Stochastic Unit Commitment Considering Uncertain Wind Production in an Isolated System

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***Abstract*—Wind Energy has become the renewable energy with the highest installed capacity in some European countries mainly due to its advanced technology and to existing political incentives. In countries like Spain, installed wind capacity amounts to 17% of total installed power capacity as of today. As power produced from wind grows, difficulties created by its intermittency nature (namely, the difficulty to predict wind generation output with enough accuracy and its volatility) make the operation of the system more difficult. Stochastic programming has been proposed as an adequate way to handle this uncertainty. In this article, the unit commitment problem is modelled taking into account the stochastic nature of wind production. The model is applied to the isolated power system of Gran Canaria island. We have analyzed the impact of increasing installed wind capacity and the value of having to deal with the uncertainty associated with wind in this power system.**

***Index Terms*—Stochastic Unit Commitment, Wind prediction error, Renewable Energies**

I. Introduction

UNCERTAINTY has always been present in electrical power systems, in the form of possible unit failures or errors in demand prediction. In the last years, electricity production from wind has increased significantly and thus, as well, the problems associated with this form of electricity generation regarding the uncertainty about wind output and its variability. Policy makers are willing to support renewable energies and especially wind energy. Thus, wind energy and its special characteristics have to be taken into account when planning and operating electrical power systems. This has several implications. On the one hand, significant reseracth must be devoted to making wind output predictions more accurate. On the other, new flexible, fast-reacting generation technologies, as well as new types of electricity storage, have to be developed and employed to manage the variability and unpredictability of wind electricity production.

To cope with the mentioned uncertainty in wind output prediction, stochastic optimization is used in this paper to obtain optimal unit commitment decisions taking into account various representative wind production scenarios.

The paper will be structured as follows: A short literature review explaining the different modelling approaches proposed for this problem is presented in chapter II. This review is divided into two parts. The first one discusses the general modelling of stochastic optimization problems, as well as the modelling of stochastic integer problems, (part II-A). In the second part, II-B, recent works dealing with uncertain wind production and its impacts on power systems are annalyzed. The modelling approaches used in this paper to represent the unit commitment problem with stochastic wind production are described in section III. The approaches described in section III are applied to the Case of Gran Canaria. Results are displayed in section IV. Finally, conclusions can be found in section V.

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II. Literature Review

A. Stochastic optimization

Stochastic programming cares about optimization problems which contain uncertainty of at least one of the input parameters. This is the opposite of a deterministic optimization model, which assumes all input parameters to be certain. Basic textbooks on stochastic optimization can be found with [1], [2] and [3]. In [4] stochastic programming is used for different applications in power systems.

A special case of a stochastic program, stochastic integer programming, has been employed in various fields such as capacity expansion, energy planning or power system operation. In these problems, some integer variables are used. In many cases, these variables are binary, as in the unit commitment problem formulated and solved in this paper in chapters III and IV. This is expressed using an extra restriction in the stochastic optimization problem assigning the corresponding decisions variables a solution space in integer numbers.

Special consideration is given to stochastic problems with integer variables in [5]. The author looks at implications on analysis and algorithm design of including integer variables in stochastic programming. He remarks that the breakdown of convexity and the inclusion of integer variables are the main problems when changing from stochastic linear programming to stochastic integer programming. [6] as well as [7] give an introduction to stochastic integer programming. They survey structural properties of this special type of problem and algorithms to solve them. The authors analyse mainly linear two-stage models with mixed-integer recourse and their multi-stage extensions. Multistage stochastic integer programs are the focus of the paper written by [8], who, apart from looking at the dynamic formulation of this problem, examine the conditions for optimality and stability of the solution. A stochastic integer program is used by [9] to incorporate day-ahead trading of electricity into hydro-thermal unit commitment.

Solution algorithms to stochastic integer programs are treated in many works ([10],[6], [7]). Stochastic programs can become of a very large size due to their special characteristics with random parameters. Thus, decomposition might be needed to solve the problem by parts. Special emphasis is given to decomposition algorithms in the thesis of [11]. In [12] a new decomposition framework is elaborated for stochastic optimization of unit commitment. [13] proposes another decomposition method to solve this kind of problem.

Due to the big size and the quite complex nature of stochastic programs in comparison to a deterministic one, it is interesting and important to quantify the advantage of using a stochastic optimization program over solving a series of deterministic optimization programs fixing in each one the value of the random parameter. This can be done with two measures: the Expected Value of Perfect Information (EVPI) and the Value of the Stochastic Solution (VSS).

EVPI indicates how much perfect information about the future would be worth. Since decision makers would benefit greatly from having exact data about the future, EVPI expresses their willingness to pay. It is calculated by comparing the so-called wait-and-see solution (solving each scenario as a deterministic optimization problem, WS) to the solution of the recourse problem (the stochastic optimization problem, RP). The wait-and-see solution is the weighted average of all deterministic optimization problems. These are calculated taking in each deterministic problem one particular realization of the random parameter.

$$WS = E_{\xi}[min_x z(x, \xi)] \tag{1}$$

E_{ξ} is the probability of the random parameter which is multiplied with the outcome of the deterministic problem. The recourse problem corresponds to the stochastic problem. EVPI results from the difference $RP - WS$.

The Value of Stochastic Solution can be described as the cost of taking into account random parameters as certain although they comprise uncertainty. It can be determined as the difference between the expected result of using the Expected Value solution (EEV) and employing the solution from the recourse problem. The expected value solution is simply the deterministic optimization solution considering the weighted average of the possible values of the random parameter. EEV uses this solution to fix the first-stage decisions x in the stochastic problem, which are those variables whose outcome does not depend on the scenario considered. Thus, the stochastic problem is only used to decide the value of variables in the subsequent stages. This is expressed in equation 2.

$$EEV = E_{\xi}[z(\bar{x}^{\bar{\xi}}, \xi)] \tag{2}$$

Finally VSS is obtained by subtracting RP from EEV.

B. Optimization of operation with wind production

In the last years the prediction od the wind output and the wind associated problems in power systems has attracted the attention of various authors.

Some authors focus on changes in generation scheduling in a system with high wind power production. [14], [15] and [16] look at changes in generation scheduling. Authors in [17] and [18] model different market environments and analyse the influence of stochastic wind input using a multi-stage stochastic optimization approach. The case of some countries in Europe and USA dealing with wind power is treated in [19]. Other authors work furthermore on the impacts of wind power on security. These issues are discussed in [20] for systems with significant power generation. Strategies for unit commitment and dispatch for a wind park are examined in [21].

Some authors have dedicated their work to examine how the use of hydro plants can absorb wind over- or underproduction. Thus, [22] applies a two-stage optimization model to cope with uncertain electricity production from wind and uncertain market prices. Here, pumped storage units are used to produce in case wind energy is lower than the energy offered in the market. [23] analyses the optimization of the daily operation of a wind-hydro power plant.

A literature review of wind forecasting technology can be found in [24].

III. The Modeling Approach

Unit Commitment problems try to determine the minimum cost scheduling for power plants to meet the system demand in the short term and to satisfy further restrictions in the power system. Results are startup and shutdown decisions for each generation plant in each hour. Unit commitment problems have been the focus of much research, since poor management of power resources can turn out to be very costly.

In the considered optimization problem, operational costs are to be minimized taking into account the demand balance constraint, up- and down reserve, minimum and maximum generation capacities, ramping constraints and the logic sequence for the startup and shutdown decisions.

The approach follows the structure of a two-stage stochastic problem. The unit commitment problem here proposed is solved for one day. This problem could be applied to compute decisions for the day-ahead market. Unit commitment decisions have to be made in advance (in Spain between 14 -38 hours in advance), while the exact production level of generation units is determined later on.

First-stage decisions are the startup and shutdown decisions, arr_p^t and par_p^t respectively, and the unit commitment ones ac_p^t. In the second stage of the problem, three scenarios are considered with probability $Prob_s$. Production output levels over the technical minimum production for the corresponding plants, $prodt_{p,s}^t$, and non-served energy $pns_{p,s}$ are determined in a 24-hour timeframe. Depending on the scenario, these variables might adopt different values. In the objective function (equation 3), the operational cost of the whole power system, $costeop$, is minimized.

$$\begin{gathered} costeop = \textstyle\sum_{p,t}[CosteTF^t ac_p^t \\ +CosteTV^t ProdTMin_p^t ac_p^t \\ +CosteArr^t arr_p^t + CostePar^t par_p^t \\ + \textstyle\sum_s Prob_s[CosteTV^t prodt_{p,s}^t \\ +CostePNSpns_{p,s}]] \end{gathered} \tag{3}$$

In the former equation, p refers to time periods, t to thermal generators and s to scenarios. First-stage decisions as the unit commitment ones ac, startup decisions arr and shutdown decision par are weighted with the corresponding cost, namely fixed cost, $CosteTF^t$, startup costs, $CosteArr^t$, and shutdown costs, $CostePar^t$, respectively. In the second stage, the term including the minimum production cost is active when the generation unit is committed in this period. Then, minimum production $ProdTMin_p^t$ and production output over minimum $prodt_{p,s}^t$ are weighted with the variable production cost $CosteTV^t$ for all possible hours and scenarios. Each unit of non-served energy $pns_{p,s}$ is deemed to cost $CostePNS$ in each period and scenario.

Constraints are shown in equations 4 to 10:

$$Dem_p - ProdI_{p,s} - pns_{p,s} = \sum_t ProdTMin_p^t ac_p^t + prodt_{p,s}^t \tag{4}$$

$$\sum_t (ProdTMax_p^t - ProdTMin_p^t) ac_p^t - prodt_{p,s}^t \geq RsSub_p \tag{5}$$

$$\sum_t -prodt_{p,s}^t \geq RsBaj_p \tag{6}$$

$$prodt_{p,s}^t \leq (ProdTMax_p^t - ProdTMin_p^t) ac_p^t \tag{7}$$

$$prodt_{p,s}^t - prodt_{p-1,s}^t \leq ProdTSub^t \tag{8}$$

$$prodt_{p-1,s}^t - prodt_{p,s}^t \leq ProdTBaj^t \tag{9}$$

$$ac_p^t - \left\{ \begin{array}{ll} Acp^t & \text{, for p = 1} \\ ac_{p-1}^t & \text{, for p} \geq 1 \end{array} \right\} = arr_p^t - par_p^t \tag{10}$$

Equation 4 ensures that demand is balanced all the time. Demand Dem_p and intermittent wind production $ProdI_{p,s}$ are given parameters. Up- and down-reserve ($RsSub_p$ and $RsBaj_p$) constraints (equations 5 and 6) make sure that a reliability margin exists in case it is needed because of the failure of one of the generation plants and errors in wind or demand prediction. In equation 7 the maximum output of a generation plant $ProdTMax$ limits production over the technical minimum production $prodt$. Equations 8 and 9 take into account the maximum variation of production output between two consecutive hours. Ramps are represented as $ProdTSub$ and $ProdTBaj$ for each generation unit. The formulation of the unit commitment restriction (eq. 10) takes into account the state of each generator in the preceding hour. While unit commitment variables are binary, startup and shutdown decisions can be continuous since equation 10 forces them to take binary values.

A. Deterministic Problem

To compare the stochastic problem, where uncertainty is taken into account, to the case where future is known with certainty, the deterministic problem must be formulated and solved. Using the formulation provided below together with the one for the stochastic problem, the Value of the Stochastic Solution and the Expected Value of Perfect Information mentioned in chapter II on 2 can be determined.

The objective function of the deterministic two-stage problem can be formulated as follows.

$$costeop = \sum_{p,t} [CosteTF^t ac_p^t + CosteTV^t ProdTMin_p^t ac_p^t + CosteTV^t prodt_p^t + CosteArr^t arr_p^t + CostePar^t par_p^t + CostePNS pns_p] \tag{11}$$

The production outcome $prodt_p^t$ and the amount of non-served energy pns_p do not depend on the scenario.

$$Dem_p - ProdI_p - pns_p = \sum_t ProdTMin_p^t ac_p^t + prodt_p^t \tag{12}$$

The demand constraint, equation 12 assumes that the parameters corresponding to wind production $ProdI_p$ are scenario-independent. The rest of constraints stays the same as in equations 5 to 10 but neglecting the scenario dependence of the two decision parameters $prodt_p^t$ and pns_p.

The deterministic problem assumes each of the scenario-dependent parameters to be given and certain in order to calculate the wait-and-see solution mentioned earlier. In this case, three different deterministic problems can be solved, one for each wind output scenario. Alternatively, an average scenario may be considered using average values of the input parameters.

IV. Case Study in Gran Canaria

Gran Canaria is a small island in Spain. It has been chosen as the case example system because it has a small power system and must cope with demand coverage on its own, since it is not interconnected with other grids. Being an island, wind production is becoming an important influencing factor in the generation mix. Over- or underproduction caused by wind cannot be smoothed by importing or exporting electricity, but has to be compensated by local power generation (or demand). Gran Canaria does not have at its disposal hydro plants which could react to wind production variability as proposed by some authors mentioned in subsection II-B. Since demand management schemes are not yet implemented, only the effects of uncertain wind production on the operation of power generation and reliability variables will be examined in this case example. We shall identify which generation technologies will be replaced by wind.

A. Data and scenarios

The generation park considered in the case example corresponds to the one possibly available in 2011. Precast data is based on the Energetic Plan of the Canary Islands [25]. Gran Canaria has two generation sites, one in Jinamar close to the capital of Gran Canaria and another one in Barranco Tirajana, consisting of a total of 20 units nowadays. By 2011 an additional unit will be available. There will be two combined cycle plants, one of which is not yet in operation. The already existing combined cycle consists of two gas turbines and a steam turbine and is currently used with gasoil. The currently existing plant and the plant to be constructed can be run as well with natural gas, which is not yet available on the Canary islands. In total there are four types of generation technology: combined cycle, gas turbine, steam turbine and diesel motor. Electricity generation is mainly based on heavy fuels such as gasoil and fueloil. Generation cost for these units are regulated in Canarias and were taken from [26]. Generation cost for the additional CCGT plant to be installed was assumed to be the same as for the existing CCGT plant. Hourly demand and wind data are based on historic series in Spain which have been scaled down considering the annual demand, the peak demand and installed wind generation in Gran Canaria. Annual demand and peak demand provisions are taken from [25]. For 2011 they are assumed to be 4.183 TWh and 768.38 MW, respectively, which corresponds to an increase of 17.9% and 19.4% compared to 2007 levels. Further expected increases for 2015 are in similar ranges. In this case study, the reference year is 2011. Being an island, wind potential is high in Gran Canaria. [25] states that the installed wind capacity in 2007 was 76 MW and predicts that it will more than triple to 272 MW in 2011 and will amount to 411 MW in 2015 .

Stochasticity lies in the wind prediction errors. These are deducted from historic prediction errors and realizations of them are considered in three different scenarios. Wind prediction errors are usually bigger the further the prediction reaches into the future. In a 24 hour time frame, the error of wind forecasts may grow to as much as 20% [24] of installed capacity. Wind prediction errors are used to correct the actual value of wind production when computing the amount of production considered in the dispatch.

In the first scenario, prediction errors were positive. This means that wind production was foreseen to be lower than it actually was. The second scenario considers as well positive prediction errors and the last scenario shows during the first part of the day negative and at the end positive errors.

scenario	wind prediction error	probability
1	+	0.3
2	++	0.4
3	-+	0.3

TABLE I
SCENARIOS AND THEIR PROBABILITY

A sensitivity analysis has been carried out changing the installed wind generation capacity. Values assumed for wind capacity range between the one installed in year 2008, the previewed in 2011 and 2015. Computations to compare stochastic and deterministic approaches have been carried out assuming 211 MW of installed wind capacity.

Figure 1 shows the original demand and the demand after substracting wind production (including the wind prediction error) for the three possible installed wind capacities and the three wind prediction error scenarios.

Taking into account that the Gran Canaria case example considers 24 time periods p, 3 scenarios s and 20 generation units t, the two-stage stochastic problem to be solved has 6456 constraints, 2472 continuous variables and 480 binary variables.

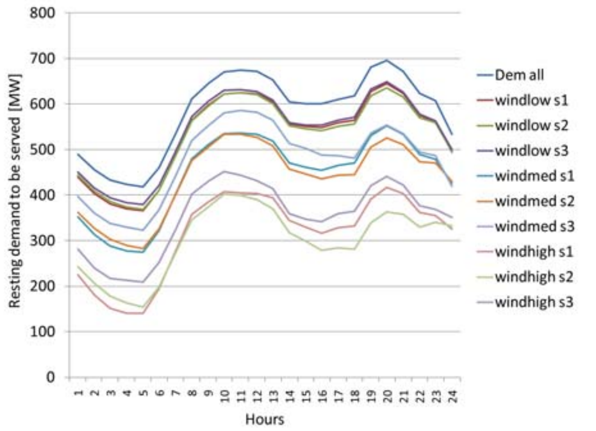

Fig. 1. Resting demand to be supplied in different wind scenarios

B. Results and discussion

The stochastic unit commitment problem for the results presented here has been calculated for one specific day during winter (a Thursday in the end of february).

1) Comparison stochastic versus deterministic approach : In the stochastic approach unit commitment decisions are unique while in the deterministic equivalent these decisions can adapt depending on the wind situation given in each scenario. As in the stochastic approach each scenario is taken into account with its probability, unit commitments might differ especially in peak hours with very different wind scenarios.

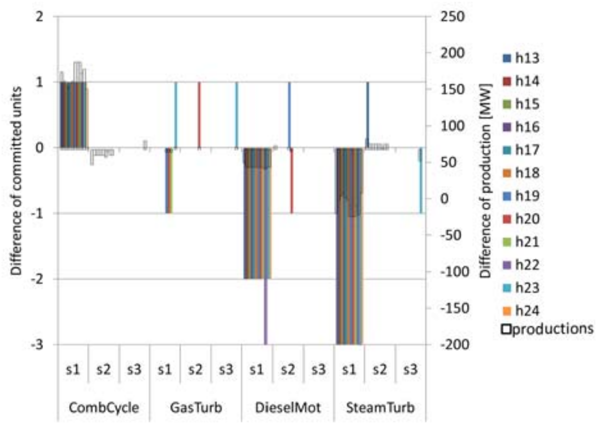

Fig. 2. Difference of units committed and production levels between stochastic and deterministic approach in hours 13 to 24

Figure 2 shows the difference of unit commitments and production between the stochastic and the deterministic approach during the evening from 13 to 24 o´clock. On the left axis unit commitments are shown. Combined cycle have one more unit committed during all hours which results on average in 140 MW more production in scenario 1. On the contrary diesel motors and steam turbines have fewer units commited in this first scenario. In the three deterministic scenarios unit commitments and thus production levels are very different. The outcome of the stochastic scenario shows little difference to scenarios 2 and 3 of the deterministic approach but high differences in scenario 1, where stochastic considerations seem to use less expensive power plants. So, high wind prediction errors may be smoothed using a stochastic approach and unit commitments can be adapted to very different wind prediction situations.

This results in an Expected Value of Perfect information (see page 2) of around 13.200 Euro in one day, which is a cost advantage of 1% of the stochastic approach. That would be the value of knowing the uncertain future with certainty. The Value of the Stochastic Solution expressing the cost of taking into account the random parameter wind error as certain has been determined to 5.420 Euro.

	Demand [MW]	Wind prevision [MW]	Wind error [MW] Scen. 1	Scen. 2	Scen. 3
h13	653	109	24	36	-21
h14	605	111	23	36	-20
h15	601	117	23	38	-19
h16	601	124	23	41	-11
h17	611	123	22	44	0
h18	618	126	21	47	10
h19	681	130	19	46	15
h20	696	129	14	41	13
h21	672	128	10	34	10
h22	624	125	10	26	5
h23	608	118	12	20	4
h24	534	108	-1	-5	6

TABLE II
DEMAND, WIND AND WIND ERRORS FOR 13-24 O´CLOCK

The difference of technologies applied in the peak between the two approaches is mainly due to the variable, fixed and start-up cost considered. These are regulated costs based on real plants (see subsection IV-A).

2) Scenario analysis of different installed wind capacities : A scenario analysis has been conducted changing the installed wind capacity from 76 MW installed nowadays to more than triple this capacity to 272 MW and 411 MW. This high capacity is taken from the energy plan previsions and may be true in 2011 and 2015 as renewable support in Spain is given and offshore wind capacity is supposed to rise in the coming years.

Figure 3 indicates on the left hand side the difference of unit commitment from the 272 MW to the 76 MW installed wind capacity case. First of all only unit commitment reductions and no increases can be observed during all hours as was expected when more installed wind generation is available and thus less demand has to be covered. In all shown hours one, two or even three diesel motors less will be committed. In some hours additional steam turbine unit reduction can be observed. As gas turbines act only in few hours as marginal units gas turbine unit commitment reduction occurs only in hours during the evening peak (20 and 22). Thus additional wind generation saves thermal production of marginal units.

On the right hand side the difference between the 411 MW to the 272 MW installed wind capacity case is shown. In the results it can be observed that in the case of 411 MW one unit less of the combined cycles is replaced by one or two units of steam turbines. In the merit order combined cycles stand before steam turbines. But steam turbines seem to be

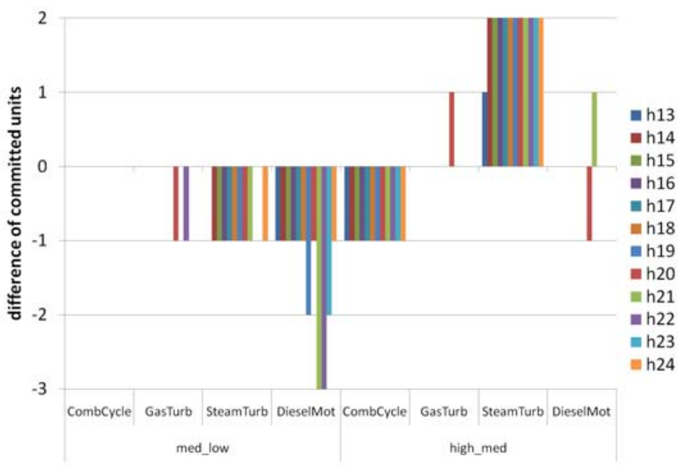

Fig. 3. Difference of units committed between 411/272MW and 272/76MW installed wind capacity in hours h13 to h24

more flexible to react to a higher wind production and thus to a possibly higher wind error to be considered.

Since the model is optimizing over 24h it takes into account the wind production and the resting demand to serve in all hours. In the case of the 411 MW wind production wind error scenarios result in resting demands that are more widespread than in the 272 MW case (see figure 1). In one case (411 MW) it is more economic not to turn off one combined cycle and let it work at a lower production level while in the other case (272 MW) turning it off is the best solution. These results indicate that higher wind production not always means less need of conventional thermal capacity. On the contrary, it may be that some conventional plants have to run on their minimum stable load to avoid extra start-up cost to cope with variable stochastic wind input in upcoming hours.

V. CONCLUSIONS

Wind energy causes already today alterations in generation scheduling. It has been shown that wind replaces more expensive diesel motors in scenarios with high wind production, but when wind production is low more expensive generation plants have to be committed due to their fast reaction ability. Furthermore it has been observed that very high wind input might lead to problems of thermal generation reserve. Taking into account various wind scenarios in stochastic optimization instead of looking at simulations with deterministic optimization, brings advantages as it has been demonstrated with the Expected Value of Perfect Information and the Value of the Stochastic Solution. Future research primarily in new storage possibilities and its implementation into stochastic modelling used for operation and planning is indispensable to cope with volatility in wind production.

REFERENCES

[1] J. R. Birge and F. Louveaux, *Introduction to Stochastic Programming*. New York: Springer, 1997.
[2] P. Kall and S. W. Wallace, *Stochastic Programming*. Chichester: Wiley, 1994.

[3] A. Prékopa, *Stochastic Programming*. Dordrecht: Kluwer Academic Publishing, 1995.
[4] T. K. Kristoffersen, *Stochastic programming with applications to power systems*. PhD thesis, Department of Operations Research, University of Aarhus, 2007.
[5] R. Schultz, "Stochastic programming with integer variables," *Mathematical Programing*, pp. 285–309, July 2003.
[6] W. Klein Haneveld and M. van der Vlerk, "Stochastic integer programming: General models and algorithms," *Ann. Operations Res.*, vol. 85, pp. 39–57, 1999.
[7] F. Louveaux and R. Schultz, *Stochastic integer programming*. Elsevier Science.
[8] W. Römisch and R. Schultz, *Multistage stochastic integer programs: an introduction*. Springer, Berlin, 2001.
[9] R. S. Matthias P. Nowak and M. Westphalen, "A stochastic integer programming model for incorporating day-ahead trading of electricity into hydro-thermal unit commitment," *Optimization and Engineering*, vol. 6, pp. 163–176, 2005.
[10] S. Takriti, J. Birge, and E. Long, "A stochastic model for the unit commitment problem," *Power Systems, IEEE Transactions on*, vol. 11, pp. 1497–1508, Aug 1996.
[11] C. C. C. Carøe, "L-shaped decomposition in stochastic integer programming." Master Thesis, 1995.
[12] P. Carpentier, G. Gohen, J.-C. Culioli, and A. Renaud, "Stochastic optimization of unit commitment: a new decomposition framework," *Power Systems, IEEE Transactions on*, vol. 11, pp. 1067–1073, May 1996.
[13] D. Dentcheva and W. Römisch, *Optimal power generation under uncertainty via stochastic programming*, pp. 22–56. Springer, Berlin, 1998.
[14] F. Li and B. Kuri, "Generation scheduling in a system with wind power," *Transmission and Distribution Conference and Exhibition: Asia and Pacific, 2005 IEEE/PES*, pp. 1–6, 2005.
[15] B. Ummels, M. Gibescu, E. Pelgrum, W. Kling, and A. Brand, "Impacts of wind power on thermal generation unit commitment and dispatch," *Energy Conversion, IEEE Transaction on*, vol. 22, pp. 44–51, March 2007.
[16] K. Methaprayoon, C. Yingvivatanapong, W.-J. Lee, and J. Liao, "An integration of ann wind power estimation into unit commitment considering the forecasting uncertainty," *Industry Applications, IEEE Transactions on*, vol. 43, pp. 1441–1448, Nov.-dec. 2007.
[17] R. Barth, H. Brand, P. Meibom, and C. Weber, "A stochastic unit-commitment model for the evaluation of the impacts of integration of large amounts of intermittent wind power," *Probabilistic Methods Applied to Power Systems, 2006. PMAPS 2006. International Conference on*, pp. 1–8, June 2006.
[18] P. Meibom, R. Barth, H. Brand, and C. Weber, "Wind power integration studies using a multi-stage stochastic electricity system model," *Power Engineering Society General Meeting, 2007. IEEE*, pp. 1–4, June 2007.
[19] M. Hoogwijk, D. van Vuuren, B. de Vries, and W. Turkenburg, "Exploring the impact on cost and electricity production of high penetration levels of intermittent electricity in oecd europe and the usa, results for wind energy," *Energy*, vol. 32, no. 8, pp. 1381 – 1402, 2007.
[20] F. Bouffard and F. Galiana, "Stochastic security for operations planning with significant wind power generation," *Power Systems, IEEE Transactions on*, vol. 23, pp. 306–316, May 2008.
[21] C. Moyano and J. P. Lopes, "Unit commitment and dispatch strategies for a wind park," *Power Engineering, Energy and Electrical Drives, 2007. POWERENG 2007. International Conference on*, pp. 12–17, April 2007.
[22] J. Garcia-Gonzalez, E. Parrilla, A. Mateo, and R. Moraga, "Building optimal generation bids of a hydro chain in the day-ahead electricity market under price uncertainty," *Probabilistic Methods Applied to Power Systems, 2006. PMAPS 2006. International Conference on*, pp. 1–7, June 2006.
[23] E. Castronuovo and J. Lopes, "On the optimization of the daily operation of a wind-hydro power plant," *Power Systems, IEEE Transactions on*, vol. 19, pp. 1599–1606, Aug. 2004.
[24] Y.-K. Wu and J.-S. Hong, "A literature review of wind forecasting technology in the world," *Power Tech, 2007 IEEE Lausanne*, pp. 504–509, July 2007.
[25] Gobierno de Canarias, "Plan energético de canarias," tech. rep., Gobierno de Canarias, Consejería de Industria, Comercio y Nuevas Tecnologías, 2007.
[26] Boletín Oficial de Estado, "Boe núm. 77." Viernes 31 marzo 2006, pp. 12484-12556.