A Heuristic Methodology to Economic Dispatch Problem Incorporating Renewable Power Forecasting Error and System Reliability

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Abstract

With the constant increment of wind power generation driven by economic and environmental factors, the optimal utilization of generation resources has become a critical problem discussed by many authors. Within this topic, determination of optimal spinning reserve (SR) requirements is a key and complex issue due to the variable and unpredictable nature of renewable generation besides of generation unit reliability. Cost/benefit relationship has been suggested as a way to determine the optimal amount of power generation to be committed by taking into account renewable power forecasting error and system reliability. In this paper, a technique that combines an analytical convolution process with Monte Carlo Simulation (MCS) approach is proposed to efficiently build cost/benefit relationship. The proposed method uses discrete probability theory and identifies those cases at which convolution analysis can be used by recognizing those situations at which SR does not have any effect; while in the other cases MCS is applied. This approach allows improving significantly the computational efficiency. The proposed technique is illustrated by means of two case studies of 10 and 140 units, demonstrating the capabilities and flexibility of the proposed methodology.

Keywords: Insular power systems, power system reliability, probabilistic economic dispatch, wind power forecasting error.

Nomenclature

s	Index for discretization levels of normal standard PDF $s\epsilon[1,S]$
q	Index for discretization levels of wind power PDF $q\epsilon[1,Q]$
p	Index for discretization levels of thermal power PDF $p\epsilon[1,P]$
n	Index for generation units $n\epsilon[1,N]$
m	Number of failure events of a determined unit $m\epsilon[1,M]$
a	Index for discretization levels of FCC PDF $a\epsilon[1,A]$
h	Index for discretization levels of initial power generation
t	Index for time step
M	Number of MCS trials
f_W	Discretized Weibull PDF
f_R	Discretized Wind power PDF
f_G	Discretized PDF of power generation loss (Convolution)
f_M	Discretized PDF of power generation loss (MCS)
$f_{IPG,n}$	Discretized PDF of initial power generation of unit n
f_C	Discretized PDF of FCC

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F_N	Standard normal CDF
F_W	Weibull CDF
F_G	Discretized CDF of power generation loss (Convolution)
$F_{IPG,n}$	Discretized CDF of initial power generation of unit n
ΔWP	Discretization step of wind power PDF
ΔTPG	Discretization step of thermal power PDF
ΔFCC	Discretization step FCC PDF
WS_s	Value of discretization levels of Weibull PDF
TPG_p	Value of discretization levels of thermal power PDF
FCC_a	Value of discretization levels of FCC PDF
WP_q	Value of discretization levels of wind power PDF
TPG^{max}	Maximum thermal power production
TPG^{min}	Minimum thermal power production
FCC^{max}	Maximum value of FCC
FCC^{min}	Minimum value of FCC
$WPG(\cdot)$	Function to estimate the power production of wind farm
v	Value of a determined wind speed velocity
R_p	Rated power of a single wind turbine of the wind farm
N_t	Number of wind turbines of the wind farm
α, β, σ	Parameters of the function $WPG(\cdot)$
v_i	Cut-in wind speed of wind turbine
v_r	Rated wind speed of wind turbine
v_o	Cut-off wind speed of wind turbine
FOR_n	Failure outage rate of unit n
$E\{\cdot\}$	Function to estimate expect value of a determined variable
λ	Intermediate discretization parameter
μ_s	Intermediate distribution of the transformation process
$\o_s$	Value of discretization levels of normal standard PDF
ω_s	Central value of discretized level WS_s
ξ_h	Discretization interval of CDF of initial power generation
$IPG_{n,h}$	Initial power generation of unit n and interval ξ_h
I_n	Intermediate variable for $E\{ENS_t\}$ and $E\{FCC_t\}$ calculation
Φ_h	Weight associated with the values $IPG_{n,h}$; $n\epsilon[1, N]$
L_t	Load demand at time t
$G_{t,q,n,h}$	Thermal power of unit n at time t considering WP_q and $IPG_{n,h}$
$G_{min,n}$	Minimum generation of unit n
$G_{max,n}$	Maximum generation of unit n
UR_n	Ramp-up limit of unit n
DR_n	Ramp-down limit of unit n
$WPD_{t,q,h}$	Wind power dispatched at time t considering WP_q and $IPG_{n,h}$
$NL_{t,q,h}$	Net load at time t considering WP_q and $IPG_{n,h}$
$l_{t,q,h}$	Maximum power of thermal units at time t considering WP_q and $IPG_{n,h}$
$ENS_{t,q,h}$	ENS at time t considering WP_q and $IPG_{n,h}$
η_q	Weighted values of ENS according to wind generation
τ_h	Weighted values of ENS according to initial power generation
θ_h	Weighted values of FCC according to initial power generation
ENS_t	ENS at time t
FCC_t	FCC at time t
$VOLL$	Value of loss load
TGC	Total generation cost
FCC	Fuel consumption cost
ENS	Energy not supplied

1. Introduction

Besides of their remote and isolated location, insular systems have high operating costs due to their fuel consumption and the costs related to its transportation. In most of cases, power generation is based on steam turbines (STs), combined cycle gas turbines (CCGTs), diesel engines (DEs), open cycle gas turbines (OCGTs), and renewable sources (REN); a representative example is the case of Canary Islands, at which STs represent 22.4%, CCGTs represent 28.8%, DEs represent 17.7%, OCGTs represent 20%, REN represent 10%, while cogeneration and other power sources represent 1% of the total installed capacity [1]. However, most of these systems have good potential for exploitation of renewable energy sources like solar and wind energy; a representative situation is the case of Cyprus, where grid parity for installation of photovoltaic (PV) generation has been reached due to the high selling prices of energy and the considerable reduction in the prices of PV panels [2]. Under these circumstances, it is expected a strong growth of renewable generation in the next years; however, the variability and uncertainty related to renewable generation is an important factor, which limits the integration of these sources to the grid. Variability of renewable generation impacts spinning reserve (SR) requirements and the utilization of renewable generation. In the case of mainland power grids; by one hand, primary reserves could increase between 0.3% and 0.8%, while all other reserves could increase between 6% and 10% of the corresponding installed wind power generation. On the other hand, conventional generators could reduce their efficiency up to 9% [3]. A way for solving this problem consists on improving the flexibility of the system by adding an energy storage system (ESS); however, its successful integration since an economic point of view strongly depends on capacity tariffs, wind power potential and investments costs [4]. Another option consists on implementing a demand response (DR) program; a reference case is the Canary Islands, where cost savings related to the implementation of DR program are estimated up to 30% [5]. However, the success of any DR program depends on awareness and knowledge of the consumers as well as the automation of household appliances. Other inexpensive option consists on improving the quality of renewable power forecasting in order to reduce total generation costs, reduce renewable power curtailment, and reduce the commitment of OCGTs [6]. Nevertheless, it is not possible predicting renewable power generation perfectively; besides of this, improvements on forecasting tools has a limited enhancement on power system performance [7]; so that, incorporation of mathematical models for renewable power generation to solve economic dispatch (ED) and unit commitment (UC) problems to estimate the amount of SR required is a critical necessity.

SR requirements could be determined by using a traditional approach based on the solution of deterministic UC problem, solving stochastic UC problem taking into account failures and contingencies of generating units; as well as, wind power forecasting error, incorporating a probabilistic constraint on UC problem based on estimating the probability of load curtailment as a consequence of any contingency, and analysing the cost/benefit relationship [8]. In the traditional approach, SR requirements are adjusted so that the system be able to face the failure of the generation unit with highest capacity among the committed generators plus a determined margin based on the amount of wind power forecasted [9]. Then, deterministic UC problem constrained to the SR requirements aforementioned is solved typically using mixed-integer linear programming (MILP) optimization approach, some formulations widely suggested in the literature can be found in references [10-12]. Another way consists on represent the uncertain nature of any contingency and wind power generation by means of a representative set of scenarios relaxing the constraint related to the SR requirements in the mathematical formulation. As any potential contingency and wind power generation condition is represented explicitly by means of the scenario set, the corresponding amount of SR could be implicitly determined by solving stochastic UC problem. Generation of the required scenario set could be carried out by using Monte Carlo Simulation (MCS) approach in combination with a scenario reduction technique [13]. Several approaches have been proposed in the literature for solving stochastic UC problem. In [14], an optimization framework based on stochastic programming (SP) approach was proposed. Such a framework is composed of two stages: at the first stage the commitment decisions are taken (before the uncertain parameters are realized), while at second stage dispatch decisions are taken (once uncertain parameters are known); the goal of the method consists on find the optimal commitment decisions common to all scenarios considered in order to minimize the total operating cost; it is carried out by solving the equivalent deterministic optimization problem of the stochastic model. According to the reported results, stochastic approach suggests an adequate estimation of the SR requirements; however, the computational time required is high for a limited amount of scenarios; so that, decomposition techniques, addition of SR requirements for each scenario; as well as, an appropriate modelling of optimization problem (regarding the relaxation of the integrality constraints and modelling unit failures as load increments [15]) are suggested. In [16] has been proposed a long-term security constrained unit commitment (SCUC) using Lagrangian relaxation and including mixed integer programming (MIP) to face coupling constraints over the analysed period. The model was structured under dual relaxation where the large-scale system was decomposed into many short-term SCUC sub-problems without constraints. A hybrid subgradient and Dantzig–Wolfe decomposition approach was proposed for managing the Lagrangian multipliers in the large-scale dual optimization. In [17] has been proposed an SCUC model where outages of generation units, transmission lines, and load forecasting inaccuracies were modelled using MCS approach. For dual optimization, coupling constraints among scenarios are relaxed and decomposed into deterministic long-term SCUC sub-problems using Lagrangian relaxation combined with MIP model without resource constraints. In proposed work it was referred that the computational efforts for solving scenario-based optimization models is influenced by the number of scenarios to be considered to minimize the average generation cost. In [18] has been proposed a fast SCUC where were included some components such as single-hour UC with network, security, single-hour UC adjustment, UC, ED, and hourly network security checking, including a MIP approach. It was referred that under increment of power systems, SCUC models face serious problems such as modelling accuracy and computational burden. The proposed model was performed and analysed considering some different power systems, namely, an 1168-bus system with 169 conventional units, a 4672-bus system with 676 conventional units, and two other large systems with 1352 and 2704 conventional units, considering or not fuel and emissions constraints and among others. In [19] has been proposed a SCUC model considering the well-known features of wind power generation, i.e. forecasted wind power generation. In the first step, wind power volatility is represented by scenarios. Then, it is considered the initial dispatch in the sub-problem and generation re-dispatch in order to satisfy the hourly volatility of wind power from the computed scenarios. In case of failure, Benders model cuts are introduced in the main problem to revise the commitment solution. The aforementioned procedures and interactions between the commitment problem and its feasibility continued till the forecasted wind power generation be accommodated by re-dispatch procedure. In [20] has been solved a contingency-constrained single-bus UC problem which incorporates a security criterion. The method was based on robust optimization using umbrella contingency definition as a counterpart of the original problem, resulting in a bi-level programming problem solved by its transformation to an equivalent single-level MIP problem. In [21] has been carried out a comparison between scenario-based and interval optimization approaches to stochastic SCUC, where the wind power generation and other uncertainties were addressed for comparison of both models. Furthermore, MCS was included in scenario-based model to compute the wind power generation uncertainty, while lower and upper bounds of the aforementioned uncertainty were adopted in the interval optimization model. Meanwhile, the stochastic SCUC problem was formulated as MIP problem and solved using the two aforementioned models. In [22] has been proposed a probabilistic model of SCUC to minimize the energy cost, SR and possible loss of load. It was also presented a new formulation for the expected energy not served considering the probability distribution of forecast errors of wind and load, as well as outage replacement rates of generators; furthermore the proposed model was solved using MILP. In [23] has been proposed a two-stage adaptive robust optimization model for SCUC problem, where the first-stage UC decision and the second-stage dispatch decision were robust against all uncertain nodal net injection realizations and the second-stage fulfilled the adaptability uncertainty. The proposed model incorporated network, ramp-rate and transmission security critical-constraints. In [24] has been proposed a model to solve SCUC based on the concept of loadability set. It consists on projecting those feasible solutions onto the demand space in order to refine SCUC. The main advantage of this approach is the reduction on the computational effort while the accuracy of the obtained solution is preserved under light and heavy transmission congestions. In [25] has been presented an optimization model based on chance-constrained programming using an estimation of the confidence level of stochastic variables in order to supply demand taking into account several simultaneous contingencies, while the mathematical structure of the optimization problem is formulated as a MILP problem. In a similar way; in [26] effectiveness of chance-constrained programming to solve SCUC was verified. In [27] has been proposed a methodology based on constrained ordinal optimization, at which a sample of UC solutions are analysed in order to determine a reasonable solution considering a set with large number of scenarios. The feasibility of each UC solution sampled is verified by using analytical conditions.

Estimation of SR requirements based on probabilistic analysis consists on the application of a criterion derived from the full capacity outage probability distribution on the UC solution. The computational effort of this approach is low while the accuracy of the obtained solution is reasonable [28]. The analysis of cost/benefit relationship consists of an auxiliary process carried out for each period of time (without considering inter-temporal characteristics of UC problem) prior to the solution of UC problem. During the auxiliary process, SR requirements are optimized taking into account the benefit related to SR margins and the corresponding cost of provide it. Then, UC problem incorporating SR constraints is evaluated by considering the inter-temporal characteristics of unit scheduling problem [29]. In [30], optimization of SR requirements by the analysis of cost/benefit relationship was improved by adding a checking process based on MCS approach.

In this paper, a special attention on the estimation of the cost/benefit relationship [29,30] is paid and a hybrid approach has been developed and described. The proposed approach estimates the cost/benefit relationship used to determine SR requirements by a hybrid technique that combines a convolution-based approach and MCS method, in order to determine the optimal amount of power to be committed taking into account wind power forecasting error and generation unit reliability. Forecasting error of wind speed is represented by a discretized Weibull probability distribution function (PDF), which is evaluated on the corresponding power curve of the wind farm in order to consider the non-linear characteristics of wind generation, which is frequently modelled by a Gaussian PDF of net load, avoiding the estimation of some possible curtailment of renewable generation.

The paper is organized as follow: section 2 briefly describes the cost/benefit relationship and how to use it for determining the optimal capacity to be committed; section 3 describes the proposed methodology including the model of wind power forecasting error and system reliability which is modelled by a convolution process and MCS approach; in section 4 proposed methodology is illustrated by the analysis of two case studies of 10 and 140 units; finally, conclusions are presented in section 5.

2. Cost/benefit relationship for SR requirements determination

Extensively analysed by Ortega-Vazquez and Kirschen, cost/benefit relationship optimizes the SR requirements by balancing the cost related to SR and the economic benefit obtained from this reserve margin, optimal SR is determined by finding the amount of power to be committed in order to minimize generation cost according to (1),

$$\min E\{TGC\} = E\{FCC\} + VOLL \times E\{ENS\}. \tag{1}$$

Fig. 1 illustrates the behaviour of cost/benefit relationship, it is possible observing how as the committed capacity increases (or in other words SR increases), the fuel consumption cost (FCC) increases while the cost related to energy not supplied (ENS) decreases. Then, when the addition of both costs is carried out, a local minimum on the generation cost can be identified and consequently the optimal SR required. In

[29], the analysis of cost/benefit relationship only considering generation unit reliability was carried out; expected value of ENS was obtained by means of the capacity outage probability table [31] in order to consider forced outage rate (FOR) of each unit. In [30], the methodology aforementioned was extended in order to consider the influence of wind power generation, where forecasting error of net load is represented as a Gaussian PDF under the assumption of large amount of wind turbines which are geographically dispersed. In more detail, net load forecasting error is modelled by means of a discretized Gaussian PDF of seven segments; then, the optimal SR is obtained for each interval analysing the cost/benefit relationship according to [29]; finally, optimal SR required is determined as the summation of the optimal SR of each interval weighted according to the probability of occurrence of the corresponding interval.

"See Fig. 1"

Optimal SR requirements are determined for each time interval without taking into account the inter-temporal characteristics of the optimization problem (ramp constraints of UC problem). Once the optimal SR for each period of the scheduling horizon has been obtained, a traditional reserve constrained UC problem is solved (incorporating ramp constraints of UC problem) in order to determine the optimal scheduling and power dispatch [29].

3. Proposed methodology

As was stated before, this paper focus on the efficient evaluation of cost/benefit relationship in order to determine the optimal SR requirement taking into account wind power forecasting error and generation unit reliability. Building cost/benefit relationship requires solving ED problem under uncertain conditions at which wind power generation and any failure event of generation system are the main sources of uncertainty. In our previous work presented in [32], ED problem was extensively analysed and according to the obtained results, the estimation of expected ENS by convolution could give overestimated results since the effects of SR on ENS were not taken into account. However, when the load to be supplied is higher than the total capacity committed there is no SR and expected ENS can be accurately determined by a convolution process. This condition is particularly useful to build cost/benefit relationship.

In this paper, we have divided cost/benefit relationship in two different regions according to Fig. 2. In Region I, the committed capacity is lower than the minimum net load to supplied; so that, SR does not have any impact on system operation; while in Region II the committed capacity is high enough and SR has a relevant influence of the operation of the system. Under this circumstance, those points of Region I can be analysed by means of the convolution process; while those points of Region II can be analysed by means of MCS method. This hybrid approach allows us carrying out an efficient analysis of cost/benefit relationship due to the fact that the computational effort is concentrated in those points of high relevance (Region II), while the others are analysed by analytical methods (Region I) in an efficiency and fast way. Moreover, the methodology proposed in this paper uses a discretized Weibull PDF combined with the power curve of the wind farm to model wind power uncertainty, which allows incorporating the non-linear characteristics of wind generation on the cost/benefit relationship. On the other hand, power production of thermal units at previous instant is modelled by using discretized PDF and incorporated on the solution of ED problem, so that the inter-temporal characteristics are taken into account.

"See Fig. 2"

Next sub-sections describe the mathematical models of wind speed and wind power generation, generation unit reliability, and their incorporation on ED problem in order to estimate generation costs.

3.1 Probabilistic modelling of wind power forecasting error

Wind speed has been probabilistically modelled by using a Weibull PDF since many years ago; Weibull distribution only depends on two parameters which give it high flexibility, and these parameters could be estimated in a simple way with high accuracy [33]. As power generation of conventional generators depends on the behaviour of wind power production, the PDF of wind generation should be included on ED optimization problem through a discretization process. In this sense, Barbiero [34] has developed a general-purposes discretization method and it has been used here to represent Weibull PDF. In the discretization process a support represented by $\o_S$ with S elements is built according to (2), the parameter λ is set according to the preferences of the user ($\lambda = 3$ is suggested in [34]). Then, each value of the support is evaluated on the cumulative distribution function (CDF) of a normalized Gaussian distribution

(Equation (3)) and the obtained values are evaluated on the inverse CDF of a Weibull distribution with the required parameters (Equation (4)); after that, the centres of each interval are determined (Equation (5)), and the corresponding discretized PDF is determined (Equations (6)-(8)),

$$\o_s = -\lambda - \frac{2\lambda}{S-1} + \left(\frac{2\lambda}{S-1}\right)s; s = 1,2,\dots,S \tag{2}$$

$$\mu_s = F_N(\o_s); s = 1,2,\dots,S \tag{3}$$

$$WS_s = F_W^{-1}(\mu_s);\; s = 1,2,\dots,S \tag{4}$$

$$\omega_s = \frac{WS_s + WS_{s+1}}{2}; s = 1,2,\dots,S-1 \tag{5}$$

$$f_W(WS_1) = F_W(\omega_1); s = 1 \tag{6}$$

$$f_W(WS_s) = F_W(\omega_s) - F_W(\omega_{s-1}); s = 2,\dots,S-1 \tag{7}$$

$$f_W(WS_S) = 1 - F_W(\omega_{S-1}); s = S. \tag{8}$$

Once discretized PDF of wind speed has been created (f_W), this is evaluated on the power curve of wind farm connected to the power system. In this paper, we have used the general-purposes power curve shown in Fig. 3, and mathematically described in (9)-(12) [35,36],

"See Fig. 3"

$$WPG(v) = \begin{cases} 0 & ; 0 \leq v \leq v_i, v > v_o \\ \alpha + \beta v + \sigma v^2 & ; v_i \leq v \leq v_r \\ N_t R_p & ; v_r \leq v \leq v_o \end{cases} \tag{9}$$

$$\alpha = \frac{1}{(v_i - v_r)^2}\left[v_i(v_i + v_r) - 4v_i v_r \left(\frac{v_i + v_r}{2v_r}\right)^3\right] \tag{10}$$

$$\beta = \frac{1}{(v_i - v_r)^2}\left[4(v_i + v_r)\left(\frac{v_i + v_r}{2v_r}\right)^3 - (3v_i + v_r)\right] \tag{11}$$

$$\sigma = \frac{1}{(v_i - v_r)^2}\left[2 - 4\left(\frac{v_i + v_r}{2v_r}\right)^3\right]. \tag{12}$$

Wind power PDF is discretized in several intervals or states (Q) between 0 and the maximum capacity of the wind farm ($N_t R_p$) with a step (ΔWP) defined according to (13),

$$\Delta WP = \frac{N_t R_p}{Q - 1}. \tag{13}$$

Then, wind power generation PDF (f_R) can be obtained by applying the algorithm presented in Fig. 4. In this algorithm, for a determined interval (s) of wind speed (WS_s) the corresponding wind power generation ($WPG(WS_s)$) is determined; after that, the interval of wind generation (q) that corresponds to the results obtained from the evaluation of the power curve is determined and the probability of occurrence of the wind speed interval ($f_W(WS_s)$) is assigned to this value of power. This process is repeated for all the intervals of discretized wind speed PDF; so that, wind power generation PDF is obtained.

"See Fig. 4"

3.2 Probabilistic modelling of generation unit reliability

As stated in section 3, expected value of ENS of those points of Region I are determined by convolution. In order to build PDF of ENS, several states (P) are established between TPG^{min} and TPG^{max} with a step (ΔTPG) defined according to (14),

$$\Delta TPG = \frac{TPG^{max} - TPG^{min}}{P - 1}, \tag{14}$$

ENS CDF can be obtained by applying (15) in a recursive way [31], starting from the CDF F_G shown in Fig. 5 (left side) and ending with the CDF presented in Fig. 5 (right side). Finally, ENS PDF can be obtained from Fig. 5 by subtraction of probability values, resulting in the PDF shown in Fig. 6. The term $G_{t,q,n,h}$ in (15) is the power generation of unit n when the interval of power generation q, and the interval of initial power generation h are considered; it is obtained from the solution of ED dispatch problem solved as previous step before the application of (15) (see Fig. 8),

$$F_G(TPG_p) = (1 - FOR_n)F_G(TPG_p) + FOR_nF_G(TPG_p - G_{t,q,n,h}). \tag{15}$$

"See Fig. 5"

"See Fig. 6"

Now, the required expected value of ENS is estimated by means of (16),

$$E\{ENS\} = \sum_{p=1}^{P} f_G(TPG_p)TPG_p. \tag{16}$$

Expected value of ENS of those points of Region II is obtained by using MCS method at which, failure events are modelled by using a Binomial PDF presented in (17) [37],

$$f_M = \binom{M}{m}(1 - FOR_n)^m(FOR_n)^{M-m}. \tag{17}$$

3.3 Incorporation of forecasting error and system reliability in the estimation of total generation cost

In order to build cost/benefit relationship, estimation of expected value of ENS and FCC taking into account system reliability and forecasting error is required. In this sense, a discretized PDF of FCC is built by considering values between FCC^{min} and FCC^{max} with step ΔFCC defined by (18),

$$\Delta FCC = \frac{FCC^{max} - FCC^{min}}{A - 1}. \tag{18}$$

In this paper, power generation at previous time step $(t-1)$ is incorporated by considering some selected scenarios chosen by using quintile concept from the analysis of discretized PDF of power generation. Fig 7 presents CDF of power generation of unit n $(F_{IPG,n})$ at time step $t-1$. Dividing the interval [0,1] in several points (H) each of these points (ξ_h) can be evaluated in the CDF $F_{IPG,n}$ in an inverse way; so that, a correlated power production is estimated among all generation units. This approach allows us reducing the number of possible starting points of ED optimization problem. All chosen scenarios are finally saved in the matrix of initial power generation $(IPG_{n,h})$ to be used for determining the optimal power dispatch [32].

"See Fig. 7"

As the number of possible scenarios of initial power production has been reduced, the corresponding weight to represent the probability of occurrence of each scenario is estimated according (19) [32],

$$\Phi_h = \frac{\prod_{n=1}^{N}\left(f_{IPG,n}\left(IPG_{n,h}\right)\right)}{\sum_{h=1}^{H}\prod_{n=1}^{N}\left(f_{IPG,n}\left(IPG_{n,h}\right)\right)}; h = 1,2,\ldots,H. \tag{19}$$

For the actual time step t, expected value of ENS and FCC is estimated according to the algorithm shown in Fig. 8. In this algorithm each interval of wind power discretization (q) and initial power generation (h) is considered; so that, for each combination of discrete states, ED problem is solved and discretized PDF of FCC is built; then, the region of the cost/benefit relationship is determined by considering the value of the net load $(NL_{t,q,h})$. Note that each value of ENS and FCC is weighted according to the probability of occurrence of wind power generation (f_R) and initial power production (Φ_h). Finally, the required expected values are obtained by summation of all weighted values.

"See Fig. 8"

4. Case studies

The methodology described in previous sections to build cost/benefit relationship is illustrated by analysing two power systems of 10 units and 140 units provided with wind power generation. As the proposed methodology models initial power generation of thermal units as a discretized PDF, all of them have been obtained by MCS method. To carry out this task, three time steps have been considered, at $t-2$ the value of initial power generation has been assumed as a constant value for all the units; while for $t-1$ and t, discretized PDF of initial power generation is obtained by solving ED problem. Then, discretized PDF at time $t-1$ is used as an input in our proposed approach and the results obtained at time t are used to carry out a comparative analysis between the proposed methodology and MCS approach. At time t, wind speed is modeled as a Weibull PDF with the same characteristics for all case studies, changing the parameters of the wind farm according to the respective case under analysis.

Fig. 9 shows discretized PDF of wind speed at time t with shape factor equal to 2 and scale factor equal to 7, discretization was carried out by applying the procedure previously described in sub-section 3.1 using equations (2)-(8) and λ=5. Regarding the wind farm model, in all cases a single wind turbine was assumed to have v_i=3 m/s, v_r=12 m/s, v_o=25 m/s, and R_p=2 MW. The value of N_t was defined by the particular case study under analysis.

"See Fig. 9"

4.1 10-units power system

In this sub-section results obtained from the analysis of a small capacity system are presented. Table 1 shows the characteristics of thermal generators under analysis [38].

"See Table 1"

First, a comparison between the results obtained from convolution process and MCS method is carried out in order to evaluate their quality and efficiency. For this purpose only the commitment of the units 1-6 was considered. As was stated before, three different time steps are considered, at time $t-2$ thermal units generate 1,412 MW, at time $t-1$ load demand is 1,600 MW, and at time t load demand is 1,750 MW. Regarding wind speed forecasting error, at time $t-1$ it was modeled as a Weibull PDF with shape factor equal to 10 and scale factor equal to 3. The number of wind turbines of wind farm was assumed to be 50 (N_t=50). Fig. 10 shows discretized PDF of wind power generation at time t obtained by evaluating equations (9)-(13) and the algorithm shown in Fig. 4, assuming Q=24.

"See Fig. 10"

4.1.1 Analysis of the Region I points

In order to analyse the quality of the results obtained from the convolution process, the first 6 generators are committed. It is important to note that, as the committed capacity cannot supply the load demand, SR does not have any influence on the analysis; so that, convolution process could be directly applied. Discretization of conventional power production was carried out by assuming TPG^{min}=0 MW, TPG^{max}=1,500 MW, and P=150. Discretization of wind generation was carried out by assuming Q=24. Regarding the initial power production, the number of scenarios considered was 5 (H=5); MCS approach was adopted as a reference considering 10,000 trials (M=10,000). Table 2 shows the results from the comparative analysis between convolution method and MCS approach; as can be observed, an error of 7.39% in the estimation of FCC and 0.73% in the estimation of ENS was found in a reduced computational time.

"See Table 2"

4.1.2 Analysis of the Regions I/II points

As the analysis of cost/benefit relationship progress, some points could belong to Region I or II depending on the discretized value of wind power generation. In order to analyse this condition, number of wind turbines has been increased to 250 (N_t=250), load demand at $t-1$ was changed to 1,400 MW and 1,500 MW in t. Discretized PDF was built by considering TPG^{min}=0 MW, TPG^{max}=1,700 MW, and P=100. As in the sub-section 4.1.1, the number of MCS trials was adjusted to 10,000 (M=10,000) for the reference analysis; however, the number of MCS trials considered for our proposed approach was adjusted to 500 (M=500) and the number of discrete levels of wind power generation to 3 (Q=3) in order to reduce the computational efforts. The number of scenarios considered to represent the initial power generation was 5 (H=5). According to the results reported in Table 3, an error of 4.65% in the estimation of FCC and 3.07% in the estimation of ENS was found, reducing the computational effort.

"See Table 3"

4.1.3 Building cost/benefit relationship (10-Units system)

In this sub-section, cost/benefit relationship is analysed by taking into account all the units of the system under the operating conditions described in sub-section 4.1.2 and $VOLL$=1,000 \$/MWh. Fig. 11 shows the most relevant part of cost/benefit relationship, the black line is the relationship obtained by evaluating 5,000 trials in 2,384.8 s (expected cost 60,114.91 \$); while, those grey ones were obtained by evaluating different sets between 10 and 1,000 trials, obtaining computational times between 9.3 s and 477.8 s. The optimal amount of power to be committed depends on the amount of MCS considered; in this case, optimal capacity is around 1,607 MW ($E\{TGC\}$ equal to 32,149.236 \$) for low number of MCS ($M \longrightarrow$10); however, this value increases to 1,662 MW ($E\{TGC\}$ equal to 58,307.81 \$) as the number of MCS trials increases ($M \longrightarrow$1,000).

"See Fig. 11"

Table 4 presents the frequency at which the analysis is in Region I or II and the corresponding computational time. As can be observed, when the committed capacity gets its minimum value, the analysis is carried out by convolution in a reduced computational time; then, as the committed capacity increases, the relevance of SR increases and at some intervals MCS approach is applied, incrementing the calculation effort; finally, as the total capacity of the system is reached, the mathematical efforts are incremented due to in each MCS trial an optimization problem (ED) committing all units has to be solved. In general sense, proposed methodology only applies MCS approach in those cases at which SR has an important influence on the results; while in the rest of cases convolution process is used in order to improve the computational efficiency.

"See Table 4"

4.2 140-units power system

The behaviour of the proposed methodology analysing large scale systems is investigated by means of the systems described in Table 5 [39]. Wind power generation has been modelled by means of a wind farm with 9,000 turbines (N_t=9,000). Load demand at $t-2$ was assumed to be 60,000 MW, at time $t-1$ was assumed to be 49,342 MW, and at t was assumed to be 51,000 MW. Discretized PDF was built by considering TPG^{min}=0 MW, TPG^{max}=65,000 MW, and P=100. The number of MCS trials was adjusted to 1,000 (M=1,000) for the reference analysis; however, the number of MCS trials considered for our proposed approach was adjusted to 100 (M=100) and the number of discrete levels of wind power considered was 3 (Q=3); while, the number of scenarios considered to represent the initial power generation was 3 (H=3).

"See Table 5"

This large amount of MCS trails for our proposed methodology was considered in order to have a good reference of comparison; the cost/benefit relationship obtained is shown in Fig. 12, where the optimal capacity to be committed is 56,360 MW; this curve was built in a computational time of 22,638.097 s.

"See Fig. 12"

Fig. 13 presents the region analysis for this case study, where it is possible observing a similar behaviour for the 10-units case study; when low capacity is committed most of the calculations are carried out by convolution; however, as the committed capacity is increased, application of MCS is required in order to consider the effects of SR.

“See Fig. 13”

Fig. 14 presents the computational time as a function of the committed capacity (expressed in percent of the total computational time 22,638.097 s), where the increment in the calculation effort as a consequence of MCS approach is observed.

“See Fig. 14”

The computational time could be reduced by using MCS approach with a lower set of trials, a lower amount of discretized levels to represent wind power generation and initial power production. For example, if the number of MCS is reduced to 10 (M=10), the number of discrete states of wind generation is adjusted to 2 (Q=2), and only one state of initial power generation (H=1) is considered by adjusting $\xi_{h=1}$=0.5; the computational time could be reduced to 564.998 s, obtaining a similar result regarding to optimal committed capacity; although, the estimation of total generation cost could be highly distorted; in our case this is estimated as 1,607,668.225 $; while for our reference solution it was estimated as 1,444,166.681$. Generally speaking, the amount of MCS trials should be selected according to the computational resources and calculation time available; however, low amount of MCS trails directly impacts on the estimation of $E\{TGC\}$. The proposed approach was implemented in MATLAB programming language using a computer provided of i7-3630QM CPU at 2.40 GHz with 8 GB of memory and 64 bit operating system.

5. Conclusions

In this paper, the cost/benefit relationship has been exhaustively analysed and a methodology to build this curve based on discrete probability theory and MCS approach was developed and tested. The proposed method aims to significantly improve the efficiency of the calculation required to build the cost/benefit relationship used for optimal SR requirements determination by identifying those cases at which a convolution analysis can be used; while in the rest of the cases, those at which calculation of expected ENS is influenced by SR, are estimated by means of MCS. Accordingly, the computational efficiency is considerably improved, while a reasonable result is reached. Two case studies of 10 and 140 units were analysed under wind power penetration, demonstrating the flexibility of the proposed technique reached by adjusting the number of discrete states and MCS trials.

Acknowledgements

This work was supported by FEDER funds through COMPETE and by Portuguese funds through FCT, under FCOMP-01-0124-FEDER-020282 (PTDC/EEA-EEL/118519/2010), UID/CEC/50021/2013 and SFRH/BPD/103079/2014. Also, the research leading to these results has received funding from the EU Seventh Framework Programme FP7/2007-2013 under grant agreement no. 309048.

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Figures

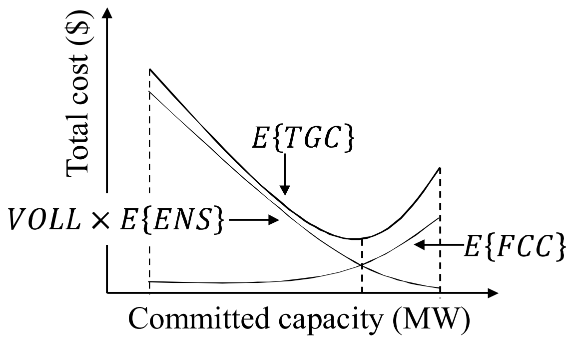

Fig. 1: Cost/Benefit relationship for a determined time step.

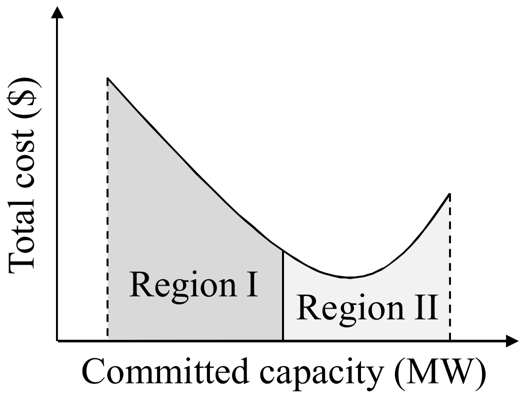

Fig. 2: Regions of analysis of cost/benefit relationship for a determined time step.

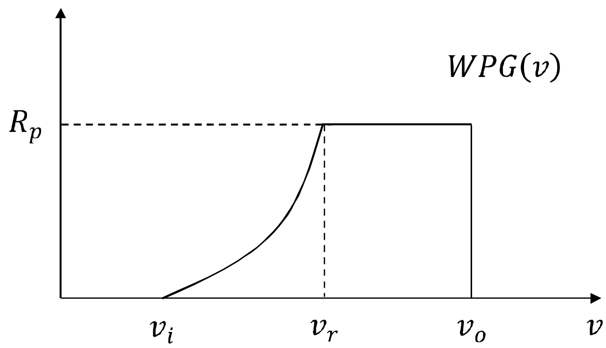

Fig. 3: Power curve of a single wind turbine.

$f_R(WP_q) = 0; q = 1,2,\ldots,Q$
$WP_q = 0, \Delta WP, \ldots, N_t R_p - \Delta WP, N_t R_p$
for $s = 1,2,\ldots,S$
    if $(WPG(WS_s) \leq WP_1 - \Delta WP/2)$
        $f_R(WP_1) = f_R(WP_1) + f_W(WS_s)$
    elseif $(WPG(WS_s) \geq WP_Q + \Delta WP/2)$
        $f_R(WP_Q) = f_R(WP_Q) + f_W(WS_s)$
    else
        for $q = 1,2,\ldots,Q$
            if $(WPG(WS_s) \geq WP_q - \Delta WP/2)$ and $(WPG(WS_s) < WP_q + \Delta WP/2)$
                $f_R(WP_q) = f_R(WP_q) + f_W(WS_s)$
            end
        end
    end
end

Fig. 4: Algorithm for discretization of wind power generation.

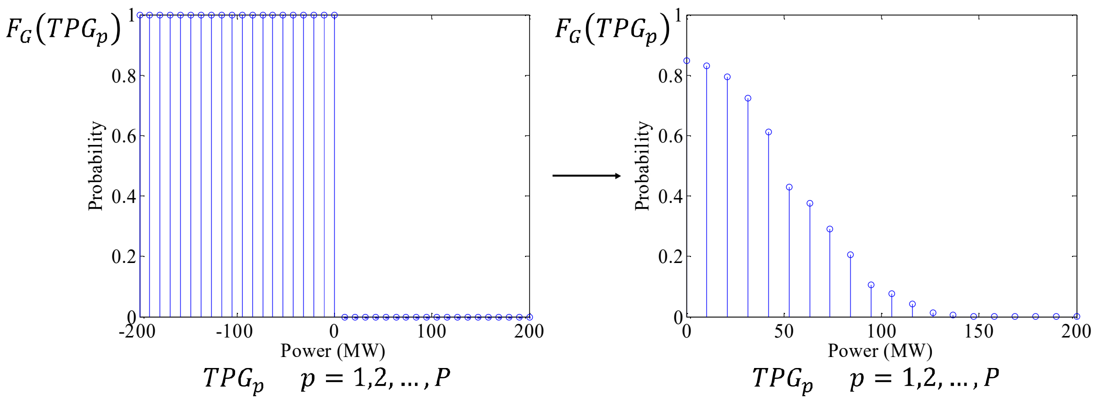

Fig. 5: Determination of ENS probability distribution by convolution.

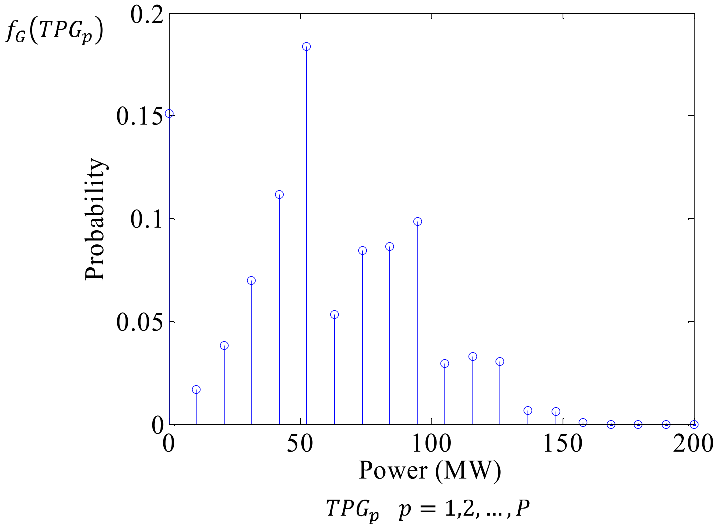

Fig. 6: Probability distribution of ENS.

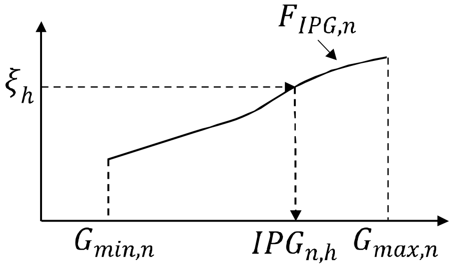

Fig. 7: Analysis of CDF of power generation of unit n.

for $h = 1,2,\dots,H$
  $I_n = IPG_{n,h}; n = 1,2,\dots,N$
  $f_C(FCC_a) = 0; a = 1,2,\dots,A$
  for $q = 1,2,\dots,Q$
    $K_{t,q,h} = min\sum_{n=1}^{N}\left\{\gamma_n + \delta_n\left(G_{t,q,n,h}\right) + \varepsilon_n\left(G_{t,q,n,h}\right)^2\right\}$
    $G_{t-1,q,n,h} = I_n; n = 1,2,\dots,N$
    $\sum_{n=1}^{N}\{G_{t,q,n,h}\} + WPD_{t,q,h} = L_t$ — ED problem
    $G_{t,q,n,h} - G_{t-1,q,n,h} \le UR_n; n = 1,2,\dots,N$
    $G_{t-1,q,n,h} - G_{t,q,n,h} \le DR_n; n = 1,2,\dots,N$
    $G_{min,n} \le G_{t,q,n,h} \le G_{max,n}; n = 1,2,\dots,N$
    $0 \le WPD_{t,q,h} \le WP_q$
    $FCC_a = FCC^{min}, FCC^{min} + \Delta FCC, \dots, FCC^{max} - \Delta FCC, FCC^{max}$
    if $\left(K_{t,q,h} \le FCC_1 - \Delta FCC/2\right)$
      $f_C(FCC_1) = f_C(FCC_1) + f_R\left(WP_q\right)$
    elseif $\left(K_{t,q,h} \ge FCC_A + \Delta FCC/2\right)$
      $f_C(FCC_A) = f_C(FCC_A) + f_R\left(WP_q\right)$
    else
      for $a = 1,2,\dots,A$
        if $\left(K_{t,q,h} \ge FCC_a - \Delta FCC/2\right) and \left(K_{t,q,h} < FCC_a + \Delta FCC/2\right)$
          $f_C(FCC_a) = f_C(FCC_a) + f_R\left(WP_q\right)$
        end
      end
    end
    $NL_{t,q,h} = L_t - WPD_{t,q,h}$
    $l_{t,q,h} = \sum_{n=1}^{N}\{min\left(G_{t-1,q,n,h} + UR_n, G_{n,max}\right)\}$
    if $\left(NL_{t,q,h} > l_{t,q,h}\right)$
      ▪ Determine $E\{ENS_{t,q,h}\}$ by convolution
    else
      ▪ Determine $E\{ENS_{t,q,h}\}$ by MCS approach
    end
    $\eta_q = E\{ENS_{t,q,h}\} \times f_R\left(WP_q\right)$
  end
  $\tau_h = \left(\sum_{q=1}^{Q}\eta_q\right) \times \Phi_h$
  $\theta_h = \left(\sum_{a=1}^{A} FCC_a \times f_C(FCC_a)\right) \times \Phi_h$
end
$E\{ENS_t\} = \sum_{h=1}^{H}\tau_h$
$E\{FCC_t\} = \sum_{h=1}^{H}\theta_h$

Fig. 8: Algorithm for incorporation of forecasting error and system reliability.

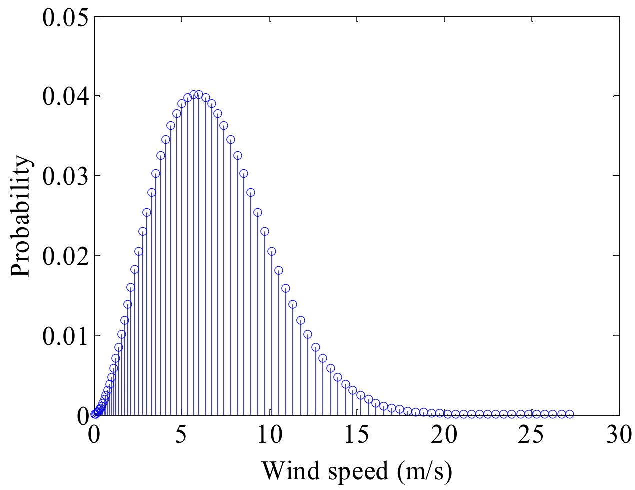

Fig. 9: Discretized wind speed PDF.

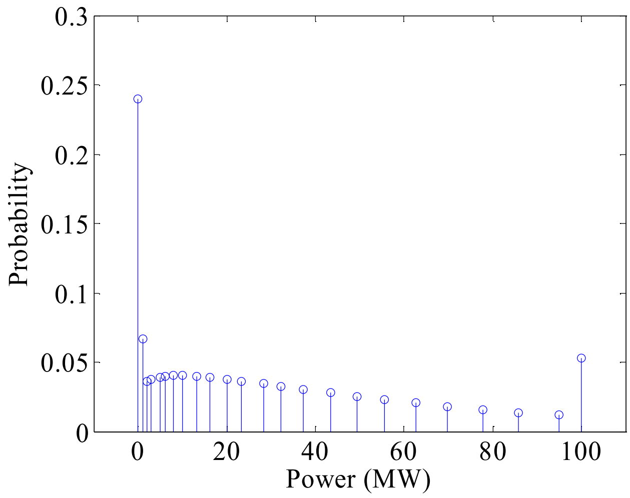

Fig. 10: Discretized wind power PDF.

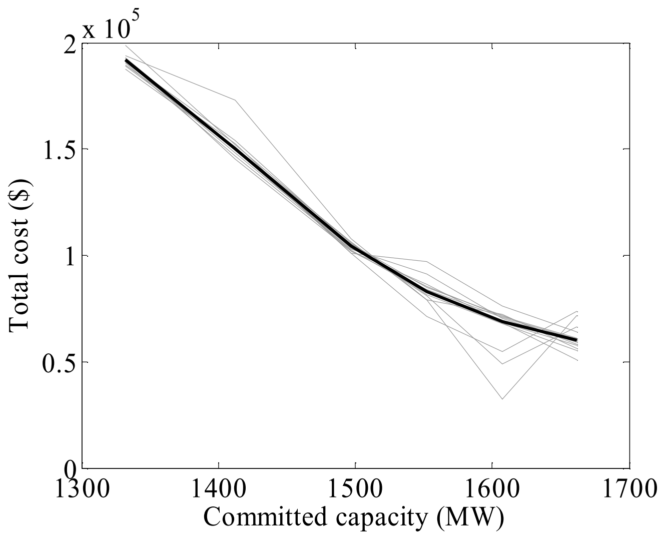

Fig. 11: Cost/benefit relationship for 10-units power system.

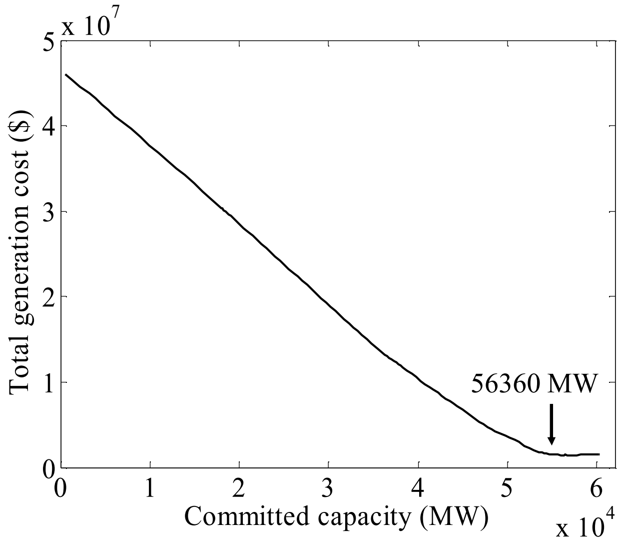

Fig. 12: Cost/benefit relationship for 140-units power system.

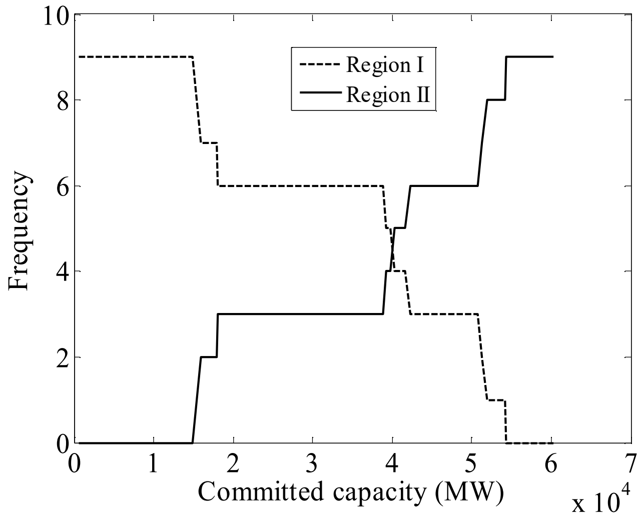

Fig. 13: Region analysis of 140-Units system.

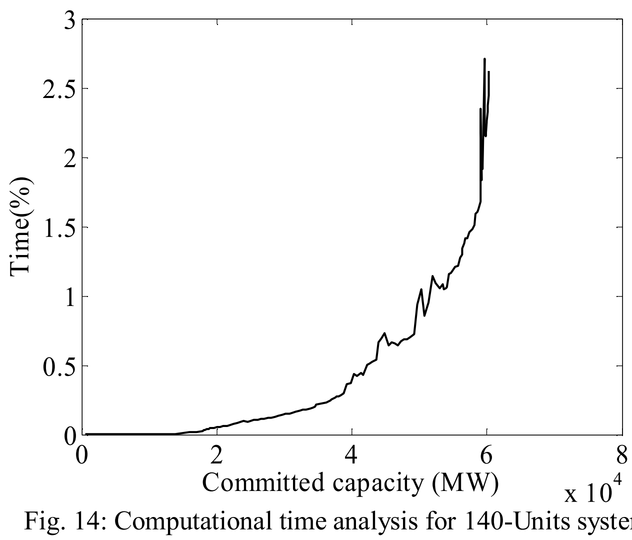

Fig. 14: Computational time analysis for 140-Units system.

Tables

Table 1: Data of 10-units power system.

n	$G_{min,n}$ (MW)	$G_{max,n}$ (MW)	γ_n ($/h)	δ_n ($/MW)	ε_n ($/MW^2)	DR_n (MW/h)	UR_n (MW/h)	FOR_n
1	150	455	1000	16.19	0.00048	130	130	0.05
2	150	455	970	17.26	0.00031	130	130	0.05
3	25	162	450	19.7	0.00398	90	90	0.1
4	20	130	680	16.5	0.00211	60	60	0.1
5	20	130	700	16.6	0.002	60	60	0.1
6	20	80	370	22.26	0.00712	40	40	0.1
7	25	85	480	27.74	0.00079	40	40	0.1
8	10	55	660	25.92	0.00413	40	40	0.0001
9	10	55	665	27.27	0.00222	40	40	0.0001
10	10	55	670	27.79	0.00173	40	40	0.0001

Table 2: Comparison between MCS and convolution methods (Region I).

Variable	MCS	Convolution	Time (s)
$E\{FCC_t\}$	27,048.784	29,048.000	142.726
$E\{ENS_t\}$	409.991	412.999	12.875

Table 3: Comparison between MCS and convolution/MCS methods (Regions I/II).

Variable	MCS	Convolution	Time (s)
$E\{FCC_t\}$	26,136.951	27,352.252	144.633
$E\{ENS_t\}$	117.155	120.749	25.173

Table 4: Region analysis and computational time (10-Units).

Unit (MW)	Region I	Region II	Time (s)
455 (1)	15	0	0.219
910 (1-2)	10	5	5.875
1072 (1-3)	10	5	8.344
1202 (1-4)	6	9	16.236
1332 (1-5)	5	10	20.923
1412 (1-6)	5	10	23.938
1497 (1-7)	5	10	26.674
1552 (1-8)	1	14	39.111
1607 (1-9)	1	14	44.127
1662 (1-10)	0	15	51.878

Table 5: Data of 140-units power system.

ID	$G_{min,n}$ (MW)	$G_{max,n}$ (MW)	γ_n ($/h)	δ_n ($/MW)	ε_n ($/MW^2)	DR_n (MW/h)	UR_n (MW/h)	FOR_n
NUCLEAR#01	360	580	226.799	2.842	0.000064	18	18	0.04
NUCLEAR#02	415	645	382.932	2.946	0.000252	18	18	0.04
NUCLEAR#03	795	984	156.987	3.096	0.000022	36	36	0.04
NUCLEAR#04	795	978	154.484	3.04	0.000022	36	36	0.04
NUCLEAR#05	578	682	332.834	1.709	0.000203	204	138	0.04
NUCLEAR#06	615	720	326.599	1.668	0.000198	216	144	0.04
NUCLEAR#07	612	718	345.306	1.789	0.000215	216	144	0.04
NUCLEAR#08	612	720	350.372	1.815	0.000218	216	144	0.04
NUCLEAR#09	758	964	370.377	2.726	0.000193	48	48	0.04
NUCLEAR#10	755	958	367.067	2.732	0.000197	48	48	0.04
NUCLEAR#11	750	1007	124.875	2.651	0.000324	54	36	0.04
NUCLEAR#12	750	1006	130.785	2.798	0.000344	54	36	0.04
NUCLEAR#13	713	1013	878.746	1.595	0.00069	30	30	0.04
NUCLEAR#14	718	1020	827.959	1.503	0.00065	30	30	0.04
NUCLEAR#15	791	954	432.007	2.425	0.000233	30	30	0.04
NUCLEAR#16	786	952	445.606	2.499	0.000239	30	30	0.04
NUCLEAR#17	795	1006	467.223	2.674	0.000261	36	36	0.04
NUCLEAR#18	795	1013	475.94	2.692	0.000259	36	36	0.04
NUCLEAR#19	795	1021	899.462	1.633	0.000707	36	36	0.04
NUCLEAR#20	795	1015	1000.367	1.816	0.000786	36	36	0.04

COAL#01	71	119	1220.645	61.242	0.032888	120	30	0.03
COAL#02	120	189	1315.118	41.095	0.00828	120	30	0.03
COAL#03	125	190	874.288	46.31	0.003849	60	60	0.03
COAL#04	125	190	874.288	46.31	0.003849	60	60	0.03
COAL#05	90	190	1976.469	54.242	0.042468	150	150	0.03
COAL#06	90	190	1338.087	61.215	0.014992	150	150	0.03
COAL#07	280	490	1818.299	11.791	0.007039	300	180	0.03
COAL#08	280	490	1133.978	15.055	0.003079	300	180	0.03
COAL#09	260	496	1320.636	13.226	0.005063	510	300	0.03
COAL#10	260	496	1320.636	13.226	0.005063	510	300	0.03
COAL#11	260	496	1320.636	13.226	0.005063	510	300	0.03
COAL#12	260	496	1106.539	14.498	0.003552	510	300	0.03
COAL#13	260	506	1176.504	14.651	0.003901	600	600	0.03
COAL#14	260	509	1176.504	14.651	0.003901	600	600	0.03
COAL#15	260	506	1176.504	14.651	0.003901	600	600	0.03
COAL#16	260	505	1176.504	14.651	0.003901	600	600	0.03
COAL#17	260	506	1017.406	15.669	0.002393	600	600	0.03
COAL#18	260	506	1017.406	15.669	0.002393	600	600	0.03
COAL#19	260	505	1229.131	14.656	0.003684	600	600	0.03
COAL#20	260	505	1229.131	14.656	0.003684	600	600	0.03
COAL#21	260	505	1229.131	14.656	0.003684	600	600	0.03
COAL#22	260	505	1229.131	14.656	0.003684	600	600	0.03
COAL#23	260	505	1267.894	14.378	0.004004	600	600	0.03
COAL#24	260	505	1229.131	14.656	0.003684	600	600	0.03
COAL#25	280	537	975.926	16.261	0.001619	300	300	0.03
COAL#26	280	537	1532.093	13.362	0.005093	300	300	0.03
COAL#27	280	549	641.989	17.203	0.000993	360	360	0.03
COAL#28	280	549	641.989	17.203	0.000993	360	360	0.03
COAL#29	260	501	911.533	15.274	0.002473	180	180	0.03
COAL#30	260	501	910.533	15.212	0.002547	180	180	0.03
COAL#31	260	506	1074.81	15.033	0.003542	600	600	0.03
COAL#32	260	506	1074.81	15.033	0.003542	600	600	0.03
COAL#33	260	506	1074.81	15.033	0.003542	600	600	0.03
COAL#34	260	506	1074.81	15.033	0.003542	600	600	0.03
COAL#35	260	500	1278.46	13.992	0.003132	660	660	0.03
COAL#36	260	500	861.742	15.679	0.001323	900	900	0.03
COAL#37	120	241	408.834	16.542	0.00295	180	180	0.03
COAL#38	120	241	408.834	16.542	0.00295	180	180	0.03
COAL#39	423	774	1288.815	16.518	0.000991	600	600	0.03
COAL#40	423	769	1436.251	15.815	0.001581	600	600	0.03
LNG_CC#01	160	250	3427.912	56.613	0.024493	702	702	0.07
LNG_CC#02	160	250	3751.772	54.451	0.029156	702	702	0.07
LNG_CC#03	160	250	3918.78	54.736	0.024667	702	702	0.07
LNG_CC#04	160	250	3379.58	58.034	0.016517	702	702	0.07
LNG_CC#05	160	250	3345.296	55.981	0.026584	702	702	0.07
LNG_CC#06	160	250	3138.754	61.52	0.00754	702	702	0.07
LNG_CC#07	160	250	3453.05	58.635	0.01643	702	702	0.07
LNG_CC#08	160	250	5119.3	44.647	0.045934	702	702	0.07
LNG_CC#09	165	504	1898.415	71.584	0.000044	1350	1350	0.07
LNG_CC#10	165	504	1898.415	71.584	0.000044	1350	1350	0.07
LNG_CC#11	165	504	1898.415	71.584	0.000044	1350	1350	0.07
LNG_CC#12	165	504	1898.415	71.584	0.000044	1350	1350	0.07
LNG_CC#13	180	471	2473.39	85.12	0.002528	1350	1350	0.07
LNG_CC#14	180	561	2781.705	87.682	0.000131	720	720	0.07
LNG_CC#15	103	341	5515.508	69.532	0.010372	720	720	0.07
LNG_CC#16	198	617	3478.3	78.339	0.007627	2700	2700	0.07
LNG_CC#17	100	312	6240.909	58.172	0.012464	1500	1500	0.07
LNG_CC#18	153	471	9960.11	46.636	0.039441	1656	1656	0.07
LNG_CC#19	163	500	3671.997	76.947	0.007278	2160	2160	0.07
LNG_CC#20	95	302	1837.383	80.761	0.000044	900	900	0.07
LNG_CC#21	160	511	3108.395	70.136	0.000044	1200	1200	0.07
LNG_CC#22	160	511	3108.395	70.136	0.000044	1200	1200	0.07
LNG_CC#23	196	490	7095.484	49.84	0.018827	1014	1014	0.07
LNG_CC#24	196	490	3392.732	65.404	0.010852	1014	1014	0.07
LNG_CC#25	196	490	7095.484	49.84	0.018827	1014	1014	0.07
LNG_CC#26	196	490	7095.484	49.84	0.018827	1014	1014	0.07
LNG_CC#27	130	432	4288.32	66.465	0.03456	1350	1350	0.07
LNG_CC#28	130	432	13,813.00	22.941	0.08154	1350	1350	0.07
LNG_CC#29	137	455	4435.493	64.314	0.023534	1350	1350	0.07
LNG_CC#30	137	455	9750.75	45.017	0.035475	1350	1350	0.07
LNG_CC#31	195	541	1042.366	70.644	0.000915	780	780	0.07
LNG_CC#32	175	536	1159.895	70.959	0.000044	1650	1650	0.07

LNG_CC#33	175	540	1159.895	70.959	0.000044	1650	1650	0.07
LNG_CC#34	175	538	1303.99	70.302	0.001307	1650	1650	0.07
LNG_CC#35	175	540	1156.193	70.662	0.000392	1650	1650	0.07
LNG_CC#36	330	574	2118.968	71.101	0.000087	1620	1620	0.07
LNG_CC#37	160	531	779.519	37.854	0.000521	1482	1482	0.07
LNG_CC#38	160	531	829.888	37.768	0.000498	1482	1482	0.07
LNG_CC#39	200	542	2333.69	67.983	0.001046	1668	1668	0.07
LNG_CC#40	56	132	2028.945	77.838	0.13205	120	120	0.07
LNG_CC#41	115	245	4412.017	63.671	0.096968	180	180	0.07
LNG_CC#42	115	245	2982.219	79.458	0.054868	180	120	0.07
LNG_CC#43	115	245	2982.219	79.458	0.054868	180	120	0.07
LNG_CC#44	207	307	3174.939	93.966	0.014382	180	120	0.07
LNG_CC#45	207	307	3218.359	94.723	0.013161	180	120	0.07
LNG_CC#46	175	345	3723.822	66.919	0.016033	318	318	0.07
LNG_CC#47	175	345	3551.405	68.185	0.013653	318	318	0.07
LNG_CC#48	175	345	4322.615	60.821	0.028148	318	318	0.07
LNG_CC#49	175	345	3493.739	68.551	0.01347	318	318	0.07
LNG#01	3	19	669.988	75.464	0.90236	210	210	0.0002
LNG#02	3	28	134.544	129.544	0.110295	366	366	0.0002
OIL#01	94	203	1269.132	89.83	0.014355	120	120	0.0001
OIL#02	94	203	1269.132	89.83	0.014355	120	120	0.0001
OIL#03	94	203	1269.132	89.83	0.014355	120	120	0.0001
OIL#04	244	379	4965.124	64.125	0.030266	480	480	0.0001
OIL#05	244	379	4965.124	64.125	0.030266	480	480	0.0001
OIL#06	244	379	4965.124	64.125	0.030266	480	480	0.0001
OIL#07	95	190	2243.185	76.129	0.024027	240	240	0.0001
OIL#08	95	189	2290.381	81.805	0.00158	240	240	0.0001
OIL#09	116	194	1681.533	81.14	0.022095	120	120	0.0001
OIL#10	175	321	6743.302	46.665	0.07681	180	180	0.0001
OIL#11	2	19	394.398	78.412	0.953443	90	90	0.0001
OIL#12	4	59	1243.165	112.088	0.000044	90	90	0.0001
OIL#13	15	83	1454.74	90.871	0.072468	300	300	0.0001
OIL#14	9	53	1011.051	97.116	0.000448	162	162	0.0001
OIL#15	12	37	909.269	83.244	0.599112	114	114	0.0001
OIL#16	10	34	689.378	95.665	0.244706	120	120	0.0001
OIL#17	112	373	1443.792	91.202	0.000042	1080	1080	0.0001
OIL#18	4	20	535.553	104.501	0.085145	60	60	0.0001
OIL#19	5	38	617.734	83.015	0.524718	66	66	0.0001
OIL#20	5	19	90.966	127.795	0.176515	6	12	0.0001
OIL#21	50	98	974.447	77.929	0.063414	300	300	0.0001
OIL#22	5	10	263.81	92.779	2.740485	6	6	0.0001
OIL#23	42	74	1335.594	80.95	0.112438	60	60	0.0001
OIL#24	42	74	1033.871	89.073	0.041529	60	60	0.0001
OIL#25	41	105	1391.325	161.288	0.000911	528	528	0.0001
OIL#26	17	51	4477.11	161.829	0.005245	300	300	0.0001
OIL#27	7	19	57.794	84.972	0.234787	30	18	0.0001

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