Electric Power Systems Research 81 (2011) 984–994

Contents lists available at ScienceDirect

Electric Power Systems Research

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

Flexible investment decisions in the European interconnected transmission system

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ARTICLE INFO

Article history:
Received 22 July 2010
Received in revised form
30 November 2010
Accepted 2 December 2010
Available online 8 January 2011

Keywords:
Flexible AC transmission systems
Power system planning
Power transmission lines
Optimization
Uncertainty

ABSTRACT

Investment decisions in the power transmission system are vulnerable to substantial long-term uncertainties. Especially, in large interconnected power systems like in Europe, the impact of different influencing factors on the decision-making process is hard to estimate. In the presented approach, stochastic simulations incorporate uncertainties like the development of fuel costs and demand growth. The resulting operation plan of the available power plants and the respective utilization of the transmission network are obtained by calculating the (least-cost) optimal power flow. The performance of possible network upgrades in uncertain scenarios is evaluated by applying a real options approach based on Monte Carlo simulations. The focus of the presented work is on the strategic flexibility that FACTS devices can offer in order to appropriately cope with the uncertain development of the future. A case study for the cross-border connection between Germany and the Netherlands shows the applicability and practicability of the presented approach.

1. Introduction

The Europe-wide economic integration of the past decades has primarily been based on the creation of common markets, in which the member countries of the European Union (EU) are able to trade their goods without borders. Similarly, the liberalization of the EU power markets has taken place at virtually the same time, seeking for the creation of an Integrated Electricity Market as one of its main objectives.

But, the integration of these markets is confronted with quite different barriers, which are mainly defined by technical constraints of the transmission infrastructure [1]. This integration scenario has raised the cross-border power transfers in particular leading to highly congested TL in many interconnection corridors among countries, which significantly reduces the integration level of the EU power markets.

This situation is further aggravated by the increment of installed wind capacity, leading to new challenges for the operation of the transmission system. The output of offshore wind farms in particular has to be transported over long distances to the load centres. In addition, the regional and temporal mismatch of generation and load due to fluctuations of the actual feed-in from wind energy converters adds complexity to congestion forecasting.

These bottlenecks require congestion management methods in order to operate the electric system in an efficient and reliable way, e.g., auction, re-dispatch and counter-trade. However, these methods provide a short-term solution. On a related note, grid investments seem to be needed for relieving congestion in the long-term. The efficiency of these network investments can be quantified by the social welfare, i.e. the difference between the cost saving on the generation side, non-supplied energy and the investment costs on the grid side [2].

Nevertheless, a progressive adaptation of the transmission grid infrastructure is not an easy task due to the scale economies, lumpiness and irreversibility of Transmission Investments (TI), significantly increasing the possibility of overinvestment or under-investment scenarios. Due to the aforesaid characteristics, large and infrequent TI with low adaptability are quite common, having an high level of exposure to ongoing key uncertainties in power markets. In addition, the theory and tools for valuing TI are still below the practical needs of the new power markets, mainly in aspects such as the flexibility assessment and the utilization of FACTS [3].

In such a risky environment, the expansion plans need enough flexibility to quickly adapt to unlikely scenarios, seizing opportunities or cutting losses according to how the uncertainties develop. This flexibility should include contingent strategies at different stages of the expansion horizon, such as the options to defer, expand, contract or even abandon the project. On a related note, the flexibility to adjust to changing market conditions has a considerable value [4], which has to be considered during the

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doi:10.1016/j.epsr.2010.12.001

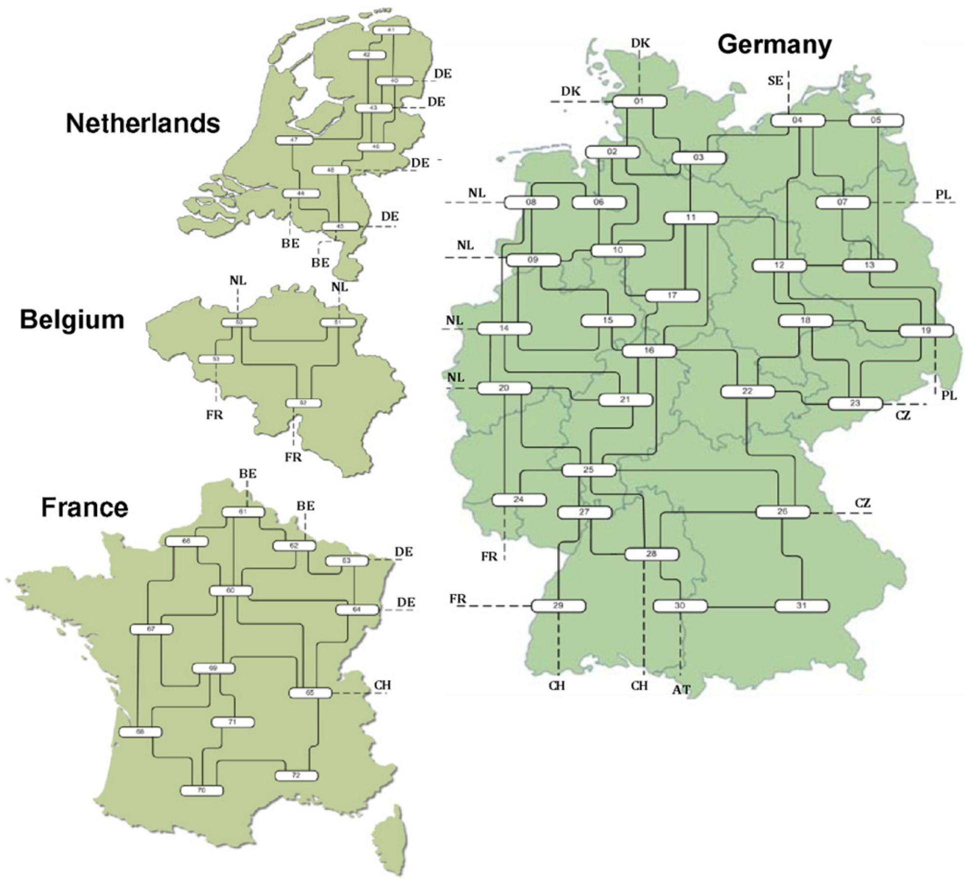

Fig. 1. Structure of the network model.

decision-making process. The real options (RO) approach is a risk management method that is becoming the subject of attention in research [4], as it allows uncertainties to be managed properly which are unresolved at the time of making investment decisions.

The incorporation of electronic-based devices, such as FACTS controllers, into the transmission expansion portfolios could significantly improve its flexibility. With this in mind, options such as deferral TLs, electronic component resale, or device relocation offer an additional value to FACTS. Some contributions have recently been made in this area [2,5–7]. However, these papers apply investment decision rules based on the Net Present Value (NPV) approach, and do not quantify the flexibility value of the FACTS.

This paper is an extension of a previous research paper presented by the authors in [8] and it aims at presenting a method for assessing flexible TI in the large European interconnected power system under uncertain scenarios. The proposed methodology accounts for FACTS devices, which add flexibility to the TI portfolio through new strategic options such as relocation and abandonment. These investments are evaluated according to the RO method by applying the Least Square Monte Carlo (LSM) approach [9], showing how the flexibility valuation is a key factor for making efficient and well timed TI.

2. Model and data

The present ENTSO-E system of Continental Europe can be expanded by alternative reinforcement measures. Their impact on the transmission capacities, and consequently, on the generating unit commitment are quantified by a market simulation based on an optimal load dispatch model. The uncertainties of how fuel prices and load growth will develop are considered by stochastic simulation and investments in new power plants by way of scenario analysis. Finally, the saving of generation costs and additional network costs can be compared by taking into account the flexibility value and a list of preferred reinforcements can be drawn up.

2.1. Network model

The optimal power flow (OPF) calculations are performed on a reduced network model which is developed to reproduce realistic situations of the transmission system in the Central Western European (CWE) region (Belgium, France, Germany, Luxembourg, and the Netherlands (NL)). In order to take possible loop-flows into consideration, nodes are also modelled in Austria, the Czech Republic, Poland, and Switzerland. The detailed features of the sample network and the utilized data are described in [10] for the German system. Fig. 1 gives an overview of the structure of the network model. In the German part, the 31 nodes are also allocated to the 16 federal states. This information is useful as relevant statistical data are often divided up into the federal states. These data comprise current and expected values of installed capacity in renewable energies like wind energy, photovoltaics, and biomass as well as the use of combined heat and power.

The model accuracy of the other considered regions and markets is nearly the same as for Germany although the focus of the entire model is the implications for the German market and the transmission system, e.g. TL loadings or necessary network upgrades. The

Table 1
Development of the power plant mix in Germany (in GW).

	2007	2010	2015	2020
Nuclear	20.5	16.5	13.0	1.3
Lignite	20.5	22.6	22.0	22.0
hard coal	30.5	33.0	34.6	32.8
natural gas	25.3	27.8	33.6	42.8
Total	96.8	99.9	103.4	98.9

numbers of nodes of the other regions are the following: Belgium: 4 nodes; France: 13 nodes; and, The NL: 9 nodes. Luxembourg is not modelled explicitly as most of it is linked to the German control area and it does not have its own power exchange.

Besides the network topology and the load situation, the feed-in from conventional power plants and its future development is essential for the analysis of possible congestions. A detailed dataset of the power plants in the modelled regions is available for the present situation. The included units can be differentiated by installed capacity, fuel type, and age. These units are assigned to the nodes of the model using geographical information.

The net generating capacity of the conventional power plants in Germany is nearly constant until 2020 with increasing capacities in hard coal and natural gas-fired plants. This is mainly due to the phase out of nuclear energy which is currently under discussion again and could end up being delayed. Moreover, the use of renewable energies, especially wind energy, is expected to increase further (Table 1).

2.2. *Stochastic simulation of the transmission investment in power markets*

As part of this work, generation cost saving is used as a yardstick to evaluate the performance of economic network upgrading. Therefore, a market model is necessary in order to replicate the behaviour of the market players and to estimate the production cost in both scenarios, with and without the proposed investment. In this work, a DC OPF calculation is carried out in order to estimate the optimal generation cost. The OPF model has been widely used in many pool-based deregulated electricity markets to calculate the generation dispatch based on the bids submitted by generators and loads, also taking into account the network constraints. The most common objective is to maximize the social welfare or to minimize the generation cost if loads are inelastic. Obviously, the OPF calculation neglects some characteristics of the real market behaviour within the system considered. For example, national borders and the respective cross-border trading cannot be looked at explicitly but are incorporated by the capacity limits of the lines. The advantage of the OPF calculation is that the results represent the true value of network upgrades irrespectively of the actual market behaviour. For the minimization of the generation cost, the optimization problem can be stated mathematically as follows:

$$\min \left[\sum_i \sum_g C_g(P_g^i) \right]$$
$$s.t. \begin{cases} \sum_g P_g^i - \sum_d P_d^i - \sum_l F^i = 0 \\ P_g^{i,\min} \le P_g^i \le P_g^{i,\max} \\ F_l^{\min} \le F_l \le F_l^{\max} \end{cases} \tag{1}$$

where C_g is the supplier bid curve and P_g^i and P_d^i are the power generated and demanded by unit g and customer d respectively at node i. The flow in all lines connected to node i is denoted by F_l. The operation limits of each generator unit are stated by $P_g^{i,\min,\max}$ and the network constraints are set by $F_l^{\min,\max}$.

The stochastic behaviour of the power market model taken as a basis in this paper can be characterized as a fundamental or bottom–up model, since annual generation costs are directly influenced by the long-term stochastic movements of fuel costs and load demand.

From an economical point of view, the stochastic cash flow, defined by the annual generation cost saving for each realization, is used in order to evaluate the performance of the transmission investment. Through setting the investment cost, stochastic discounted cash flow calculations are performed. Finally, RO techniques are applied for adding the flexibility value of each investment alternative.

2.2.1. *Load growth modelling*

Load demand growth is the major driver of expansions in power systems. Usually, aggregated power demands are modelled to be price-inelastic, replicating the lack of control of customers over their consumption at short notice. Although the load is considered price-inelastic, it is commonly assumed that customers will not be willing to consume any energy if the spot price rises above the cost of being curtailed. This cost, also referred to as the value of loss load (VOLL), is generally established by policy-makers in order to account for scenarios with power shortages because the available generating capacity is not enough to completely supply the demand.

A consistent stochastic load model should be established for some deterministic patterns as well as stochastic fluctuations around this deterministic component. To avoid unnecessary complexity, this particular component of the load model is usually modelled as an annual drift, commonly characterized as growth on an annual basis. The random deviations of the growth rate around the expected values of the annual drift, interpreted as an error of forecasted growth, are commonly assumed to be Gaussian – according to the Central Limit Theorem – by following a generalized Wiener process. This process might be formulated as shown below:

$$dz = \varepsilon \cdot \sqrt{dt} \tag{2}$$

where the variation in the variable z during a short period Δt is defined by the product of a random variable and the square root of the period length. ε is the so-called white noise, i.e. a independent and identically distributed (i.i.d.) random variable which has a Gaussian distribution with an expected value equal to 0 and a variance of 1. Then, the stochastic model of the demand growth rate dR_i, along an interval dt, can be represented by a generalized Brownian motion according to the following expression:

$$dR(t) = \mu_{d_i} \cdot dt + \sigma_{d_i} \cdot dz \tag{3}$$

where μ_{d_i} is the estimated unconditional mean load growth rate for the year t, $\sigma_{d_i}^2$ the estimated unconditional variance for this time interval and dz the Wiener process.

In this paper, the demand growth of the German power system is taken as an uncertain variable. The demand growth within the other countries looked at is taken as covered by new local generation, which is due to the lack of information about the generation capacity expansion in those countries. Nevertheless, a stochastic fluctuation around this null growth is taken into account, representing the possible inability of new generation entrance. The parameters used in the stochastic process are shown in Table 2.

2.2.2. *Generation cost modelling*

The main impact of a transmission investment on social welfare is reflected as generation cost savings through bringing down

Table 2
Demand growth parameters [11].

Country	$\mu_{d_i}{}^{\text{peak}}(0)$ [%]	$\sigma_{d_i}{}^{\text{peak}}$	$\mu_{d_i}{}^{\text{base}}(0)$ [%]	$\sigma_{d_i}{}^{\text{base}}$
Germany	1.5	0.15	1.5	0.1
Other countries	0	0.1	0	0.1

the network-related system operational costs such as out-of-merit generation costs caused by network bottlenecks. Fluctuations in transmission investment performance according to this benchmark are mainly related to generation cost fluctuations of the thermal units, which are strongly correlated with their own fuel prices. Often, the average marginal cost of generation of the unit generator g at each instant t, denoted as $\overline{MC}_g(t)$, can be derived from the average thermal efficiency $\overline{\eta}_g$ and the prevailing fuel prices p_g^F at that time:

$$\overline{MC}_g(t) = \frac{p_g^F(t)}{\overline{\eta}_g} \tag{4}$$

Therefore, the uncertainty over the generation cost savings is strongly linked with fuel price uncertainties. A reasonable and realistic way to replicate the uncertain evolution of the fuel prices is through a mean-reverting stochastic process [12]. A mean-reverting process is one where the stochastic paths evolve fluctuating around a known long-run mean. The simplest mean-reverting process is presented below:

$$d(\ln p_g(t)) = \alpha \cdot (\ln \bar{p}_g - \ln p_g(t)) + \sigma^{\ln p_g(t)} \cdot dz \tag{5}$$

where α is the speed of reversion to the mean, $\sigma^{\ln p_g(t)}$ is the volatility of natural logarithmic of fuel prices, and $\bar{p}_g$ is the normal level of the natural logarithmic of fuel price $p_g(t)$, i.e. the level to which it tends to revert.

The historical as well as the forecast data [13] on costs and prices have been used to estimate the numerical parameters of Eq. (5). These parameters are listed in Table 3. In the simulations, nuclear fuel cost prices are assumed constant over the time horizon. The main fundamental of this assumption is based on the fact that the uranium cost is only a small fraction of the total variable cost (around 5%) in nuclear plants and the deviations around the expected value are quite narrow in comparison to the fossil fuel price fluctuations [14].

2.2.3. *Weighting of the wind scenarios considered*

In order to reduce the number of calculated situations for each realization and each year, two load situations (base load and peak load) and three wind situations are taken into consideration. The probability of each wind situation occurring is determined according to the empirical histogram shown in Fig. 2. The underlying data are actual values of the wind feed-in in Germany during 2006 in a 15 min resolution. The overall installed capacity in Germany is around 19.5 GW. The histogram is divided into three sections. The first section on the left-hand side, low wind, comprises 50% of all values. The next 30% of the values are in the second section, medium wind, and the remaining 20% represent a high wind condition.

The actual wind feed-in that is used in the calculations is defined as the median in these three sections. With the assumption that 70% of the year can be represented by a base load situation, Table 4 shows the six possible combinations is obtained. Therefore, for

Table 3
Mean reversion process parameters.

Fuel type	$p_g^F(0)$ [€/MW]	$\bar{p}_g^F$ [€/MW]	$\sigma \ln p_g^F(t)$ [%]
Gas	12.46	17.94	0.129
Oil	20.99	28.21	0.3
Coal	5.51	6.64	0.14

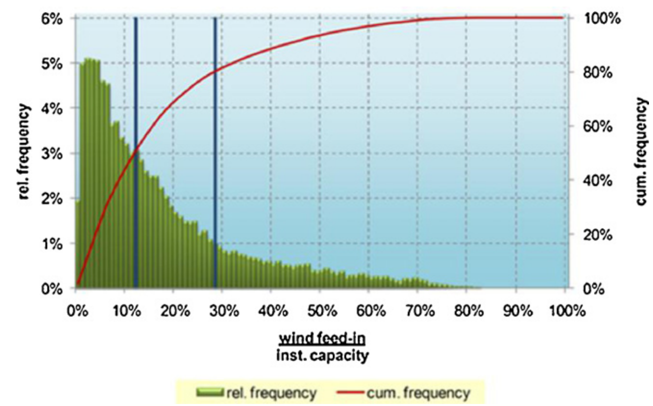

Fig. 2. Weighting of the calculations based on the frequency distribution of the wind feed-in.

each realization and each year, six situations are calculated and weighted according to their probability of occurrence in order to get representative results of one year.

2.2.4. *Modelling of pumping storage units*

The complexity in the modelling of pumping storage units results from the interdependency of the pumping and generating process. Units without any natural inflow can only generate that amount of electricity that was stored before, taking into account the limited process efficiency. In this paper, this problem is solved by a sequential simulation of the base load situation first, followed by the peak load situation. During the different base load situations, the pumping storage units are considered as dispatchable loads in the OPF. Depending on the price, a certain amount of electricity is stored in the reservoir. The assumed size of the reservoir results from the assumption that every unit is able to generate maximum power during all peak load hours. According to the previous section, 30% of the time, 7.2 h per day respectively, is considered as peak load scenario. Therefore, the reservoir has to be filled completely during the 16.8 base load hours. As a dispatchable load is modelled with negative values in the OPF model, this results in the following two constraints.

$$P_{g,\text{base}}^{i,\max} = 0 \tag{6}$$

$$P_{g,\text{base}}^{i,\min} = -\frac{P_{g,\text{inst}}}{\bar{\eta}_g} \cdot \frac{7.2 \text{ h}}{16.8 \text{ h}} \tag{7}$$

with the installed generating capacity $P_{g,\text{inst}}$ and the total process efficiency $\bar{\eta}_g$. The maximum price for storing electricity is also linked to the efficiency as the expected profit during peak load hours has to cover the expenses for the pumped energy. The expected profit is calculated on the basis of the mean of the peak prices of the previously simulated year. For the first year an assumption has to be made. If the resulting price at node i where unit g is installed is below the value $\bar{p}_i^{\text{base}}(t)$ in the base load situation, then electricity is stored in the reservoir. The cost for operation and maintenance (O&M) are also considered for calculating the value.

$$\bar{p}_i^{\text{base}}(t) = \bar{p}_i^{\text{peak}}(t-1) \cdot \bar{\eta}_g + \text{O\&M} \tag{8}$$

Table 4
Weighting of the Wind feed-in scenarios.

	Low wind (*lw*)	Medium wind (*mw*)	High wind (*hw*)	
Peak load	15%	9%	6%	30%
Base load	35%	21%	14%	70%
	50%	30%	20%	100%
Wind power feed-in	6%	19%	46%	

In the subsequent simulation of the peak load situation, the maximum generating capacity $P^{i,\max}_{g,\text{peak}}$ is set according to the stored energy; the minimum capacity is set to zero.

$$P^{i,\min}_{g,\text{peak}} = 0 \tag{9}$$

$$P^{i,\max}_{g,\text{peak}} = (l^{lw} \cdot dur^{lw} + l^{mw} \cdot dur^{mw} + l^{hw} \cdot dur^{hw}) \cdot \frac{\bar{\eta}_g}{7.2\ \text{h}} \tag{10}$$

where l^{lw}, l^{mw}, and l^{hw} represent the dispatch of the pumping storage unit during base load, multiplied by the respective duration of each wind situation. The price or marginal cost of the unit results from the weighted sum of the stored energy.

$$\bar{p}_i^{\text{peak}}(t) = \frac{(\bar{p}_i^{\text{base},lw}(t) \cdot l^{lw}(t) \cdot dur^{lw} + \bar{p}_i^{\text{base},mw}(t) \cdot l^{mw}(t) \cdot dur^{mw} + \bar{p}_i^{\text{base},lw}(t) \cdot l^{hw}(t) \cdot dur^{hw})}{(l^{lw}(t) \cdot dur^{lw} + l^{mw}(t) \cdot dur^{mw} + l^{hw}(t) \cdot dur^{hw}) \cdot \overline{\eta_g}} + \text{O\&M} \tag{11}$$

2.2.5. FACTS devices modelling

The development of flexible controllers of transmission systems, based on the progress made in power electronics, is essential to efficiently utilize the existing grid and generation infrastructure. Flexible Alternating Current Transmission System (FACTS) devices have been widely investigated during the last decades [15]. The impacts of these power electronic-based controllers on the power systems are well established; numerous investigations have analyzed FACTS on congestion management, as well as their ability to improve controllability and the security of interconnected systems [7]. These are key features in a competitive environment, where the fast-reacting FACTS controllers can really help to avoid or relieve bottlenecks, delaying the execution of large transmission line (TL) investment projects.

As mentioned, perhaps the most outstanding feature, still barely explored, that FACTS devices offer for managing network investments under uncertainty is a set of options that enhance transmission investment flexibility. Those options, such as: relocation, abandonment, operational flexibility, expansion and contraction, offer a substantial additional value to these investments and consequently, must be fairly evaluated.

Within this research, the Thyristors Controlled Series Compensator (TCSC) is analyzed under steady state operation. This FACTS was chosen since it is most appropriate for controlling power flows in the new power markets. In comparison to more conventional compensation strategies (e.g. fixed series compensation), it has the advantage of a very fast output reaction to changes in control values. In fact, given that this work tries to analyze the electric system operation under uncertainty; a continuous and flexible compensation according to the unfolding of the uncertain variables is preferred rather than fixed and discrete series compensation [8].

The mathematical model of this device modifies the reactance of the TL, allowing the TCSC to operate as capacitive or inductive compensation respectively. The rating of TCSC is defined by the reactance and current capacity of the transmission link where the TCSC is installed:

$$b_{ij} = \frac{1}{X_{Line} + X_{TCSC}}; \quad X_{TCSC} = r_{TCSC} \cdot X_{Line} \tag{12}$$

where X_{Line} is the TL reactance and r_{TCSC} is the rate which defines the degree of compensation by TCSC.

For static implementations, FACTS devices can be modelled by power injection models (PIM). The PIM model depicts FACTS as devices that inject a certain amount of active and reactive power into its nodal connections; meaning that this controller operation is replicated by these injection flows. The advantages of the PIM are that it does not lose the symmetrical structure of the admittance matrix and allows an efficient and convenient integration of FACTS devices into existing power system analytical tools [16]. On the basis of a DC power flow model, the active power flow along the TL i–j with a TCSC can be formulated as:

$$P_{ij} = b_{ij} \cdot (\theta_i - \theta_j) \tag{13}$$

These power injections are the following:

$$P_{F,i} = -P_{F,j} = \frac{X_{TCSC}}{X_{ij} \cdot (X_{ij} - X_{TCSC})} \cdot (\theta_i - \theta_j) \tag{14}$$

These power injections must be added along with the nodal power balance constraints to the classic DC-OPF problem (Eq. (1)). Moreover, the TL transfer capacity, where the TCSC is installed, may increase (10–12%) due to the stability improvement [17]. Therefore, the constraints related to the power transfer limit in the compensated branch must be also modified.

Due to the TCSC, power injections are a function of voltage angles as well, which are state variables in DC-OPF linear programming, there are no fixed limits for these power injections (although there are fixed limits for X_{TCSC}). Therefore, its operating constraints can be formulated with two additional inequality constraints, which have to be added to the DC-OPF problem (Eq. (1)). To avoid overcompensation, the working range of the TCSC is chosen between $0.7 \cdot X_{Line}$ and $0.2 \cdot X_{Line}$ [18].

$$P_{F,i} + \frac{X_{TCSC}^{\max}}{X_{ij} \cdot (X_{ij} - X_{TCSC}^{\max})} \geq 0; \quad P_{F,i} + \frac{X_{TCSC}^{\min}}{X_{ij} \cdot (X_{ij} - X_{TCSC}^{\min})} \leq 0 \tag{15}$$

3. Financial evaluation

3.1. Decision-making of investment portfolios in the transmission system

By means of the Monte Carlo simulation, the cost savings (CS) are estimated for each realization on the investment horizon. Thus the stochastic project cash flow is defined by these cash flows and the capital expenditures of the expansion project. The resulting cash flow of a Monte Carlo realization is composed of the annual $CS^s_{i,\omega}$, investments costs (I_{s,t_n}) and operation cost ($\text{O\&M}_{s,t_n}$).The resulting cash flow is discounted by the financial cost of the investment (ρ) in order to obtain the present value of the Incremental Social Welfare (ISW), according to the following expressions:

$$PV(ISW)_{s,\omega,t_n} = \sum_{y=t_n}^{M} \left(\frac{CS^s_{y,\omega}}{(1+\rho)^y} \right) \tag{16}$$

$$NPV(ISW)_{s,\omega,t_n} = \sum_{t=t_n}^{M} \left(\frac{CS^s_{t,\omega} - I_{s,t} - \text{O\&M}_{s,t}}{(1+\rho)^t} \right) \tag{17}$$

$$E\left[NPV(ISW)_{s,\omega,t_n}\right] = \sum_{\omega=1}^{\Omega} \frac{1}{\Omega} (NPV(ISW)_{s,\omega,t_n}) \tag{18}$$

where $CS^s_{i,\omega}$ and $I_{s,i}$ are the generation cost savings and the investment cost respectively in the ω realization, $PV(ISW^j_{s,k})$ and $NPV(ISW^j_{s,k})$ are the Present Value (PV) and NPV of the ISW by executing the investment strategy s in the year t_n and by M the investment horizon, finally, $E[NPV(ISW)_{s,\omega,t_n}]$ is its expected value for Ω Monte Carlo realizations. In each case, the subscripts correspond to the h-th hour, t-th year, ω-th realization of the Monte Carlo power system simulation.

If the decision was made taking the traditional NPV approach, the decision-making rule would dictate: "*When the NPV is positive, the investment should be executed*" [19]. Nevertheless, this decision rule often overlooks some implicit assumptions. Most importantly, it is assumed that the investment decisions are of a now-or-never nature when the investment is irreversible, that is, the only decisions which the investor could make are to either immediately execute the investment or discard the project. Although some investments meet these conditions, most do not. Nowadays, irreversibility and the chance of postponement are quite relevant characteristics of most investments. In fact, the ability to delay irreversible investment expenditure can have a considerable impact on the decision to invest [19]. These features often undermine the simple NPV rule, and thus the theoretical foundation of the standard neoclassical investment models.

The basic theory of irreversible investment under uncertainty, developed in [19,20], emphasizes the option-like features of the investment opportunities and proposes to develop decision rules based on methods for pricing financial options. Thus, to stress the analogy with the financial options, the opportunities to take investment decisions are called ROs. Besides the deferral option, there are many other contingent claims (e.g. abandonment, expansion, relocation, etc.), which act as a hedge for the investments in case unfavourable market conditions should turn out to be worse than anticipated. These options enhance the flexibility of investments, and represent an opportunity cost that must be included as part of the investment. This opportunity cost of investing can be large and highly sensitive to the uncertainties over the future value of the project, and investment rules that ignore it can lead to gross errors. Within the transmission network, investments cannot normally be undone and the expenditures recovered. Therefore, it is somehow necessary to redefine the NPV decision rule by including the opportunity cost of the flexibility options.

3.2. Valuing flexible investment portfolios in the transmission system

RO is a novel investment valuation technique for valuing flexibility, which applies concepts derived from financial option theory. It refers to choices regarding whether and how to proceed with investment projects. In the first RO applications, valuations were bound to options for which financial appraisal could be directly applied. The introduction of multiple interacting options into the RO models then increases the problem complexity, making these traditional analytical approaches impracticable.

In recent years, simulation procedures for solving multiple American options have been successfully proposed. One of the most promising approaches is the LSM method proposed by Longstaff and Schwartz [9]. The LSM approach is based on a Monte Carlo simulation algorithm for valuing the financial American options. More recently, Gamba [21] presented an extension of this approach for valuing a wide set of investment problems with many embedded ROs taking into account the interaction and strategic interdependence among the options. Given an American option, with a state variable X_τ, payoff $\Pi(\tau, X_\tau)$ that can be exercised from t_0 until T, its valuation function can be expressed as follows:

$$F(t, X_\tau) = \max_{\tau \in T} \left\{ E_t^* \left[\Pi(\tau, X_\tau) \cdot (1+\rho)^{-(\tau - t)} \right] \right\} \tag{19}$$

where τ is the optimal stopping time ($\tau \in [t, T]$) and the operator $E_t^*[\cdot]$ represents the risk neutral expectation conditional on the information available at t_n, which could also be expressed by $E^*\left[\cdot \middle| \mathcal{F}_t\right]$. The discount factor between any two periods is $df = (1+\rho)^{-1}$.

Under this approach, the underlying asset evolution is simulated through a Monte Carlo simulation. Then the optimal stopping policy for each simulated path is obtained using Bellman's principle of optimality: "*An optimal policy has the property that, whatever the initial action, the remaining choices constitute an optimal policy with respect to the sub-problem starting at the state that results from the initial action*" [19]. This means it is possible to split the decision sequence into two parts, the immediate period and the whole continuation beyond that:

$$F(t_n, X_{t_n}) = \max \left\{ \Pi(t_n, X_{t_n}), E_{t_n}^* \left[F(t_{n+1}, X_{t_{n+1}}) \right] \cdot df \right\} \tag{20}$$

At this point the LSM makes its key contribution. This approach proposes to compute the continuation for all previous time-stages by regressing from the discounted future option values on a linear combination of functional forms of current state variables [22]. Working recursively until $t = t_0$, the optimal decision policy on each path can be computed, choosing the largest between the immediate exercise and the expected continuation value. Finally, the American option value is calculated by applying the following equation:

$$F(0) = \frac{1}{\Omega} \sum_{\omega=1}^{\Omega} \Pi(\tau(\omega), X_{\tau(\omega)}) \cdot (df)^{-\tau(\omega)} \tag{21}$$

As pointed out in [8], traditional investment appraisal methods are normally inappropriate when assessing transmission investments, since the presence of uncertainties dramatically increases the risk involved in irreversible large-scale decisions. Moreover, these investments have embedded multiple flexible options which are difficult to assess but which have a significant impact on optimal decision-making.

The following have been considered as investment alternatives: firstly, a FACTS device and secondly, a TL. Therefore, the available investment strategies either invest in the FACTS first, in the line first or both in the FACTS and the line. The strategic flexibility of postponing both investments as well as abandoning or relocating the FACTS device are compounded options. Hence, these available options are valued by means of the LSM method, by applying the following Bellman's equations [8]:

1. Option to invest in the FACTS first:

$$F_F(t_n, X_{t_n}) = \max \left\{ \begin{array}{l} \Pi_F(t_n, X_{t_n}) + \max(F_R(t_{n+1}, X_{t_{n+1}}); F_A(t_{n+1}, X_{t_{n+1}}); F_{TL}^F(t_{n+1}, X_{t_{n+1}})) \cdot df; \cdots \\ E_{t_n}^*[F_F(t_{n+1}, X_{t_{n+1}})] \cdot df \end{array} \right\} \tag{22}$$

2. Option to invest in the line first:

$$F_{TL}(t_n, X_{t_n}) = \max \left\{ \Pi_{TL}(t_n, X_{t_n}) + F_F^{TL}(t_{n+1}, X_{t_{n+1}}) \cdot df; E_{t_n}^*[F_{TL}(t_{n+1}, X_{t_{n+1}})] \cdot df \right\} \tag{23}$$

3. Option to invest both in the FACTS and the line:

$$F_{TL\&F}(t_n, X_{t_n}) = \max \left\{ \begin{array}{l} \Pi_{TL\&F}(t_n, X_{t_n}) + \max(F_R^{TL\&F}(t_{n+1}, X_{t_{n+1}}); F_A^{TL\&F}(t_{n+1}, X_{t_{n+1}})) \cdot df; \cdots \\ E_{t_n}^*[F_{TL\&F}(t_{n+1}, X_{t_{n+1}})] \cdot df \end{array} \right\} \tag{24}$$

where $F_m^n(t_n, X_{t_n})$ is the option value and $\Pi_m^n(t_n, X_{t_n})$ the profit value, both for the option m (F: FACTS, TL: transmission line, R:

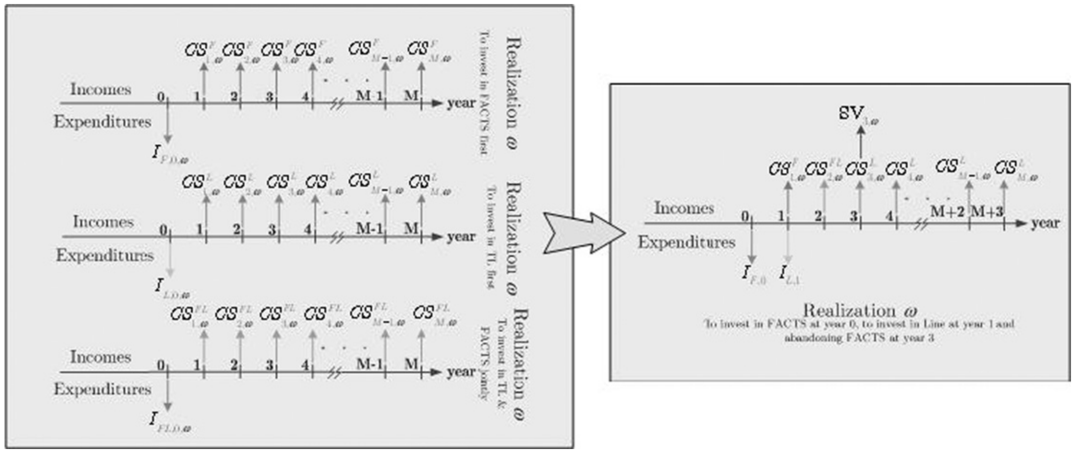

Fig. 3. Cash flow sequence of a transmission investment strategy.

FACTS relocation, A: FACTS abandon) in the state n (F: FACTS investment done, TL: line investment done, Ab: FACTS abandon done. Expanding Eq. (22):

$$F_R(t_n, X_{t_n}) = \max \left\{ \begin{array}{l} \Pi_R(t_n, X_{t_n}) + \max(F_{TL}^{R}(t_n, X_{t_n}); F_A(t_{n+1}, X_{t_{n+1}})) \cdot df; \cdots \\ E_{t_n}^{*}[F_R(t_{n+1}, X_{t_{n+1}})] \cdot df \end{array} \right\} \quad (25)$$

$$F_A(t_n, X_{t_n}) = \max \left\{ \Pi_A(t_n, X_{t_n}) + F_{TL}^{A}(t_n, X_{t_n}); E_{t_n}^{*}[F_A(t_{n+1}, X_{t_{n+1}})] \cdot df \right\} \quad (26)$$

$$F_{TL}^{F}(t_n, X_{t_n}) = \max \left\{ \begin{array}{l} \Pi_{TL}^{F}(t_n, X_{t_n}) + \max(F_R^{TL\&F}(t_{n+1}, X_{t_{n+1}}); F_{Ab}^{TL\&F}(t_{n+1}, X_{t_{n+1}})) \cdot df; \cdots \\ E_{t_n}^{*}[F_{TL}^{F}(t_{n+1}, X_{t_{n+1}})] \cdot df \end{array} \right\} \quad (27)$$

In the same way, developing Eqs. (23) and (24):

$$F_F^{TL}(t_n, X_{t_n}) = \max \left\{ \begin{array}{l} \Pi_F^{TL}(t_n, X_{t_n}) + \max(F_R^{TL\&F}(t_{n+1}, X_{t_{n+1}}); F_{Ab}^{TL\&F}(t_{n+1}, X_{t_{n+1}})) \cdot df; \cdots \\ E_{t_n}^{*}[F_F^{TL}(t_n, X_{t_{n+1}})] \cdot df \end{array} \right\} \quad (28)$$

$$F_R^{TL\&F}(t_n, X_{t_n}) = \max \left\{ \Pi_R^{TL\&F}(t_n, X_{t_n}) + F_{Ab}^{TL\&F,R}(t_{n+1}, X_{t_{n+1}}) \cdot df; E_{t_n}^{*}[F_R^{TL\&F}(t_{n+1}, X_{t_{n+1}})] \cdot df \right\} \quad (29)$$

$$F_A^{TL\&F}(t_n, X_{t_{n+1}}) = \max \left\{ \Pi_A^{TL\&F}(t_n, X_{t_n}); E_{t_n}^{*}[F_A^{TL\&F}(t_{n+1}, X_{t_{n+1}})] \cdot df \right\} \quad (30)$$

In the investment cases:

$$\Pi_m^n(t_n, X_{t_n}(\omega)) = PV(ISW)_{s,\omega,t_n} - I_{s,t_n,\omega} \quad (31)$$

where $I_{s,t_n,\omega}$ is the investment cost of the s-th investment strategy at the t_n-th year. On the other hand, in the relocation and abandon cases:

$$\Pi_R^n(t_n, X_{t_n}(\omega)) = PV(ISW_{R,t_n,\omega}) - CR_{t_n,\omega} \quad (32)$$

$$\Pi_A^n(t_n, X_{t_n}(\omega)) = SV_{t_n,\omega} - PV(ISW)_{s,\omega,t_n} \quad (33)$$

where $CR_{t_n,\omega}$ is the relocation cost and $SV_{t_n,\omega}$ is the scrap value of the FACTS devices by the t_n-th year.

The present values, expressed in Eqs. (30)–(32), are calculated according to Eq. (16) and regarded as underlying assets for the RO valuation. The resulting cash flow is calculated based on each available investment strategy. An illustrative example is shown in Fig. 3, where one strategy of investing in the FACTS first, then investing in the line one year later and finally abandoning the FACTS device during the third year, is shown. In all cases, the investment project starts running one year after the investment is made. It is important to note that all possible investment strategies and their intrinsic ROs have been evaluated exhaustively, that is all possible combinations among the available flexibility options are assessed.

The option values for each strategy are calculated by applying this procedure. Hence, the optimal investment strategy is the one with the highest value. It is important to note that the optimal decision policy obtained by the LSM approach is not a deterministic value. In fact, there is an optimal policy for each simulated path. Therefore, it is possible to determine a Probability Density Function (PDF) of option values.

The accuracy of the estimates of the value of the option values can be improved by increasing the number of time steps N, the number of simulated path Ω. Hence, the Monte Carlo stop criterion applied is the control of the relative error [23]. Setting $\delta = 10\%$ entails demanding a confidence level in the attributes assessment of 95%.

$$e_s(F_n^m(0), \sigma_{F_n^m(0)}) = \frac{\phi^{-1}(1-(\delta/2)) \cdot \sigma_{F_n^m(0)}}{F_n^m(0) \cdot \sqrt{\Omega}} \quad (34)$$

where ϕ^{-1} is the inverse of the Standard Normal Distribution (SND), $(1-\delta/2)$ the confidence level specified, $\phi^{-1}(1-\delta/2)$ the critical value of a SND with mean 0 and standard deviation 1 and $\sigma_{F_n^m(0)}$ the volatility of the expected option value. In this paper it is assumed as maximum relative error 1%.

4. Study case: simulations and results

4.1. Calculation of the investment option values

Based on the framework shown in the previous sections, the impact of two network upgrades on the OMG cost is analyzed. These upgrades are the development of a new 380-kV-double-circuit and the installation of a FACTS device. Both upgrades represent measures to strengthen the German–Dutch interconnections due to

Table 5
Ranking of strategies by applying the proposed evaluation approach and the traditional appraisal.

Strategy	Expected option value (M€)	Expected NPV value (M€)	Flexibility (M€)
S_1	278.870 (1st)	46.227 (3rd)	232.643 (1st)
S_2	194.699 (3rd)	108.826 (2nd)	85.873 (3rd)
S_3	229.866 (2nd)	141.368 (1st)	88.498 (2nd)

the fact that these are among the most important corridors within the Central Western European region. Hence, an interconnection project, which is currently under study, is compared to flexible investment in order to shed some light on the influence of the strategic flexibility on the optimal decision-making process.

The upgrades have the following features: (1) Development of a new 380-kV-double-circuit over a length of 85 km between nodes 14 and 48, leading to investment costs of about 59.5 M€ and annual operating costs of about 0.595 M€/year. (2) Installation of a TCSC device of −130/40 MVar between nodes 8 and 40, with the option to relocate it between nodes 20 and 45, leading to investment costs of about 30.8 M€ and annual operating costs of about 0.308 M€/year [17]. In addition, the scrap value of the FACTS device and its relocation cost are considered equal to 40% and 20% of the total capital cost *I* respectively [8].

Therefore, the three mutually exclusive options (strategies) are evaluated, i.e. investing in the FACTS device first (S_1), investing in the TL first (S_2) or, investing both in the FACTS and TL (S_3).

Three years are considered as the maturity for all investment options and 15 years as the investment horizon. Lead construction time is assumed to be one year and the discount rate is set to 8%/yr for all the TL projects. The network and data described in the previous sections is applied in 1000 realizations of the Monte Carlo simulations for ensuring the maximum relative error established in the last section. Thus, many OPF calculations are performed for each scenario. By this means, the stochastic annual generation cost savings is estimated.

The results of the investment evaluations are depicted in Table 5. The traditional NPV appraisal suggests S_3 as the optimal investment choice. Conversely, the RO valuation determines S_1 as the optimal decision through taking into account the flexibility provided

Table 6
Relative frequency of the optimal investment decision and relative frequency of the optimal execution of the option generated by the FACTS investment.

Option	Never	Year 0	Year 1	Year 2
Investing in FACTS first	0%	43.1%	56.9%	0%
Investing in the Line once the FACTS investment has been made	0.1%	–	1.7%	98.2%
Relocating the FACTS once the investment has been made	0%	–	0.2%	99.8%
Abandoning the FACTS once the investment has been made	100%	–	0%	0%

Table 7
Option value and volatilities.

Strategy (M€)	Volatility level		
	0%	100%	200%
S_1	225.7	278.9	283.7
S_2	154.1	194.7	202.4
S_3	177.7	229.9	230.1

by each strategy. Since the option value can be calculated according to (21), the economic value of the flexibility of each investment strategy is given by the difference between the option value and the expected NPV value.

Both the PDF as well as the cumulative distribution functions (CDF) are shown in Fig. 4. It can be seen that with a probability larger than 95%, the option value of the strategies S_1, S_2, S_3 are about 193 M€, 121 M€ and 152 M€ respectively. Therefore, the optimal flexible investment strategy, though the traditional investment appraisal (NPV) indicates S_2 as the optimal investment alternative, is to invest in FACTS devices first. The strategic flexibility of FACTS remains after the investment has been made, allowing for a better adaptation to adverse scenarios that can take place in the long term.

Table 6 portrays the relative frequency of the optimal investment policy for S_1. It can be seen that there is a slight trend to exercise the investment option in year 1. This means postponing the investments for one year. Nevertheless, the number of scenarios where FACTS is installed immediately is quite significant. It is also

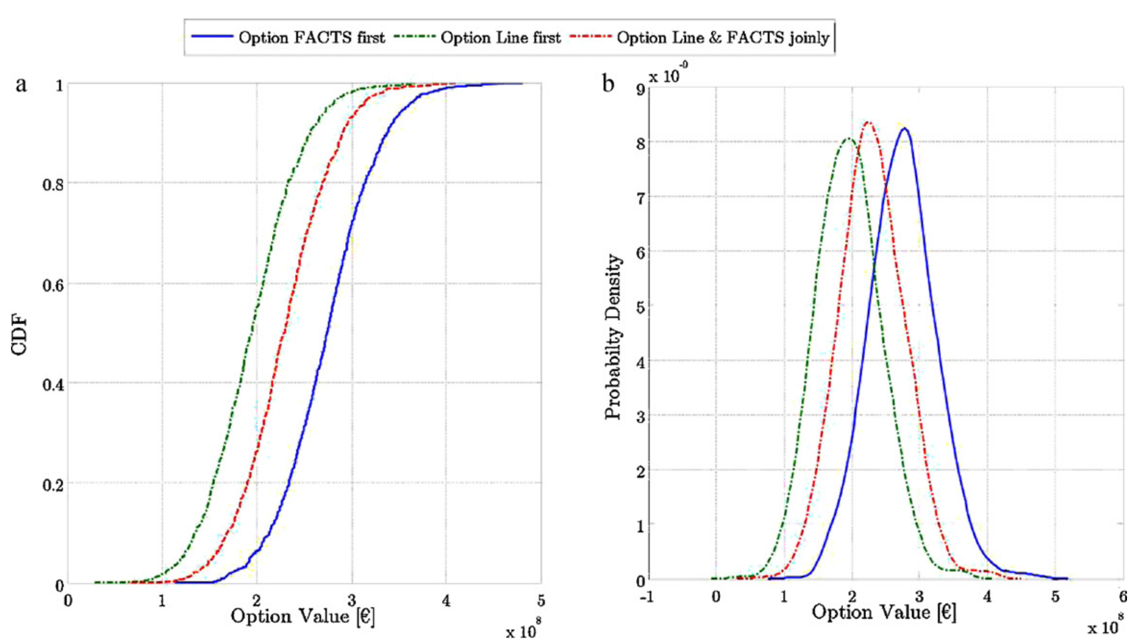

Fig. 4. (a) CDF, and (b) PDF of the analyzed strategies.

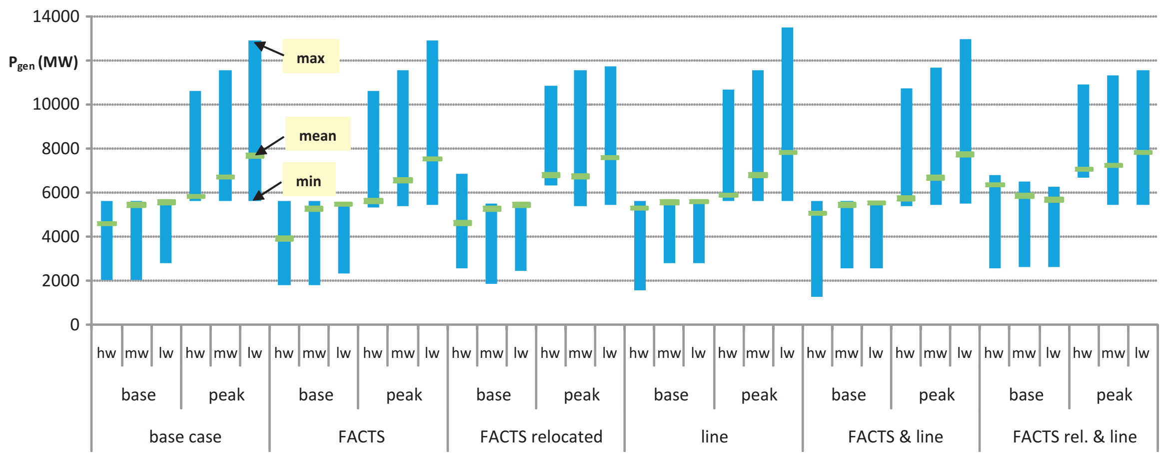

Fig. 5. Fluctuation margin of the total generation in the NL, depending on the network upgrades for all regarded load and wind situations (year 2).

Table 8
Mean Values of the loading of all cross-border lines connecting the NL (year 2).

Investment scenario	Base			Peak		
	hw	*mw*	*lw*	*hw*	*mw*	*lw*
Base case	40.8%	29.3%	27.2%	44.7%	39.4%	33.9%
FACTS	42.2%	30.3%	27.8%	45.8%	40.5%	34.7%
FACTS relocated	40.5%	30.2%	28.0%	39.0%	39.2%	34.4%
Line	34.3%	24.2%	22.6%	37.0%	32.5%	27.5%
FACTS & line	34.1%	24.9%	22.9%	37.7%	33.0%	28.0%
FACTS rel. & line	29.1%	22.8%	22.2%	31.2%	30.4%	27.5%

important to highlight that the investment is made in any scenario in either of the first two years.

In addition, the optimal execution strategy of the sequential option generated by the FACTS investment is shown in Table 6. As is shown, the options of relocation and line investment (once FACTS installed) are most likely executed on their maturity dates.

In the analytical RO approach, the most important prerequisite is the positive correlation between the value of an investment opportunity and the volatility of the underlying asset. For proving this relationship through the proposed simulative approach, the volatilities of the demand growth as well as of the fuel prices are in three different levels: firstly, completely deterministic, volatilities equal to zero; secondly, the volatilities used in the calculations done before; and thirdly, the volatilities are doubled compared to the aforementioned scenario. For these three levels, the simulations are carried out and the option values for each investment strategy are estimated. As shown in Table 7, this tendency remains. The option value increases in all cases where the volatility increases. This also shows that the investment portfolio with FACTS has improved the most. This attribute is highly desirable in view of the ongoing growth of uncertainties in the deregulated power markets.

4.2. Impact of the network upgrades

In order to analyze the impact of the different possible network upgrades from a technical point of view, the total generation in the NL is taken from the OPF calculations first of all. The generation in the NL provides an indication regarding the utilization of the transmission network because the NL can only import electricity from Germany and Belgium. Due to the power plant mix with only a few low-cost power plants, NL nearly always imports electricity.

Table 8 summarizes the mean values of the relative loading of the cross-border line connecting the NL with Germany and Belgium in year 2. This year is the first point at which one of the network upgrades can be in operation. After the decision in year 0, one year is assumed for the construction, leading to possible operation in year 2. It can be seen that the load/wind situation shows a higher influence on the line loading than the different network upgrades. The interconnections in all cases, even in the base case, are operating below their capacity rates, mainly because of the appearance of congestions in another interconnection line, which connect the cross-border flow from German wind generation to the NL. Here it should be noted that the only investment strategy which increases the power importation of the NL is the FACTS investment. This could be interpreted as the FACTS controller being able to take maximum advantage of the existing interconnected capacity by operating the existing grid infrastructure more efficiently.

Fig. 5 summarizes the resulting generation for the six load/wind situations looked at as well as the different network upgrades. Obviously, the main driver is the load level but also the actual wind generation in Germany considerably influences the generation in the NL. The high fluctuation margin within the 1000 realizations for each situation is already quite remarkable for the depicted year 2.

Despite the fluctuations within one load/wind situation, no clear trend arises from the network upgrades. Even though the total cross-border capacity between the NL and Germany is increased by any of the upgrades, the importation into NL and the respective total generation does not change significantly. Neither the mean values nor the fluctuation margins are influenced in a clear direction. This highlights on the one hand the complexity of even this reduced portion of the actual power system. On the other hand, these observations clarify the necessity to consider quite a high number of different situations and stochastic influences in order to evaluate long-term impacts on the power system in particular.

5. Conclusions

In this paper, the application of a new framework has been presented for assessing flexible investments in the European interconnected transmission network under uncertainties. The focus is on the economic valuation of the options of relocation and abandonment of FACTS devices. The main uncertain variables which define transmission operation performance have been modelled and correctly handled by selecting flexible expansion projects aiming at improving investment risk profiles. It has been revealed that traditional investment appraisal methods may be unsuitable for valuing flexible transmission investments, since the presence of uncertainties considerably increases the value of the flexibility embedded in the decision-making process. The flexibility has been quantified for the postponement, relocation or abandonment of an investment project.

In a study case, it has been shown that, by suitably combining FACTS devices and traditional investments in TLs over the investment horizon, more flexible investment strategies can be obtained and the adaptability to uncertain future scenarios is significantly improved. Furthermore, it has been illustrated how the optimal decision could be misleading under the traditional NPV rule. Through applying the RO valuation approach an important feature of FACTS devices has been highlighted: inducing investment execution in stages by means of deferring large TL projects. The impact of the fluctuating feed-in from renewable energies and the operation of pumped storage plants as well as the large influence of the generation pattern within the different countries on the cross-border power flows have also been analyzed.

Future research should be focused on assessing the uncertainty of different wind power in-feed scenarios as well as the installed wind capacity on the decision-making process. The presented approach might also serve as a basis for a decision-making tool for regulatory agencies in order to quantify the necessity for network upgrades.

Appendix A. Nomenclature

A.1. List of acronyms and abbreviations used in the text

CDF	cumulative distribution functions
DC	direct current
ENTSO-E	European network of transmission system operators for electricity
EU	European union
FACTS	flexible alternative current transmission system
iid	independent and identically distributed
LSM	least square Monte Carlo
NL	Netherlands
NPV	net present value
O&M	operation and maintenance
OMG	out-of-merit-generation
OPF	optimal power flow
PDF	probability density function
PIM	power injection model
RO	real options
SND	standard normal distribution
TCSC	Thyristor controlled series compensator
TI	transmission investments
TL	transmission line
VOLL	value of loss load

A.2. List of symbols and indexes used in the text

Latin

A	abandon FACTS option [dimensionless]
C	generation cost [€]
C_R	relocation cost [€]
CS	generation cost savings [€]
d	demand [MW]
df	discount factor [%]
dur	duration of the wind scenario [h]
dz	Wiener process [dimensionless]
F	FACTS investment option
F_m^n	real option value [€]
FF	cash flow [€]
F_l	power flow through the line l [MW]
$F_l^{\max}$	maximum power flow through the line l [MW]
$F_l^{\min}$	minimum power flow through the line l [MW]
g	generator unit [dimensionless]
h	available option [dimensionless]
h	hours [h]
hw	high wind scenario [dimensionless]
I	investment capital at year j [€]
ISW	incremental social welfare [€]
j	year [year]
k	capital opportunity [%]
K	capacity of TCSC [MVar]
l	dispatch of the pumping storage unit during base load
lw	low wind scenario [dimensionless]
M	investment horizon [year]
i, j	node [dimensionless]
MC	marginal cost [€]
max	maximum limit [unit]
min	minimum limit [unit]
mw	medium wind scenario [dimensionless]
N	standard normal distribution [dimensionless]
n	intervals [year]
NPV	net present value [€]
OS	operation cost [€]
p_g	fuel price of the generator g [€]
$\bar{p}_g$	normal level of the fuel price [€]
P_{inst}	installed generating capacity [MW]
$P_g^{\max}$	power generator maximum output [MW]
$P_g^{\min}$	power generator minimum output [MW]
$\overline{p}_i^{\text{base}}$	nodal price of the node i during the base period [€/MW]
$\overline{p}_i^{\text{peak}}$	nodal price of the node i during the peak period [€/MW]
SV	scrap value [€]
t	time [year]
T	maturity of the option [year]
TL	transmission line investment option [dimensionless]
R	relocation FACTS option [dimensionless]
y	year [year]
X	exercise price [€]
X_{Line}	reactance impedance [Ω]
X_{TCSC}	reactance compensation [Ω]
X_τ	state variable value [€]
SV	scrap value [€]
t	time [years]
T	maturity of the option [years]
F	FACTS investment option [dimensionless]
a_0	independent coefficient of the generation curve [€]
S_1,S_2,S_3,s	investment strategies [dimensionless]
a_1	lineal coefficient of the generation curve [€/MW]
a_2	quadratic coefficient of the generation curve [€/MW^2]

Greeks

α	speed of reversion to the mean [dimensionless]
ε	white noise [dimensionless]
θ_i	voltage angle of the node i [rad]
$\sigma^{\ln p_i^F(t)}$	fuel price volatility [%]

$\sigma^2_{d_i}$ estimated unconditional variance [%]
$\bar{\eta}_g$ generator thermal efficiency [%]
μ_{d_i} estimated unconditional mean load growth rate [%]
Φ continuation value [€]
Φ^{-1} inverse of the standard normal distribution [dimensionless]
Π payoff function [€]
Ω number of Monte Carlo simulations [dimensionless]
δ confidence interval [%]
ρ adjusted risk discount rate [%]
ρ_{ij} correlation factor [dimensionless]
τ optimal stopping time [year]
ω simulation path [dimensionless]

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