving the optimization problem.

Reference [9] presents a methodology to optimally size BESS on a microgrid system that has a variety of RER by including BESS in the unit-commitment formulation. This optimization is based on cost benefit analysis. The paper builds a mathematical model for both microgrid modes of operation (i.e., the grid-connected and the islanded modes) and uses mixed linear integer programing (MLIP) to minimize the total cost.

In [10,11], the papers attempt to examine the potential of using BESS in the low-voltage side of the distribution grid to defer upgrades needed to increase the penetration of PV. In [10], a multi-objective function is proposed to combine three objectives, which include the combination of maintaining voltage level, shaving peak demand, and minimizing the total cost. The work in [11] attempts to find the optimal sizing and location of distributed BESS. The aim of the optimization technique is to minimize the total cost considering price arbitrage and adopting different tariffs. GA is used to find the solution of the optimization problem.

From the literature, several goals are targeted by employing BESS such as peak shaving [6,12], minimizing the total cost [9,11],

* Corresponding author.
E-mail addresses: msamper@ieee.org (M.E. Samper), Fathalla.Eldali@colostate.edu (F.A. Eldali), sid@colostate.edu (S. Suryanarayanan).

https://doi.org/10.1016/j.ijepes.2018.07.052
Received 22 November 2017; Received in revised form 14 June 2018; Accepted 22 July 2018
Available online 03 August 2018
0142-0615/ © 2018 Elsevier Ltd. All rights reserved.

minimizing power losses in the distribution grid [13], and deferring investment [14].The main objective of this work is the assessment of risk in deferring capital-intensive investments in distribution grid assets in lieu of investments in BESS technologies, considering the stochasticity associated with the solar PV generation and the load growth. The expected flexibility of BESS options enables the system to closely follow the growths in demand and PV integration.

In capital asset management and investment portfolios, some risk-adjusted ratios (RARs) such as Sharpe ratio (SR) and Sortino ratio (SOR) are usually used for assessing returns of an investment per unit risk [15]. Hence, the objective in investment studies is to find the highest value of these ratios. In this work, we attempt to target the lowest total cost per unit of risk for distribution grid planning using modifications to such RARs.

The contributions of this work are: (i) a risk-based optimization framework for distribution expansion planning; (ii) two modified RARs for investment risk assessment; (iii) the analysis of investing in BESS on a real distribution network in Latin America along with high PV penetrations; considering actual data of solar-weather conditions and associated load data, cost values, and projected growth rates. This work builds on the initial results from our previous work [16,17]. In [16], we proposed an initial study of investing in BESS for supporting high penetration of PVs installed by the customers, without considering uncertainties. In [17], we quantified improvements in wind power forecasts by deferring ancillary services using newly developed metrics for RARs. In this paper, we further modify the new metrics from [17] to fit the application, and consider uncertainties along with the original framework from [16] to provide a comprehensive approach to assessing risk in distribution planning.

The rest of the paper is organized as follows. Section 2 explains the proposed framework of the optimization problem. Section 3 applies the optimization framework to a case study on a typical Argentinian distribution network. Finally, Section 4 provides the conclusions of the work.

2. Optimization problem formulation

The proposed optimization framework is based on stochastic Monte Carlo simulations (MCS) to take into consideration the uncertainties of the input variables in the distribution planning problem. The original (unmodified) SR considers the expected return (profit), $E[R]$, and the risk, $\sigma[R]$, associated with an investment portfolio as shown in (1) [15]. Further, the SR considers a risk-free rate, rf, which is usually represented by the minimum acceptable rate (MAR) of return on the investments. Note that the values of $E[R]$ and $\sigma[R]$ correspond to the mean and the standard deviation of the returns, respectively. This is under the assumption that the returns are nearly normally distributed, implying the skewness of the probability distribution of the returns is close to zero.

$$SR = \frac{E[R]-r_f}{\sigma[R]} \tag{1}$$

If the skewness of the returns distribution is non-negligible, the use of the downside deviation is better than the standard deviation for risk. In this sense, the original SOR considers those returns falling below a specified target value as the MAR that could be set to rf or zero. Then, the risk in an investment portfolio is evaluated as the target downside deviation (*TDD*) or semi-variance, as shown in (2) [15]

$$SOR = \frac{E[R]-MAR}{TDD[R]} \tag{2}$$

where, *TDD* is the root mean square of the deviations of the underperforming returns from the target return (i.e., MAR), which is mathematically computed as in (3).

$$TDD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Min(0, R_i-MAR))^2} \tag{3}$$

where, R_i is the i^{th} return, and N is the total number of returns.

In this work, both a modified Sharpe cost ratio (MSCR) and a modified Sortino cost ratio (MSOR), which are presented in (4) and (5) respectively, are proposed to assess risk in distribution expansion investments. The proposed modifications pertain to considering only the present value of the total costs (C_{Pre}) of –but neglecting the incomes from –the investments in BESS and distribution grid assets, that means for each expansion alternative assessed ($\overline{u}$). Further, it does not consider rf in (4), as it does not pertain to this analysis, and the target MAR in (5) is set to zero. The minus signs in (4) and (5) indicate the consideration of the above assumptions. C_{Pre} is computed in (6) using the following: investment cost for each expansion alternative ($\overline{u}$), C_{Inv}; the cost of energy losses, C_{Loss}; the penalty cost of energy supplied with poor quality (i.e., by violating voltage limits), C_{PQEN}; the penalty cost of violating the ratings of feeders and distribution power transformers by over load energy, C_{OEN}; the discount rate, r; and, the planning horizon, T. In (6) also is considered the total number of MCS, M. The variables t and i correspond to the indexes of the time horizon and MCS, respectively.

$$MSCR = \frac{E[-C_{Pre}(\overline{u})]}{\sigma[-C_{Pre}(\overline{u})]} \tag{4}$$

$$MSOR = \frac{E[-C_{Pre}(\overline{u})]}{-TDD(-C_{Pre}(\overline{u}))} \tag{5}$$

$$C_{Pre}(\overline{u}) = \sum_{t=1}^{T}\sum_{i=1}^{M}\left(\frac{C_{Inv}(\overline{u}) + C_{Loss}(\overline{u}) + C_{PQEN}(\overline{u}) + C_{OEN}(\overline{u})}{(1+r)^t}\right)i,\ t \tag{6}$$

Either the MSCR or the MSOR could be minimized as the objective function of the optimization problem. Based on a simply analysis performed in the previous work [17], in this work the objective function of the optimization method is to minimize the MSOR (5) by considering constraints vis-a-vis load flow, as shown in (7), and later the MSCR is just calculated for the best solutions found (corresponding to the expansion plan). The objective function is the minimizing of MSOR as follows:

$$\text{Min}\left\{\frac{E[-C_{Pre}(\overline{u})]}{-TDD(-C_{Pre}(\overline{u}))}\right\} \tag{7}$$

$$\text{subjectto} IL_{j,t} = IL_{Maxj,t} + \triangle IL_{EXCEj,t} \tag{8}$$

$$IT_{DS,t} = IT_{Max,t} + \triangle IT_{EXCE,t} \tag{9}$$

$$P_{Load,t} + P_{Loss,t} = P_{DS,t} + P_{DER,t} \tag{10}$$

The constraints (8)–(10) represent the line capacity constraint, the DS capacity constraint, and the power balance constraint, respectively. Where, the current that exceeds the capacity of a line (j), $\triangle IL_{EXCE}$, is then used to compute the overload energy, OEN; the maximum capacity of the power distribution substation (DS), IT_{Max}, is determined by the power rating of the transformers, and the current that exceeds the DS capacity, $\triangle IT_{EXCE}$, is also used to compute the *OEN*. In turn, with the power losses, P_{Loss}, the energy losses are calculated; and the nodes with high voltage drops are considered to evaluate the energy supplied with poor quality, P_{QEN}. The power of distributed energy resources (DER) that considers the power injection of both the solar PV distributed generators and the BESS is presented in (10), as well as the possibility of BESS consuming electric energy as a load; along with the power load demand, P_{Load}, and the P_{Loss}, assuming the DS as the slack node.

Each expansion alternative ($\overline{u}$) takes into account the decision variables of the optimization problem, including both conventional reinforcements of networks (such as upgrading feeders, installing capacitor banks, and expanding the DS) and the installation of BESS.

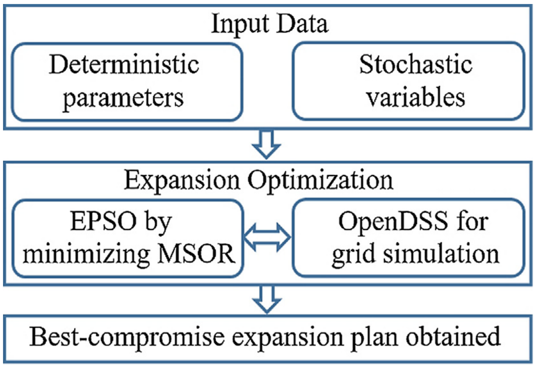

Fig. 1. General flowchart of the risk-based optimization framework.

Because the decision variables include integer, binary, real, and complex types, we can justify using heuristic optimization techniques for finding near-optimal solutions. Particularly, the Evolutionary Particle Swarm Optimization (EPSO) algorithm is applied to solve the expansion problem. It is well used in several complex power system problems, presenting appropriate qualities such as mainly self-adaptation of the algorithm parameters, robustness, and fast convergence [16,18]. Moreover, the OpenDSS® software is used for running power flow simulations and computing the energy losses, the energy supplied with poor quality (PQEN) and the over load energy (OEN). OpenDSS® is an open-source tool developed by Electrical Power Research Institute (EPRI) to model and simulate the electrical behavior of distribution grids [19,20]. This paper does not commercialize the OpenDSS® software nor does it support its exclusive use for such studies; rather, the authors present it as one of the freely available software options for conducting such distribution studies.

Fig. 1 depicts the proposed risk-based optimization problem, where the input includes deterministic parameters such as the network data to be analyzed, demand characteristics (types of customers, and typical load curves), costs of conventional reinforcements, and discount rate as well as stochastic variables such as the load growth, the PV penetration, the solar-weather conditions (temperature and irradiance), and the cost of BESS. After running the expansion optimization, the best-compromise expansion plan is obtained as a solution.

In brief, the near-optimal solution of the proposed optimization framework is mathematically equivalent to finding the investment decision option (or expansion plan) that minimizes the expected present value of the total costs, i.e., investment and operational costs, per unit of cost deviation (or risk). In this sense, the framework considers the installation of new equipment—feeders, capacitors, transformers, or BESS—to supply the expected load requirements on time and with acceptable power quality. Particularly, when the installation of BESS is optimized, the size and allocation of BESS are also optimized considering the time of their investment (i.e., the timing). In this last sense, Fig. 2 shows the computational encoding done of the relationship between the optimization algorithm (i.e., EPSO) and the OpenDSS®environment when the BESS are taken into consideration as an expansion plan, where:

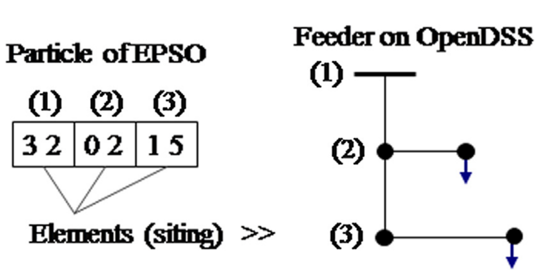

Fig. 2. Encoding of BESS as expansion plans into the optimization problem.

- the dimension or total number of elements of the particles of EPSO is equal to the number of the suggested locations for installing BESS in the network under study; and,
- each element of a particle of EPSO is represented by a two-digit integer, where the first digit represents the timing at which the BESS investment is made, e.g., 0 is not installed, 1 represents the first year, 2 denotes the second year, and so on; and the second digit indicates the sizing of BESS (i.e., the power capacity) to be installed, e.g., 1 is 250 kW, 2 is 500 kW, and 9 is 2.250 MW, where the energy capacity of BESS is also taken into account within the optimization.

Based on the encoding example in Fig. 2, the first element of the particle represents an option for installing a BESS unit in the first node of the feeder, in the third year, at a rating of 500 kW. Note that to reduce the computational time resulting from the combinatorial explosion of this large optimization problem, distributed or parallel computing may be easily used.

3. Case study and results

3.1. Data of the test system

In this study, a typical Latin American distribution network is used [16]. It is a 13.2 kV three-phase balanced network with four feeders and 20 MW of peak load demand (not coincident), as described in Table 1, where residential loads constitute 44% and 74% of the total load composition of feeders F1 and F4, respectively. Based on that, along such F1 and F4 feeders the BESS are proposed to be installed as possible allocations into the optimization framework. Fig. 3 depicts the one-line diagram of such distribution network. For this test system, actual data of load, temperature, and irradiance for the San Juan province in Argentina (30.87o S 68.98o W) are mapped [19–21]. Figs. 4 and 5 represent the typical load curves of a weekday for the residential, commercial, and industrial customers in summer and winter, respectively. Note that in the San Juan province, the average of 60% of the days per year are mostly considered summer-days and the remaining 40% as winter-days. The main data of this case study is available online on [22].

For a ten-year analysis period within the expansion planning horizon, the following parameters are assumed, in US Dollars ($), which represent typical values in Argentina:

- Cost of energy to evaluate energy losses: 100 $/MWh in year 1, growing with a constant annual rate of 5 $/MWh.
- Cost of P_{QEN} for ±5% voltage variations: 300 $/MWh.
- Cost of *OEN* for power rating violations: 1500 $/MWh.
- Annual discount rate, r: 10%.

3.2. Stochastic input data

3.2.1. Load growth

When performing MCS, the load demand growth is assumed to be governed by a geometric Brownian motion (GBM) [18]. For a time-interval, $\triangle t$, the variation of a GBM satisfies the stochastic differential

Table 1
Characteristics of Individual Demand by Customer Type.

Customer Type	Peak load		Distribution of load per feeder (%)				Power factor	Annual growth rate (%)
	MW	(%)	F1	F2	F3	F4		
Residential	8.50	42.5	44	00	34	74	0.80	6
Commercial	4.50	22.5	25	00	31	26	0.85	3
Industrial	7.00	35.0	31	100	35	00	0.90	2
$\sum$	22.0	100	100	100	100	100		

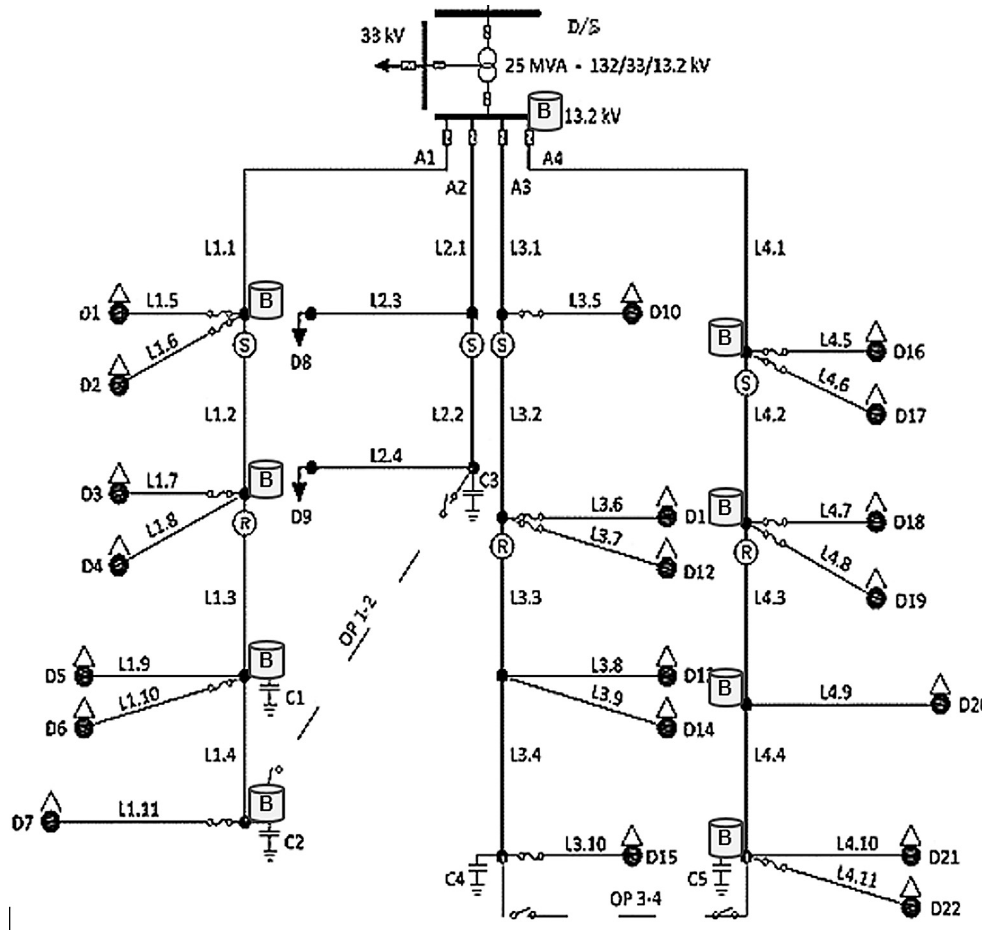

Fig. 3. One-line diagram of the distribution network under study [13], where **B** indicate the possible nodes proposed to install the BESS units.

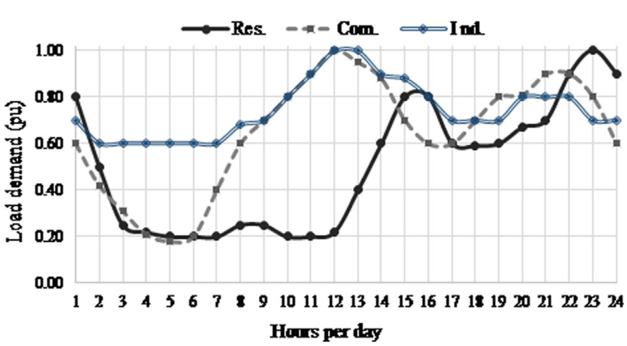

Fig. 4. Typical curves of load demand of a weekday in summer.

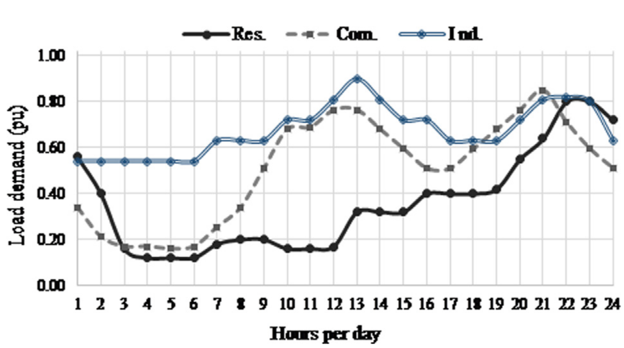

Fig. 5. Typical curves of load demand of a weekday in winter.

Eq. (11).

$$\triangle DP_{i,t} = \triangle DP_{i,t-1} \cdot (\mu \cdot \triangle t + \sigma \cdot \epsilon \cdot \sqrt{\triangle t}) \quad (11)$$

where D_p is the peak power demand per node, μ is the drift or growth rate, σ is the standard deviation or volatility, ϵ is a normally distributed random variable such that $N(0, 1)$, i is the MCS index, and t is a period of time.

Based on typical load growth data in Argentina described in [16,23], the drift values (μ) are the same annual growth rate values shown in Table 1 for each type of costumer, and the volatility values, σ, are assumed as 5% for residential customers, 4% for commercial, and 3% for industrial customers. Fig. 6 shows an example of the load growth for a residential customer of 1 MW, by running 100 MCS.

3.2.2. Solar-weather conditions

Two years of hourly solar-weather data for the San Juan province were collected and analyzed to model the distributed PV generation installed by residential customers [24]. Based on that, we performed a statistical inference study of the data to find the probability distribution functions (PDFs) for typical-weather summer and winter days. This study was performed by specifying a set of statistical models, or PDFs, and then using a model selection technique or criteria to choose the most appropriate PDF for each data set of temperature and irradiance [25]. It was specifically done by using the Open Distribution Fitting App of MATLAB® that fits univariate distributions to data by estimating its main parameters, the standard error (Std.Err) and the cumulative probability (CDF).

With the PDFs obtained, we run MCS to take into consideration the uncertainties from the temperature and the irradiance into the PV

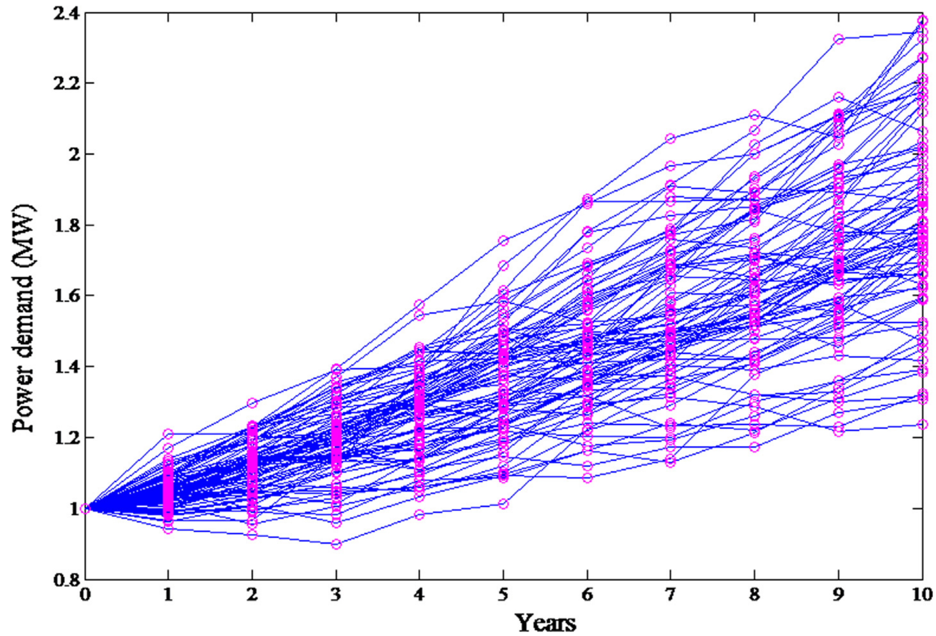

Fig. 6. Load growth for a residential customer by running 100 simulations.

Table 2
Solar-Weather Statistical Data for Summer.

Hours	irradince (kW/m^2)				Temperature (C^o)			
	Function	Parameters	Std.Err	CDF	Function	Parameters	Std.Err	CDF
06–09	Exponential(λ)	0.1004	0.0047	0.9694	Weibull (a,b)	22.856 7.483	0.1468	0.2639 0.9995
09–11	Weibull (a,b)	0.5303 3.4459	0.0073	0.1303 0.9684	Weibull (a,b)	24.5887 7.5287	0.1569	0.2642 0.9886
11–13	Weibull (a,b)	0.8993 7.7747	0.0054	0.2992 0.9917	Normal (μ, σ)	25.5081 3.6973	0.1684	0.1192 0.9996
13–15	Weibull (a,b)	1.0462 13.249	0.0036	0.5501 0.9969	Normal (μ, σ)	27.8122 3.8533	0.1755	0.1243 0.9992
15–17	Weibull (a,b)	0.9362 7.0707	0.0062	0.2835 0.9969	Normal (μ, σ)	29.6591 3.9675	0.1807	0.1279 0.9954
17–19	Weibull (a,b)	0.5775 3.2155	0.0085	0.1230 0.9866	Weibull (a,b)	32.332 9.0031	0.1720	0.3179 0.9989
19–21	Exponential(λ)	0.1316	0.0029	0.9521	Weibull (a,b)	32.0183 9.0414	0.1694	0.3282 0.9994

Table 3
Solar-Weather Statistical Data for Winter.

Hours	irradince (kW/m^2)				Temperature (C^o)			
	Function	Parameters	Std.Err	CDF	Function	Parameters	Std.Err	CDF
08–11	Exponential(λ)	0.1231	0.0056	0.9315	Normal (μ, σ)	8.7485 4.1497	0.1908	0.1351 0.9999
11–13	Weibull (a,b)	0.4330 3.9398	0.0053	0.1438 0.9987	Normal (μ, σ)	11.7648 4.4413	0.2033	0.1440 0.9999
13–15	Weibull (a,b)	0.5713 6.0784	0.0046	0.2318 0.9965	Weibull (a,b)	16.2582 3.3538	0.2406	0.1212 0.9999
15–17	Weibull (a,b)	0.4799 4.7126	0.0049	0.1717 0.9973	Weibull (a,b)	18.3536 3.9711	0.2227	0.1427 0.9991
17–19	Exponential(λ)	0.1857	0.0085	0.8840	Weibull (a,b)	18.8866 4.1604	0.2187	0.1498 0.9999

model in OpenDSS®. Also, the parameters of efficiency of the PV model were adjusted based on current PV generators installed on the roof of some houses and buildings in San Juan province [26].

Tables 2 and 3 summarize the PDFs and their statistical parameters obtained for the summer and winter seasons, respectively, where the main characteristic of the distribution functions are the rate or inverse scale parameter for the exponential function (λ), the scale parameter (a) and the shape parameter (b) for Weibull distribution, and the mean (μ) and the standard deviation (σ) for the normal function.

Based on the statistical data of Tables 2 and 3, Figs. 7 and 8 show the modeled PV generation in OpenDSS® of 100 kW by running 100 stochastic simulations for summer and winter, respectively.

3.2.3. PV penetration

In this planning study, varying levels of PV penetration between 10% and 60% are considered to account for expected growth, using uniform probability distribution. For instance, Fig. 9 presents the expected coincident power flow profile at the head of the feeder F4, which has the highest residential load demand composition (see Table 1), considering different levels of PV penetration installed by residential loads for a summer day. Similarly, Fig. 10 shows the voltage profile at the end-node of the feeder F4.

Based on the previous analysis, the BESS are set for a daily load peak-shaving operation, storing energy produced by PV generators during off-peak demand periods (between the 9th and the 12th h) and injecting it later at peak hours (between the 21st and the 24th h).

3.2.4. The cost of BESS

BESS technologies include a variety of materials such as the classic and well-known lead-acid (LA) batteries, modern redox

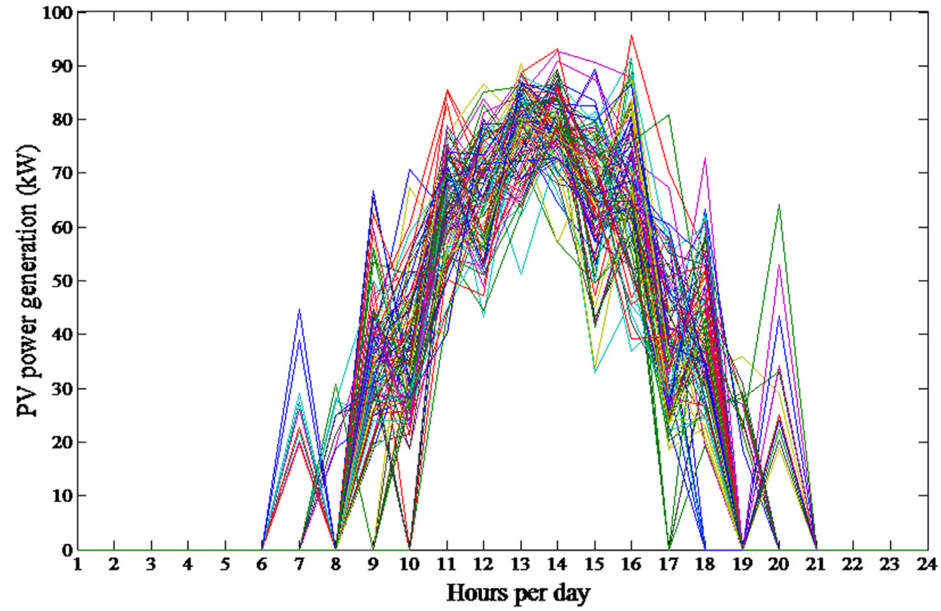

Fig. 7. PV generation in summer by running 100 stochastic simulations.

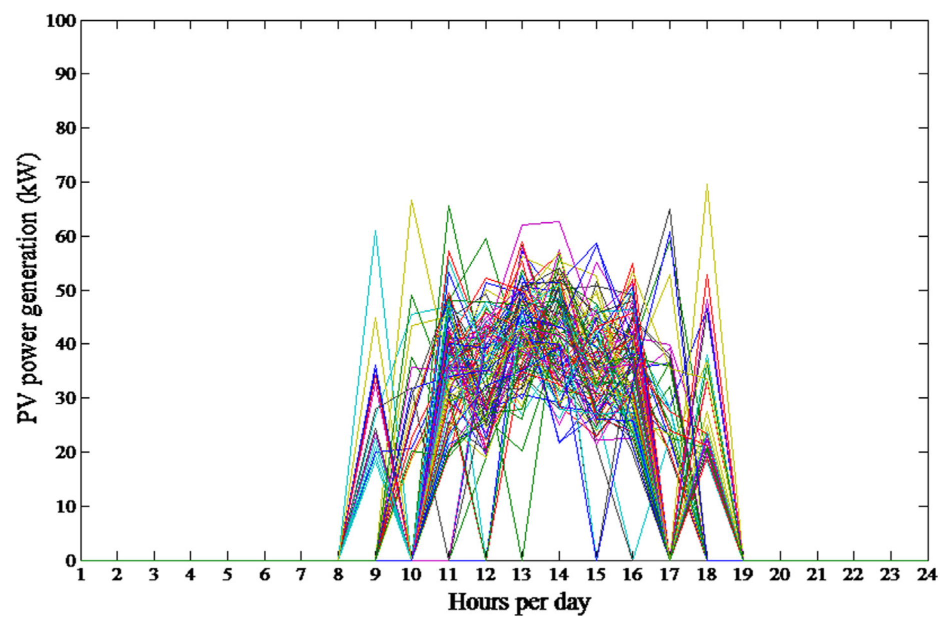

Fig. 8. PV generation in winter by running 100 stochastic simulations.

(reduction–oxidation) flow batteries, advanced-LA and new alkaline batteries such as with nickel chemistry and sodium chemistry (sodium-sulfur NaS or sodium-salt NaNiCl or ZEBRA) [2,27–30,30]. The main technical characteristics of BESS are the nominal power, in kW, the maximum energy stored, in kWh, which reflects the maximum time to store energy at the nominal power rate, their efficiency of charging and discharging, and the idling losses.

LA batteries are the most commercially mature rechargeable battery technology.Advanced-LA technologies, comprising the absorbent glass mat (AGM), have improved their efficiency and life-time cycles. NaS batteries are a commercial technology finding applications in electric utility distribution grid support, because of its long discharge period (about 6 h). ZEBRA batteries have been commercially available since 1990's for mobile applications and now are seeing deployment in the size range of 50–1000 kW. Table 4 summarizes the main characteristics of these key three kinds of batteries [28–31].

Then, advanced-LA batteries are considered for this study, assuming the following considerations: a range investment cost between 1200 $/kW and 1800 $/kW (that means between 400 $/kWh and 600 $/kWh, respectively, considering up to three hours of energy storage at maximum power); a lifetime about 4000 cycles of charging and discharging, i.e., 10 years approximately for a daily operation; and an efficiency of 10% for charging and 10% for discharging. For varying levels of this investment cost of BESS, uniform probability distribution is used.

3.3. Results

Based on the optimization problem formulation presented in the Section 2, for each expansion alternative ($\overline{u}$) and for each t year from 1 to 10-year planning horizon a MCS process is run, from 1 to M ith simulations, and then the present value of the total costs (C_{Pre}) are computed in (6). In turn, into each ith simulation the system is assessed for each-two representative day in summer and winter, considering the

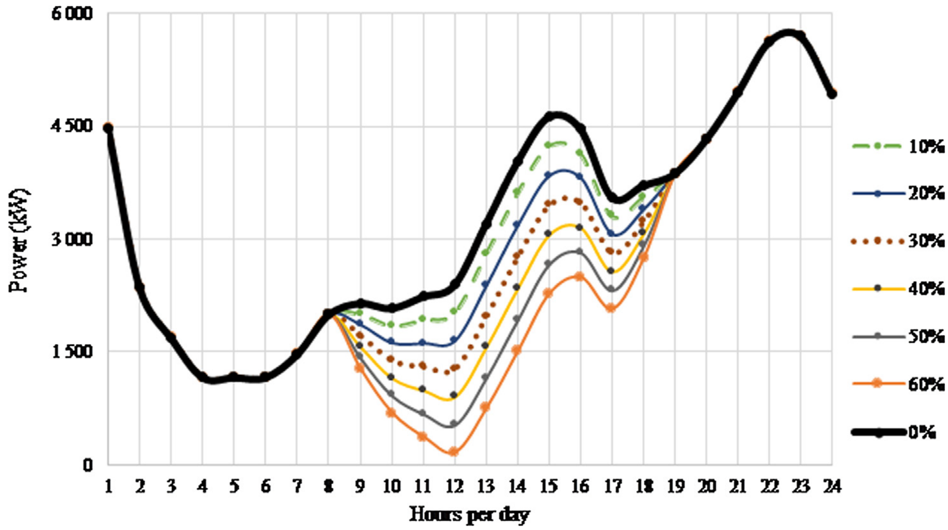

Fig. 9. Expected coincident power at the head of the feeder F4 by different levels of PV penetrations in summer.

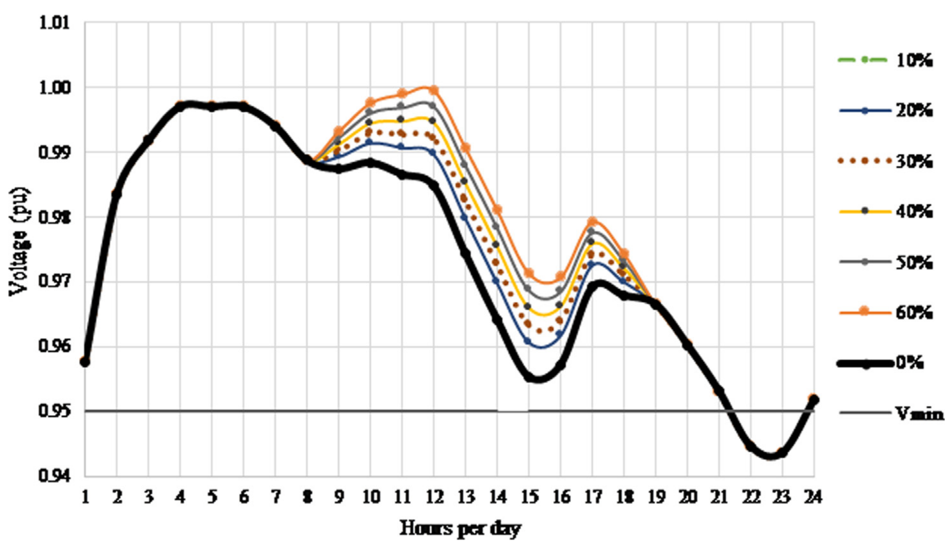

Fig. 10. Expected voltage at end-node of the feeder F4 by different levels of PV penetrations in summer.

Table 4
Characteristics of the three main BESS technologies.

BESS Technology	Efficiency	Life Cycles	Investment Cost	Energy Capital Cost
Advanced-LA	75–90 %	3000–4500 (8–12 yrs)	1000–2500 $/kW	350–750 $/kWh
NaS	75–90 %	2500–4500 (7–12 yrs)	1500–2500 $/kW	400–600 $/kWh
ZEBRA	85–90 %	2500–3000 (7–8 yrs)	1500–4000 $/kW	400–950 $/kWh

typical curve for the stochastic load demand through the GBM process (see Section 3.2.1) and the stochastic-sorted value of temperature and irradiance (based on the data depicted in the Section 3.2.2) to simulate the power generation of the solar PV penetration (through the PV model set on OpenDSS®). Later, considering the typical seasons in the San Juan province (60% summer-days and 40% winter-days, on average), the C_{Pre} are proportionally computed. This process is briefly presented in Fig. 11. Therefore, the BESS is set for a daily load peak-shaving operation, charging during the morning hours and discharging at night during the peak of demand, based on the size and allocation proposed by the optimization process itself, as observed in Fig. 12.

Then, we run the proposed risk-based optimization framework for analyzing the following three cases in the distribution network under study. For that, into the optimization process, firstly for a particular planning solution considered by the EPSO, 1000 MCS are carried out for a ten-year planning horizon, resulting in an estimation of the objective function. This procedure is iterated for a large number of planning possibilities (the search is being driven by the EPSO strategy), and the best solution at the end of the EPSO search is finally selected. Later, the best-compromise expansion plans obtained in each case were checked by running 5000 MCS.

1. Base case is the expansion planning taking into account traditional reinforcements, such as expanding the power capacity of the main distribution substation (DS), feeders, and installing fixed capacitor banks.
2. BESS option is the distribution planning for siting and sizing batteries as expansion options, by avoiding capital-intensive reinforcements such as an expansion of the main DS.
3. Flexible plan considers the installation of BESS as a flexible

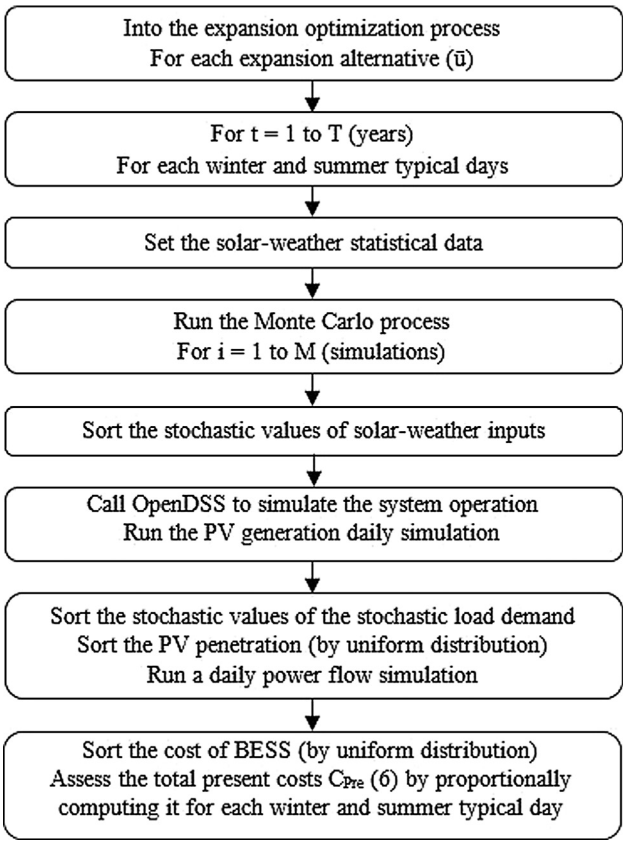

Fig. 11. Flow chart of the optimization process.

expansion option by deferring some large network reinforcement, by closely following the growth demand and the PV integration.

Table 5 and Fig. 13 summarize the results obtained for the three expansion planning cases, by running the EPSO algorithm for 50 iterations of 10 particles each, where:

- In the base case, the major investment is installing a new power transformer of 25 MVA at the main substation (DS) in the third year, with a cost of $ 3 M (which its present value is $2.25 M). The expected total cost of this plan is $3.09 M, with a significant deviation of $0.67 M (21.8%) and a MSOR equal to 0.987.
- The BESS option considers the installation of 2.0 MW in BESS, which includes installing 0.50 MW in the second year at the point of common coupling (PCC) of line L.4.4, 0.75 MW in the third year at the PCC of line L.4.3, and 0.75 MW in the fourth year at the PCC of line L.1.2.
- The flexible plan proposes to install 1.50 MW of BESS (0.50 MW in the second, third, and fourth years at the same locations, respectively, as the previous second case) by deferring the transformer investment for five years until the eight year. This plan gives a major flexibility to the distribution planner during the first half of the planning period, which could be assessed by taking into account the recovery value of such investments in BESS (through a constant-line depreciation) when the investment in expanding the main DS will be done.

Table 5
The Expansion Planning Results.

Present Value of Costs (M$)	Base case	BESS option	Flexible plan
Feeders and capacitors investments	0.1118	0.1118	0.1118
Power transformer investment at DS	2.2539	0	1.3995
Expected BESS investments:	0	2.2803	1.6363
Expected total cost	3.0917	4.9315	3.1753
Standard deviation	0.6738	0.5322	0.2615
MSCR	−4.5885	−9.2661	−12.143
TDD	3.1322	5.0055	3.2513
MSOR	0.9871	0.9852	0.9766

The second option concerns the expected present value of BESS investment of $2.28 M, without considering the large investment in expanding the main substation. In this case, the expected total cost is about 60% higher than the first case, equal to $4.93 M, but with a lower deviation of $0.53 M (10.8%) and a resultant MSOR of 0.985 (that is very close to MSOR of the base case).

The third expansion case involves the expected present value of investment of $3.03 M between both the BESS and the transformer investments, obtaining the expected total cost just about 2.7% higher than the base case, equal to $3.17 M, but with the lowest risk or deviation of $0.26 M (8.2%) and also the lowest MSOR value of 0.976.

Realizing the obtained results and specifically comparing the base case with the flexible plan indicates that their expected total costs are close ($3.09 M and $3.17 M, respectively) but the deviation of the last case is 13.6% lower than the first case, meaning the expansion plan

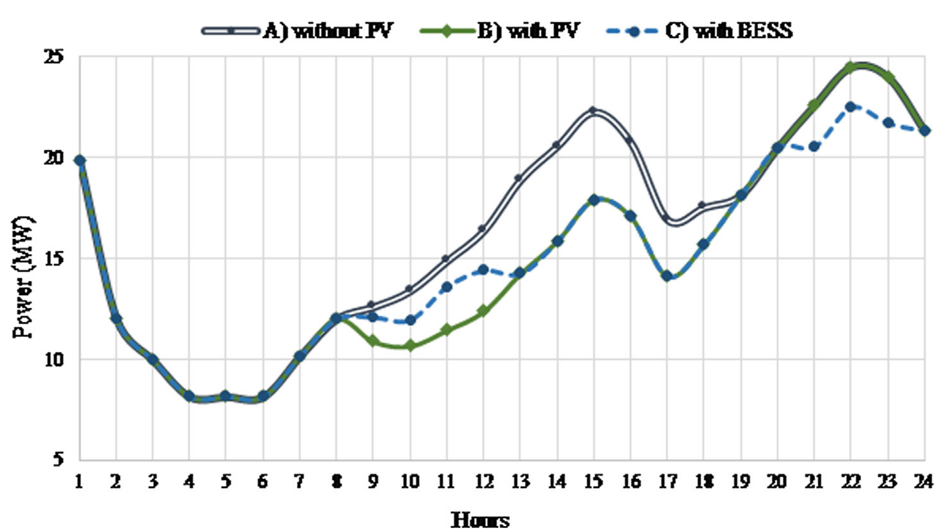

Fig. 12. Power metering at Distribution Substation for the 5th year, a summer-sunny day to: (A) considering the growthing demand but without PV generation, (B) idem to A, with a high penetration of PV distributed generation, (C) idem to B, taking into account the BESS for load peak-shaving.

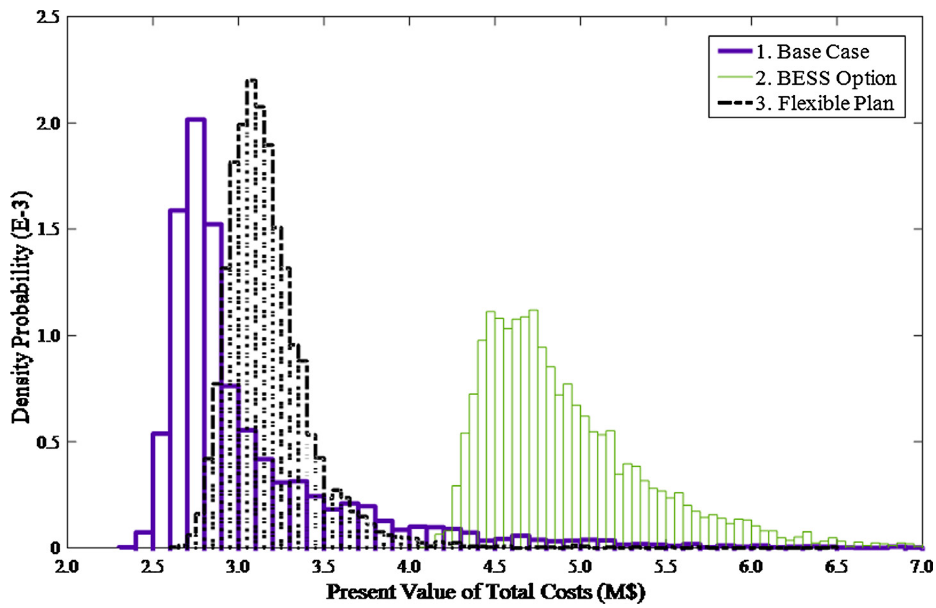

Fig. 13. Results of the risk-based expansion planning framework r.

Table 6
Sensitivity analysis of the MSOR for the base case (considering traditional reinforcements).

	PQEN	25%	50%	75%	100%	125%	150%
OEN	($/MWh)	75	150	225	**300**	375	450
25%	375	0.9996	0.9983	0.9959	0.9920	0.9800	0.9687
50%	750	0.9993	0.99975	0.9945	0.9879	0.9774	0.9719
75%	1125	0.9992	0.9978	0.9942	0.9899	0.9787	0.9696
100%	**1500**	0.9964	0.9940	0.9904	**0.9871**	0.9764	0.9672
125%	1875	0.9961	0.9938	0.9894	0.9865	0.9699	0.9586
150%	2250	0.9911	0.9867	0.9848	0.9795	0.9692	0.9623

Table 7
Sensitivity analysis of the MSOR for the flexible plan (considering the installation of BESS).

	PQEN	25%	50%	75%	**100%**	125%	150%
OEN	($/MWh)	75	150	225	**300**	375	450
25%	375	0.9962	0.9893	0.9869	0.9835	0.9724	0.9700
50%	750	0.9916	0.9822	0.9788	0.9776	0.9733	0.9673
75%	1125	0.9941	0.9881	0.9851	0.9814	0.9714	0.9689
100%	**1500**	0.9928	0.9852	0.9814	**0.9766**	0.9734	0.9702
125%	1875	0.9882	0.9853	0.9809	0.9872	0.9644	0.9549
150%	2250	0.9895	0.9871	0.9856	0.9805	0.9641	0.9519

with lower risk should be rationally chosen. In this sense, the values of both MSOR and MSCR are justly the lowest for the flexible plan.

Finally, contrasting these achieved results regarding the initial results [16], in both works the expansion plans obtained are similar. However, this work considers uncertainties and the proposed risk-adjusted cost ratios (either MSOR or MSCR) point to making near-optimal investments decisions, by choosing the expansion option with the lowest expected total cost per unit cost deviation. Based on [17], note that the MSOR allows for better decisions making to choose the option with the lower expected cost per unit of deviation.

3.4. Sensitivity analysis

Taken the base case and the flexible plan obtained in the previous section, a sensitivity analysis of both penalty costs of PQEN (energy supplied with poor quality by violating voltage limits) and OEN (over load energy by violating the ratings of feeders and distribution power transformers) was done and the results of the MSOR are presented in Tables 6 and 7. Comparing these two tables, we can confirm that in general the flexible planning is better than the base case planning, by supporting significant variations of some input parameters.

4. Conclusion

A comprehensive framework to assess risk in distribution expansion investments was proposed in this work by using modified risk-adjusted cost ratios. The framework was applied specifically to quantify the benefit of investing in BESS (battery energy storage systems), considering distributed PV generation and uncertainties in the load growth, the PV penetration, the solar-weather conditions, and the cost of BESS. Moreover, the size and allocation of BESS were optimized by considering the timing of their investment.

By application to a typical Argentinian distribution network we showed the main contribution of BESS lies in the flexibility for distribution planning by deferring large capital-intensive reinforcements. This flexibility was mainly given for closely following the uncertain growth demand along with fairly high distributed PV generation penetrations.

Future work, and under another context, may include investing in other new technological solutions such as reactive control of PV installations (to alleviate voltage fluctuations) and demand-response solutions (to tackle line congestions), instead of BESS. Besides, other extra incomes of BESS could be considered, for instance from offering ancillary services to the transmission system, by also changing the proposed modifications to the cost risk-adjusted ratios on this work, where the revenues of all kind of investment (BESS and traditional reinforcements) were neglected.

Acknowledgment

We thank the Fulbright Commission of Argentina and the CONICET for supporting the first author to visit the USA. F. Eldali is supported by the Ministry of Higher Education and Scientific Research in Libya.

References

[1] Eyer J, Corey G. Energy storage for the electricity grid: benefits and market potential assessment guide. Sandia National Laboratories 2010;20(10):5.

[2] Molina MG. Emerging advanced energy storage systems: dynamic modeling, control and simulation. Nova Science Publishers; 2013.
[3] Lyons P, Wade N, Jiang T, Taylor P, Hashiesh F, Michel M, et al. Design and analysis of electrical energy storage demonstration projects on uk distribution networks. Appl Energy 2015;137:677–91.
[4] Kraning M, Wang Y, Akuiyibo E, Boyd S. Operation and configuration of a storage portfolio via convex optimization. IFAC Proc Vol 2011;44(1):10487–92.
[5] Mitra J. Reliability-based sizing of backup storage. IEEE Trans Power Syst 2010;25(2):1198–9.
[6] Nick M, Cherkaoui R, Paolone M. Optimal allocation of dispersed energy storage systems in active distribution networks for energy balance and grid support. IEEE Trans Power Syst 2014;29(5):2300–10.
[7] Crossland A, Jones D, Wade N. Planning the location and rating of distributed energy storage in lv networks using a genetic algorithm with simulated annealing. Int J Electr Power Energy Syst 2014;59:103–10.
[8] Ekren O, Ekren BY, Ozerdem B. Break-even analysis and size optimization of a pv/wind hybrid energy conversion system with battery storage–a case study. Appl Energy 2009;86(7):1043–54.
[9] Chen S, Gooi HB, Wang M. Sizing of energy storage for microgrids. IEEE Trans Smart Grid 2012;3(1):142–51.
[10] Tant J, Geth F, Six D, Tant P, Driesen J. Multiobjective battery storage to improve pv integration in residential distribution grids. IEEE Trans Sustainable Energy 2013;4(1):182–91.
[11] Carpinelli G, Celli G, Mocci S, Mottola F, Pilo F, Proto D. Optimal integration of distributed energy storage devices in smart grids. IEEE Trans Smart Grid 2013;4(2):985–95.
[12] Reihani E, Sepasi S, Roose LR, Matsuura M. Energy management at the distribution grid using a battery energy storage system [bess]. Int J Electr Power Energy Syst 2016;77:337–44.
[13] Farrokhifar M. Optimal operation of energy storage devices with ress to improve efficiency of distribution grids; technical and economical assessment. Int J Electr Power Energy Syst 2016;74:153–61.
[14] Leou R-C. An economic analysis model for the energy storage system applied to a distribution substation. Int J Electr Power Energy Syst 2012;34(1):132–7.
[15] Rollinger TN, Hoffman ST, Sortino: A 'sharper' ratio, Chicago, IL: Red Rock Capital. http://www.redrockcapital.com/assets/RedRockSortinowhitepaper.pdf.
[16] Samper ME, Vargas A, Eldali F, Suryanarayanan S. Assessments of battery storage options for distribution expansion planning using an opendss-based framework. PowerTech, 2017 IEEE Manchester IEEE; 2017. p. 1–6.
[17] Eldali F. Spatio-temporal co-optimization of wind energy systems and the electric vehicles fleet. Preliminary Report, Dept. of Electrical and Computer Engineering, Colorado State University; 2018. p. 21–35.
[18] Miranda V, Keko H, Jaramillo A. Epso: evolutionary particle swarms. Adv Evolutionary Comput Syst Des 2007;66:139–67.
[19] Dugan RC, Taylor JA, Montenegro D. Energy storage modeling for distribution planning. IEEE Trans Ind Appl 2017;53(2):954–62.
[20] Dugan RC, Reference guide: The open distribution system simulator (opendss), Electric Power Research Institute, Inc 7.
[21] Weron R, Modeling and forecasting electricity loads, modeling and forecasting electricity loads and prices: a statistical approach (2006) 67–100.
[22] Samper M, Eldali F, Suryanarayanan S, The data of the case study, (Date last accessed on Jun. 12, 2018).https://github.com/fathallaeldali/Data.
[23] Planificacion quinquenal de crecimiento del sistema electrico provincial 2016–2020, technical report in Spanish.
[24] Mapa eolico y solar de la provincia de san juan, technical report in Spanish.
[25] Burnham KP, Anderson DR. Model selection and multimodel inference: a practical information-theoretic approach Springer Science & Business Media; 2003.
[26] Morán FA, Facchini ML, Pontoriero DH, Doña VM, Galván AG, Balance energético del comportamiento de un sistema fotovoltaico instalado en una vivienda residencial conectado a la red eléctrica de distribución, Enerǵas Renovables y Medio Ambiente (ERMA) 32.
[27] Akhil AA, Huff G, Currier AB, Kaun BC, Rastler DM, Chen SB, Cotter AL, Bradshaw DT, Gauntlett WD, Doe/epri electricity storage handbook in collaboration with nreca, Sandia Report SAND2015-1002.
[28] Kempener R, Borden E, Battery storage for renewables: market status and technology outlook, International Renewable Energy Agency (IRENA): Abu Dhabi, UAE.
[29] Li N, Hedman KW. Economic assessment of energy storage in systems with high levels of renewable resources. IEEE Trans Sustainable Energy 2015;6(3):1103–11.
[30] Subburaj AS, Pushpakaran BN, Bayne SB. Overview of grid connected renewable energy based battery projects in USA. Renewable Sustainable Energy Rev 2015;45:219–34.
[31] Zakeri B, Syri S. Electrical energy storage systems: a comparative life cycle cost analysis. Renewable Sustainable Energy Rev 2015;42:569–96.