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WIND POWER FORECASTING UNCERTAINTY AND UNIT COMMITMENT

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DISSERTAÇÃO DE MESTRADO APRESENTADA
À FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO EM
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Wind Power Forecasting Uncertainty and Unit Commitment

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Abstract

In this work we evaluate the impact of considering a stochastic approach on the day-ahead basis Unit Commitment. Comparisons between stochastic and deterministic Unit Commitment solutions are provided.

The Unit Commitment model consists in the minimization of the total operation costs considering units' technical constraints like ramping rates and minimum up and down time. Load shedding and wind power spilling is acceptable, but at inflated operational costs.

The generation of Unit Commitment solution is guaranteed by DEEPSO, which is a hybrid DE-EA-PSO algorithm, where DE stands for Differential Evolution, EA for Evolutionary Algorithms and PSO for Particle Swarm Optimization.

The evaluation process consists in the calculation of the optimal economic dispatch and in verifying the fulfillment of the considered constraints. For the calculation of the optimal economic dispatch an algorithm based on the Benders Decomposition, namely on the Dual Dynamic Programming, was developed. If possible, the constraints added to the dispatch problem by the Benders Decomposition algorithm will provide a feasible and optimal dispatch solution.

Two approaches were considered on the construction of stochastic solutions. Either the top 5 more probable wind power output scenarios are used, or a set of extreme scenarios are considered instead.

Data related to wind power outputs from two different operational days is considered on the analysis. Stochastic and deterministic solutions are compared based on the actual measured wind power output at the operational day. Through a technique capable of finding representative wind power scenarios and their probabilities we were able to analyze in a more detailed process the expected final operational costs. Also, we expose the probability that the system operator has on the operational costs being under/above certain value.

Results show that the stochastic approach leads to more robust Unit Commitment solutions than the deterministic one. The method of using the top 5 more probable scenarios on the search for the stochastic solution proved to produce preferable results.

Index Terms – unit commitment, stochastic, wind power, forecasting, uncertainty, DEEPSO, Benders Decomposition.

Resumo

Neste trabalho avaliou-se o impacto de se considerar uma abordagem estocástica no problema de *Unit Commitment*. Comparações entre soluções estocásticas e determinísticas são efetuadas.

O modelo de *Unit Commitment* consiste na minimização dos custos totais de operação, considerando restrições técnicas das unidades de geração, como janelas de operação e tempos mínimos de funcionamento. Corte de carga e desperdício de produção eólica são permitidos, mas com custos de operação inflacionados.

A criação de soluções de *Unit Commitment* é assegurada através de um algoritmo hídrido, chamado DEEPSO, que combina Evolução Diferencial, Programação Evolucionária e Otimização por Enxame de Partículas.

O processo de avaliação consiste no cálculo do despacho económico ótimo e na verificação do cumprimento das restrições consideradas. Para o cálculo do despacho económico ótimo foi criado um algoritmo baseado na Decomposição de Benders. Caso seja possível, as restrições criadas pelo dito algoritmo e acrescentadas ao problema de despacho fornecem uma solução de despacho ótima.

Duas abordagens foram consideradas na construção de soluções estocásticas. Ou são usados os 5 cenários de produção eólica mais prováveis, ou então é usado um conjunto de cenários extremos.

Dados relativos a produções eólicas de 2 dias diferentes de operação são considerados neste estudo. Soluções estocásticas e determinísticas são comparadas com base nos valores de produção eólica medidos no dia de operação. Através de uma técnica capaz de encontrar cenários de produção eólica representativos e as suas probabilidades, foi possível analisar de uma forma mais detalhada os custos de operação esperados. O risco que o operador do sistema corre em ter custos de operação superiores a determinado valor é analisado.

Os resultados mostram que uma abordagem estocástica leva a soluções de *Unit Commitment* mais robustas do que as conseguidas através de uma abordagem determinística. O método de utilizar os 5 cenários mais prováveis no cálculo da solução estocástica provou ser o mais adequado.

Palavras-chave – unit commitment, estocástico, produção eólica, previsões, incerteza, DEEPSO, decomposição de Benders.

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Abbreviations

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AC	Alternating Current
ISO	Independent System Operator
MISO	Midwest Independent System Operator
RTO	Regional Transmission Operator
SCED	Security-Constrained Economic Dispatch
SCUC	Security-Constrained Unit Commitment
UC	Unit Commitment
USA	United States of America
WPF	Wind Power Forecasting

Chapter 1

Introduction

In order to accomplish the European Union's objective of increasing the share of renewable energy to 20% until the year 2020 it has been observed a more and more significant presence of renewable energy sources in the power systems, allowing a reduction of the use of fossil fuels and their environmental impacts.

The consequent decline of conventional power generation units combined with the increasing use of fluctuating power sources create new challenges for operators of power systems, in what concerns the stability and reliability.

In a variety of countries in Europe, and even around the world, wind power is rapidly becoming a generation technology of great importance and applicability. As an example, Portugal has become, according to [1], the second country in the world with the highest share of wind generation. Although its direct economic advantages, wind power is considered as problematic for the power system operation because of the poor predictability and the variability that define it.

The integration of large amounts of wind power will have an implication both in the technical operation of the electricity system and in the electricity markets [2]. To be capable of managing the fluctuations and unpredictability of wind power, conventional units have to operate in a more flexible manner in order to maintain the power systems' stability. Larger amounts of wind power will require increased capacities of spinning and non-spinning reserves[1]. As consequence, the prices on the regulating power markets are expected to change. This happens primarily because of the uncertainty of the wind power, and not so much because of the variability. In fact, if wind power was fluctuating but perfectly predictable the conventional units will also have to be operated in a more flexible way, but the schedule could be made on a day-ahead basis and decided on conventional day-ahead spot markets. It is the unpredictable character of wind power that makes necessary the increase of reserves which has price implications.

[1] Spinning reserves are provided by online units while non-spinning reserves are provided by dedicated units for the matter.

The power systems operators must guarantee the power demand and generation balance, which can be problematic in systems with a high presence of wind power generation, particularly in periods with high wind availability and low demand, creating over-generation. As shown in [3], [4], wind curtailments are expected because of the lack of energy storage provided by pumped-hydro units.

Therefore, it's crucial that new ways of calculating the optimal selection of on-line units – Unit Commitment – are developed in such a way that could mitigate the impact of increasing wind power generation.

In this thesis we execute a performance comparison between deterministic and stochastic Unit Commitment solutions. Our method uses a variation of the EPSO (Evolutionary Particles Swarm Optimization) called DEEPSO to generate, in an iterative mode, new Unit Commitment solutions. Each created solution is then evaluated, calculating a pre-dispatch, in order to the algorithm lead to an optimal solution. This evaluation is carried out based on the Benders Decomposition that creates and adds new constraints to the pre-dispatch problem every time that in each hourly sub-problem the "shadow prices" calculated indicate to. This iterative method continues until an optimal pre-dispatch solution is found or no feasible solution can be recognized.

The Wind Power Generation impact on the Unit Commitment problem is analyzed by introducing wind power output scenarios. There are created two types of UC solutions: one stochastic and other in a deterministic way. The stochastic method takes into account several wind power output scenarios and their probability of occurrence in the generation of UC solutions. The deterministic solutions are created based on the point forecast values and, in some cases, based on the most probable scenario. The two final solutions encountered are compared based on the actual measured wind power output in the operation day. To do so, a dispatch for each solution is calculated. The comparison between the stochastic and the deterministic solutions is also made taking into account all the possible wind power scenarios for each one of the days analyzed. Thus, a better understanding of the impact of wind power uncertainty on the Unit Commitment is expected.

Chapter 2

State of the Art

In this chapter it is given a general idea of the state of the art, in what refers to the definition of the unit commitment and dispatch (2.1) and the integration of wind power into the unit commitment (2.2), namely some wind integration studies of relevance, reserve requirement for wind power and novel unit commitment algorithms. [5] was of great value in the development of this chapter.

2.1 Definition of the Unit Commitment

The main objective of a Unit Commitment (UC), namely a security-constrained unit commitment (SCUC), is to obtain a UC schedule with the minimum production cost and not compromising the system's security. Normally, the SCUC's constraints include the load balance, the reserve requirement, ramp rate limits, minimum up and down time limits and network constraints.

The SCUC is run mainly for reliability assessment purposes; on the other hand, the security-constrained economic dispatch (SCED) only schedules the on-line units, not having the responsibility of changing their commitment statuses.

According to an Independent System Operator (ISO) of the USA, the MISO – Midwest ISO – the SCUC and SCED are defined as follows [6]:

SCUC: "The SCUC software tool minimizes the cost of committing sufficient resources to meet: forecasted demand, confirmed Interchange Schedules and Operating Reserve requirements. SCUC ensures that the correct amount of generation is online, and notifies resources to come online and the expected duration for the resource to be online.".

SCED: “The SCED software tool balances energy injections (generation) and withdrawals (load), while meeting Operating Reserve requirement, managing congestion and calculating Locational Marginal Prices and Market Clearing Prices.”.

Next are listed several modelling approaches that have been considered as references to the modelling formulation of the UC used in the algorithm developed.

In 2006, *Carrion and Arroyo* [7] presented a new mixed-integer linear formulation for the unit commitment problem of thermal units. The formulation that was developed required fewer binary variables and constraints than the previously reported models. In that way, this new formulation allowed including a precise description of time-dependent start-up costs and intertemporal constraints, namely ramping limits and minimum up and down times, guarantying a significant computational saving. In this work, the formulated problem is then solved by calling on commercially available solvers, such as CPLEX. The presented model was successfully tested on a realistic case study and the numerical results revealed its accurate and computationally efficient performance.

Later, *Fu et al.* [8] introduced an efficient SCUC approach with AC constraints that obtains the minimum system operating cost verifying the security of power systems. Benders decomposition was applied to separate UC in the master problem from the network security in sub-problems. Here, the master problem uses the Lagrangian relaxation method and dynamic programming to solve the UC. Meanwhile, the sub-problem checks the AC constraints, determining whether a converged and secure AC power flow can be obtained. Benders cuts will be added to the master problem if any constraint violation arises. This iterative process will continue until no AC violations are present and a converged optimal solution is found. To exhibit the effectiveness of this proposed approach, a six-bus system and the IEEE 118-bus system with 54 units were analysed.

2.2 Integration of Wind Power into Unit Commitment

Unlike other conventional and controllable generation sources, wind power is unpredictable and has an intermittent character, which explains the enormous impact that the high penetration of wind power has on the UC problem. Therefore, due to the inherent uncertainty and variability of the wind power, it originates complications to the SCUC and the SCED. Thus, the need to revise the current SCUC and SCED algorithms arises.

In what concerns the uncertainty, Wind Power Forecasting (WPF) models are complex systems that use input data from numerical weather prediction models, local meteorological measurements, SCADA data of current wind power output and terrain characteristics. The complexity present in the weather and the wind to power conversion means that WPF will always involve a significant forecasting error [9]. Thereby, the reliability of the system can be hampered in the event of unforeseen decreases in wind power because the available ramping capability of on-line units in the system may not be enough to compensate this change [5]. Also, in the occurrence of a large upward ramp in wind power, or due to the wind power supply surplus that could happen at night, when there is often to be registered the strongest wind power and the load is low, it may be necessary to curtail wind power.

Variability is also problematic to the generation scheduling. With the objective of minimizing the system operational costs, the system operator tries to utilize wind power as much as possible, once wind power is normally assumed to have no operating costs in the SCUC. To deal with the variability of wind power, the system operator has to coordinate its others generation sources through the Unit Commitment and Dispatch.

This way, wind power needs to be considered in the system reserve procurement, load balancing and network constraints in the unit commitment formulation. As a matter of fact, even physical constraints of other non-wind units, like ramping up and down limits or minimum on and off time limits, are influent, leading to the relevant question of how to change the overall unit commitment and dispatch algorithms to incorporate wind power. Below, a short review of the current research is presented, structured into several sections.

2.2.1 Wind Integration Studies

In 2007, *Smith et al.* [10] pointed that machines with power electronic controls have demonstrated the capability of providing governor response and inertial response. Stability studies are mentioned to referrer that the doubly fed induction machine have demonstrated the ability of modern wind plants to improve system performance by damping power swings and supporting post-fault voltage recovery. It is said that an analysis of the net load variability in the different time frames, with and without wind, can give good insight into the additional reserves required to maintain a reliable system operation. Thus, it is assumed that the capacity value of wind has been shown to range from approximately 10% to 40% of the wind plant rated capacity. Finally, the authors concluded that the aggregation of wind plants over large geographical areas provide an effective mechanism to reduce wind plant variability and large balancing areas can help manage wind plant variability more easily than smaller ones.

Already in 2009, *Smith et al.* [11] described the status of integrating wind energy into electric power system. According to several investigations considering high penetrations of wind – up to 25% energy – the power system in the USA can handle these high penetration without compromising its operation. It is mentioned that the value of good wind forecasting has been clearly demonstrated to reduce unit commitment costs. Also, faster markets (e.g., 10 min rather than 1h) can reduce wind integration costs. The difficulties of maintaining system balance under conditions of light-load with significant wind variability have been illuminated, and it is suggested that some combination of system flexibility, wind curtailment, wind ramp-rate mitigation and new loads added in light-load periods will be needed. Moreover, the value of sharing balancing functions over large regions with a diversity of loads, generators and wind resources has been clearly demonstrated.

Present technology allows individual wind turbine controllers to have fault ride-through control capabilities that enable the wind turbines to stay connected during and after grid faults in the power transmission system. In normal operation conditions, the wind turbines have active and reactive power set points available for external control, supporting the power balancing and frequency control functions in the power system. As an example of the new wind plant features, it is indicated the Danish plant Horns Rev, the first large offshore wind plant. There, the wind plant main controller has operated as an integrated part of the central system control ensuring the power balance in the system. The authors consider that it is expected that such functionality will be inevitable in future power systems with large-scale wind penetration.

Mirbach et al. [12] focused their work on evaluate the impact on the generation pool and its marginal generation costs for electrical energy and the transnational interdependencies, in case of a significant share of renewable energies in the power generation systems. The substantial share of renewable energies and the connected changes in the power generation system produced a 13% reduction of variable generation costs. It is pointed that, due to export capacity shortages which interfere with the full utilization of renewable energies, additional capacities of wind power might not be economically reasonable after the year 2030.

In 2012, *Faias et al.* [3] presented a methodology for assessment and optimization of wind energy integration into power systems considering flexible backup generation and storage. The Portuguese power system was used as study example. According to their simulation results, the pumped-hydro units schedule for the future will not provide enough energy storage capacity and, for that motive, wind curtailments are expected in the Portuguese power system. One of the main reasons that is pointed for these curtailments is the combination of high wind penetration and the run-of-river hydro generation. In what concerns the transmission network, the power flow simulation showed that no constraints will occur, in any of the scenarios considered. A technical and economic analysis was made in order to consider an additional energy storage system that completely offsets the wind energy curtailments, which was discarded due to the high capital costs involved in that solution.

2.2.2 Reserve Requirement for Wind Power

In 2005, *Doherty and O'Malley* [13] presented a new methodology to quantify the reserve needed on a system taking into account the uncertain nature of wind power. The reliability of the system is used as an objective measure to determine the effect of increasing wind power penetration. The authors concluded that increasing wind power capacity causes a distinct but not excessive increase in the amount of reserve needed on the system; in fact, increasing amounts of wind capacity causes a greater necessity for categories of reserve that act over longer periods of time. It is shown that committing reserve with large forecast horizon, i.e., several hours before the hour in question, cases an increase in the amount of reserve needed, which can be explained by the extra reserve that must be committed to cater for possible wind power deficits between the time the operating decisions were made and the period in question.

Also regarding this subject, *Ortega-Vasquez and Kirschen* [14] proposed a technique to calculate the optimal amount of spinning reserve which enables the system operator to respond not only to generation outages but also to errors in the forecasts for load and wind production. The developed technique determines the amount of spinning reserve that minimizes the total cost of operating the system. It is concluded that an increased wind power penetration does not necessarily require larger amounts of spinning reserve. This conclusion should be taken with care and shouldn't be generalized to other systems because it depends heavily on the hypothesis of the study and the underlying model used in the study.

Matos and Bessa [15] suggest a new reserve management tool that is intended to support the TSO in defining the on-line operating reserves necessities for the daily and intraday markets. In this work, decision strategies like setting an acceptable risk level or finding a compromise between economic issues and the risk of loss of load are explored.

In [16], *Xue et al.* attempted a new way to consider the uncertainty of wind power forecast in the system operating reserve estimation. Credibility theory is applied for calculating a set of indices which can dynamically forecast the risk of wind power output. The tests carried on showed that the credibility of the two indices calculated can reduce the unnecessary operating reserve effectively with system security guarantee.

In 2012, *Bessa et al.* [17] reported the results and an evaluation methodology from two new decision-aid tools that were demonstrated at a TSO (REN, Portugal) during several months. The first tool is a probabilistic method that is intended to support the TSO on the decision of the operating reserve requirement, while the second one is a fuzzy power flow tool that can identify possible congestion situations and voltage violations in the transmission network. Probabilistic wind power forecasts are used as input in both tools.

The first tool, contrarily to what happens with deterministic rules, informs the decision maker about the level of risk that he is taking, making him alert to possible situation with high risk. The results showed that different forecast lead to different performances of the management tools and probabilistic wind power forecasts may lead to a decrease in reserve requirements and better decisions.

In what refers to the fuzzy power flow tool, it was clear that the use of wind power uncertainties forecasts in power flow calculations represents an additional benefit, particularly when the network is operating near its limits. The results concluded that the transmission network is robust enough to accommodate the installed wind power capacity.

Last year, in 2013, *Ahmadi-Khatir et al.* [18] proposed a decentralized methodology to optimally schedule generating units while simultaneously determining the geographical allocation of the required reserve. An interconnected multi-area power system with cross-border trading in presence of wind power uncertainty is considered on the study. The authors concluded that the proposed decentralized technique is accurate, as the final results are equal to the obtained by centralized procedure that use the whole information available in all areas. Additionally, it is said that the units schedules and the geographical allocation of the reserve in a determined area are dependent on the wind power uncertainty level and also on the tie-lines capacities between areas.

2.2.3 Novel Unit Commitment Algorithms

With their paper [19], *Tuohy et al.* examined the effects of stochastic wind and load on the unit commitment and dispatch of power systems with high levels of wind power. The impact of planning the system more frequently to account for updated wind and load forecasts were also analyzed. They believed that taking into account the stochastic nature of wind in the unit commitment algorithm, more robust schedules could be produced. The WILMAR project [20] was used as a tool. As result of their work they concluded that mid-merit gas and peaking units are used more when wind is not forecast perfectly compared to what happens with perfect forecasts. Furthermore, optimizing deterministically results in an increase in the use of those type of units, because of the less robust schedules produced. The number of hours reserve requirements are not met increases when the frequency of committing reduces, i.e., moving from committing every hour to every 6 hours. It is shown that a saving of approximately 0.25% (in 1 hour rolling) to 0.9% (in 3 hour rolling) can be achieved if the system is optimized stochastically as opposed to deterministically.

Ummels et al. [4] proposed a new simulation method that can fully assess the impacts of large-scale wind power on system operations from cost, reliability and environmental perspectives. The problem formulation included constraints such as ramp-rate for generation schedules and reserve activations and minimum up and down times of conventional units. The method developed was applied to the Dutch power system. The results obtained indicate that wind power forecast has a negligible effect on thermal system operating cost, emission reductions and wasted wind. It is concluded that for the optimization of system operation with large-scale wind power it is essential to acquire accurate, near-real-time wind power measurements and a continuous re-calculation of unit commitment and dispatch.

In 2008, *Boffard and Galiana* [21] formulated a short-term forward electricity market-clearing problem with stochastic security capable of accounting for non-dispatchable and variable wind power generation sources. In this work, the reserve requirements are determined through simulation of the wind power realization in the scenarios considered, instead of being pre-defined. The scenarios included the ability to proceed to load shedding and wind curtailment. The authors referred that the problem might become unapproachable because its dimensionality considerably grows when multiple scenarios are considered.

Later, *Wang et al.* [22] presented a security-constrained unit commitment algorithm that takes into account the intermittency and volatility of wind power generation. The uncertainty of the wind power output is included by the construction of several scenarios. In order to reduce the computational time and effort the problem is decomposed to a master problem and many sub-problems by application of Benders decomposition technique. The UC problem is solved in the master problem with the forecasted intermittent wind power generation. Succeeding, the wind power volatility is introduced by the built scenarios. An initial dispatch is verified in the sub-problems and generation redispatch is a possibility to satisfy the hourly volatility presented in the simulated scenarios. If the technical violations persist after the redispatch, Benders cuts are created and added to the master problem to revise the schedule solution. This iterative process continues until simulated wind scenarios can be accommodated by redispatch. The achieved results point out that the iterations between the master UC problem and the sub-problems allow the construction of a robust unit commitment and dispatch solution. Physical limitation of units such as ramping are found to be crucial for accommodating the volatility of wind power generation. The method described can be improved through better modeling of wind power forecasting errors and allowing wind spillage and load curtailment and using reserves to address the uncertainties in wind.

In this paper [23], *Ruiz et al.* evaluate the benefits of a combined approach that uses stochastic and reserve methods for the efficient management of uncertainty in the unit commitment problem in presence of significant amounts of wind power. Numerical studies showed that the UC solutions that were obtained with this combined approach are more robust than the others that follow the traditional approach – deterministic. It is concluded that combining scenarios with proper amount of reserve requirements leads to very robust solutions, fact which is connected to the reduction of the expected costs. Units with higher ramp limits, lower minimum up and down times and lower economic minimum capacity are preferred with stochastic formulations comparing to what happens with deterministic formulations. It is declared that stochastic policies attain lower wind curtailments than deterministic policies. It is expected that, in the future, the use of stochastic unit commitment formulations are widespread.

In 2012, *Wang et al.* [24] presented a unit commitment problem with uncertain wind power which is formulated as a chance-constrained two-stage stochastic program. The developed model ensures that, with high probability, a large portion of the wind power output will be utilized at each operating hour. A combined Sample Average Approximation algorithm is developed to solve the model effectively. Three types of policies were studied and the wind utilizations by these policies, compared. Computational results indicate that a higher level of wind power generation might increase the total power generation cost. In a related paper, *Wang et al.* [25] used this methodology to propose a price-based UC with wind power utilizations constraints. The model incorporates day-ahead price, real-time price, and wind power output uncertainties. In the first stage, the unit commitment is defined as well as the amount of energy offered for the day-ahead market. Then, the economic dispatch of generators is made. To ensure the utilization of the volatile wind power to a large extent a chance constraint is considered.

2.3 Chapter's Conclusion

The impacts that the increasing use of renewable energy has on the UC have been studied for the last years. The uncertainty of wind power plays a significant role on the UC problem. To deal with that, stochastic approaches are being considered to replace the conventional deterministic methods of scheduling generation units. The computational time and effort problems associated to the stochastic methods can be overcome by the use of approaches like Benders Decomposition.

Chapter 3

Tools and Modelling

The definition of the adopted UC model is crucial to the understanding of the work carried out and to the correct analysis of the obtained results. The considerations made on the construction of our UC model are presented in the next section.

3.1 UC Problem Modelling

The main considerations adopted in the resolution of the Unit Commitment problem are presented next. As the principal objective of this work thesis is to investigate the impact that considering a stochastic approach has on the UC problem, no constraints related to power flow were considered. In fact, no representation of an electric network is present in this study.

The decision variables in the Unit Commitment problem are $\mu_{i,k}$, that represent the unit commitment status of the unit *k* at the interval *i*; and $P_{i,k}$ which is the real power generation of the unit *k* at the interval *i*. $\mu_{i,k}$ is a binary variable, having the value “1” to the on status, and the value “0” to the off status.

The objective function was defined as follows:

$$Min \sum_{i=1}^{T} \sum_{k=1}^{M} \mu_{i,k} * \ C_k\big(\ P_{i,k}\big) + \ \mu_{i,k} * (1 - \ \mu_{i-1,k}) * c_k^{start} \tag{3.1}$$

As presented, the objective function is the minimization of the total operation costs that result of the sum of $C_k\big(\ P_{i,k}\big)$ and the unit’s start costs, c_k^{start}. $C_k\big(\ P_{i,k}\big)$ is the operation cost due to the level of generation of the unit *k* at the interval *i*, defined by an economic dispatch.

The constraints considered are presented below.

$$\sum_{k=1}^{M} \mu_{i,k} * P_{i,k} = P_i^{load} - P_i^{wind} \quad \forall_i \tag{3.2}$$

The first constraint refers to the system power balance. It forces that the generation level of the committed units equals the required level of load subtracting the wind power generation.

$$\sum_{k=1}^{M} \mu_{i,k} * P_k^{Max} \geq P_i^{load} - P_i^{wind} + P_i^{reserve} \quad \forall_i \tag{3.3}$$

$$\sum_{k=1}^{M} \mu_{i,k} * P_k^{Min} \leq P_i^{load} - P_i^{wind} \quad \forall_i \tag{3.4}$$

Equations 3.3 and 3.4 are related to the units' technical limits and the expected levels of load and reserve. Thus, the combination of all maximum generation limits of the committed units must, at least, equal the expected level of load and reserve combined, subtracting the wind power generation (3.3). Also, the sum of all units' minimum generation limits must be inferior to the expected value of load, for each operation period (3.4).

$$\mu_{i,k} * P_k^{Min} \leq P_{i,k} \leq \mu_{i,k} * P_k^{Max} \quad \forall_i, \forall_k \tag{3.5}$$

The previous equation represents the constraint of real power generation limits of the system units.

$$P_{i,k} - P_{i-1,k} \leq R_k^{up} * \Delta t \quad \forall_k \tag{3.6}$$

$$P_{i-1,k} - P_{i,k} \leq R_k^{dn} * \Delta t \quad \forall_k \tag{3.7}$$

3.6 and 3.7 are the ramping up and down constraints, respectively. The variation in the units output level is limited by the ramp up and down limits, R_k^{up} and R_k^{dn}. In our problem Δt has the value of 1 hour.

$$\left(Xon_{i-1,k} - T_k^{up}\right) * \left(\mu_{i-1,k} - \mu_{i,k}\right) \geq 0 \quad \forall_i, \forall_k \tag{3.8}$$

$$\left(Xoff_{i-1,k} - T_k^{dn}\right) * \left(\mu_{i,k} - \mu_{i-1,k}\right) \geq 0 \quad \forall_i, \forall_k \tag{3.9}$$

To implement the minimum up and down times constraints of the committed units, equations 3.8 and 3.9 had to be considered. $Xon_{i-1,k}$ and $Xoff_{i-1,k}$ represent the number of consecutive periods that unit *k* have been on and off, respectively, until period *i*-1. T_k^{up} is the minimum up time for unit *k*, and T_k^{dn} is the minimum down time.

3.2 DEEPSO

For the realization of this work was necessary the use of different tools, computational and conceptual. In this section, we introduce DEEPSO. Benders Decomposition technique will be presented in a later section. A brief reference is made on the technique behind the construction of the representative wind power scenarios in the end of this chapter.

DEEPSO is a hybrid DE-EA-PSO algorithm, where DE stands for Differential Evolution, EA for Evolutionary Programming and PSO for Particle Swarm Optimization. It was presented in [26], where it is tested for a complex study case in the domain of power systems. It departed from an algorithm denoted EPSO, for Evolutionary Particle Swarm Optimization. The beginning version of EPSO was presented in [27] and combined the exploratory power of PSO (Particle Swarm Optimization) with the self-adaptation of EA. Several works confirmed the quality and reliability of this tool [28]-[35]. The earliest version of EPSO is available from [36].

In the DEEPSO algorithm the conception of new individual is made based on

$$X^{(k+1)} = X^k + V^k \tag{3.10}$$

$$V^{(k+1)} = AV^k + B\left(X^k_{r1} - X^k\right) + P[C(b^*_G - X^k)] \tag{3.11}$$

Where **X** is a particle and **V** is called the particle velocity. **A**, **B** and **C** are diagonal matrices with the weights that are previously defined. $\boldsymbol{X^k_{rl}}$ is formed through an uniform recombination, which randomly selects, from the universe of all individual best memory solution, a coordinate for each dimension. $\boldsymbol{b^*_G}$ results from $b^*_G = b_G(1 + w_G N(0,1))$, $\boldsymbol{b_G}$ being the best point so far found by the swarm and $\boldsymbol{w_G}$ a Gaussian distributed random number.

The parameters **A**, **B** and **C** are subjected to mutation and selection in order to achieve a higher progress rate.

The general scheme of the DEEPSO algorithm could be:

1. Generating a Random Population
2. Evaluate the Current Population
3. Initiate cycle until termination criteria is not met
    a. Clone Current Population
    b. Apply DEEPSO movement rule to both populations (Current and Cloned)
    c. Evaluate both populations
    d. Create new population by competition between Current and Cloned populations
    e. Verify termination criteria:
        i. If termination criteria met, end cycle;
        ii. If termination criteria not met, return to a.

The developed functions added to the original code of DEEPSO are presented next. A detailed scheme of the created algorithm is offered.

1. The first step is to create a random population. In this first stage of the algorithm, the population's size is of 30 particles, in order to be possible to gather several feasible solutions. Each particle represents an UC solution. The dimension of the particles comes from $N_G * N_T$, where N_G is the number of generation units and N_T is the number of operation periods in the problem.
2. The created population passes through a corrective path, by the use of two functions that rearrange the UC solutions in such a way that constraints 3.3 and 3.4 can be satisfied.
3. Then, the Current population is evaluated by the use of a function that contains a routine that uses the Benders Decomposition to calculate the optimal dispatch for each of the UC solutions.
4. At this point, for computational time saving, the population's size changes from 30 particles to 10. The top 10 evaluated solutions are selected to build this shortened population.
5. A loop begins until termination criteria is not met. We defined as termination criteria a maximum number of generations. Also, the loop will end if the best solution found stays the same for 70% of the defined maximum number of generations. In this case, the termination criteria consist in either a maximum number of generation or a determined number of generations without finding a better solution.
    a. The Cloned population is created from the Current one;
    b. The DEEPSO movement rule is applied to both the populations;
    c. Both populations are adjusted in order to the UC solutions respect the constraints 3.3 and 3.4;
    d. Evaluation of the populations is carried out using the Benders Decomposition. A deterministic evaluation uses wind power point forecast in the formulation of the dispatch problem. Stochastic evaluation consists in several runs of the routine with Benders Decomposition, one for each considered scenario. The final fitness value of a stochastic solution has the scenarios probabilities weighted: $Fit_{final} = \sum_{i=1}^{scn} prob_i * fit_i$, where fit_i is the fitness value encountered for each of the i scenarios and $prob_i$ is the probability associated to the scenario i;
    e. If the termination criteria is met, the loop ends; if not, return to "a.".

3.3 Benders Decomposition – Dual Dynamic Programming

For time-sequenced problems, like the Unit Commitment problem, it can be used the dual dynamic programming via Benders Decomposition.

In this section the mathematical structure of such technique will be explained. For that, we first present the principal concepts [37] and then, through a simple example, finish the explanation.

3.3.1 Principal Concepts – Mathematical Formulation

For a given problem that extends through 3 time steps and has decision variables X_1, X_2 and X_3, one for each time step, we can mathematically formulate this problem as:

$$\begin{array}{lllll} \text{Min:} & C_1^t X_1 + C_2^t X_2 + C_3^t X_3 & & & \\ \text{Subj:} & A_1 X_1 & & & \geq b_1 \\ & E_2 X_1 + A_2 X_2 & & & \geq b_2 \\ & & E_3 X_2 + A_3 X_3 & & \geq b_3 \end{array}$$

Where C_1, C_2 and C_3 are the cost coefficients for each decision variable. It becomes clear that the matrix of constraint coefficients is sparse and also, the sub-matrix E establishes the connections between followed time stages. Without the sub-matrix E there would be 3 independent problems instead of a global one.

For a matter a simplicity, let's assume:

$$\begin{array}{lll} \text{Min:} & C_1^t X_1 + C_2^t X_2 & \\ \text{Subj:} & A_1 X_1 & \geq b_1 \\ & E_2 X_1 + A_2 X_2 & \geq b_2 \end{array}$$

The aspect of this problem can be changed by:

$$\begin{array}{lll} \text{Min:} & C_1^t X_1 + C_2^t X_2 & \\ \text{Subj:} & A_1 X_1 & \geq b_1 \\ & \qquad A_2 X_2 & \geq b_2 - E_2 X_1 \end{array}$$

Now, this is equivalent to the following formulation:

$$\begin{array}{lll} \text{Min:} & C_1^t X_1 + \alpha(X_1) & \\ \text{Subj:} & A_1 X_1 & \geq b_1 \\ \text{Where:} & & \end{array}$$

$$\alpha(X_1) = \min C_2^t X_2$$

$$\text{Subj:} \quad A_2 X_2 \geq b_2 - E_2 X_1$$

This way we now have a "Master Problem" – the one on X_1 – and a "sub-problem", which is resolved on X_2. Solving the dual of the sub-problem for a specific value of X_1^* will result in a vertex π^* of the sub-problem domain and thus finding a constraint that can be added to the master problem. In a linear optimization problem the solution is always in one of the vertex of the domain. The obtained constraint comes in the form $\alpha \geq (b_2 - E_2X_1)^t * \pi^*$. So, the master problem is now:

$$
\begin{array}{lllr}
\text{Min:} & C_1^t X_1 + \alpha(X_1) & & \\
\text{Subj:} & A_1 X_1 & & \geq b_1 \\
 & & \alpha & \geq (b_2 - E_2X_1)^t * \pi^*
\end{array}
$$

The iterative cycle of the Benders Decomposition algorithm could be written in this manner:

1. Solve the master problem and obtain a new guess X_1^*;
2. With the value X_1^*, solve the dual of the sub-problem and obtain π^*;
3. With π^*, add the new constraint $\alpha \geq (b_2 - E_2X_1)^t * \pi^*$ to the master problem e return no 1.

For stop criterion it can be chosen one of two. Either stop when no constraints are added to the master problem, or, having defined a tolerance, verify the progress in the objective function.

3.3.2 Numerical Example - Dispatch

One iteration of the Benders Decomposition algorithm will be presented next. For that an academic dispatch problem is considered. The problem consists on 2 generators and 3 operation periods. The problem data is presented in the table 1.

Table 1 – Numerical Example – Problem Data

	$C_{i,k}$	Unit1	Unit2
Costs	t_1	4	2
	t_2	1	2
	t_3	1	4

		L_i
Load	t_1	100
	t_2	70
	t_3	90

		R_k
Ramp Rate	Unit1	30
	Unit2	20

		Max	Min
Limits	Unit1	50	0
	Unit2	90	40

The problem formulation is observable bellow. First the objective function is presented, followed by the problem constraints.

$$\text{Min:} \quad \sum_{i=1}^{3}\sum_{k=1}^{3} C_{ik}^{t} * P_{ik}$$

Subj:

$$\left|\begin{array}{cccccc}
1 & 1 & 0 & 0 & 0 & 0 \\
-1 & -1 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 \\
-1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & -1 & 0 & 0 & 0 & 0 \\
\hline
-1 & 0 & 1 & 0 & 0 & 0 \\
1 & 0 & -1 & 0 & 0 & 0 \\
0 & -1 & 0 & -1 & 0 & 0 \\
0 & 1 & 0 & 1 & 0 & 0 \\
0 & 0 & 1 & 1 & 0 & 0 \\
0 & 0 & -1 & -1 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & -1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & -1 & 0 & 0 \\
\hline
0 & 0 & -1 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 & -1 & 0 \\
0 & 0 & 0 & -1 & 0 & 1 \\
0 & 0 & 0 & 1 & 0 & -1 \\
0 & 0 & 0 & 0 & 1 & 1 \\
0 & 0 & 0 & 0 & -1 & -1 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & -1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & -1
\end{array}\right|
*
\left|\begin{array}{c}
P_{11} \\ P_{12} \\ P_{21} \\ P_{22} \\ P_{31} \\ P_{32}
\end{array}\right|
\begin{array}{c|c|c|}
\geq & 100 & \\
\geq & -100 & \\
\geq & 0 & \text{Problem 1} \\
\geq & -50 & \\
\geq & 40 & \\
\geq & -90 & \\
\hline
\geq & -30 & \\
\geq & -30 & \\
\geq & -20 & \\
\geq & -20 & \\
\geq & 70 & \\
\geq & -70 & \text{Problem 2} \\
\geq & 0 & \\
\geq & -50 & \\
\geq & 40 & \\
\geq & -90 & \\
\hline
\geq & -30 & \\
\geq & -30 & \\
\geq & -20 & \\
\geq & -20 & \\
\geq & 90 & \\
\geq & -90 & \text{Problem 3} \\
\geq & 0 & \\
\geq & -50 & \\
\geq & 40 & \\
\geq & -90 &
\end{array}$$

Problems 2 and 3 can be arranged to this:

P_{21}			$\geq$	-30 + P_{11}	
-P_{21}			$\geq$	-30 − P_{11}	
		-P_{22}	$\geq$	-20 + P_{12}	
		P_{22}	$\geq$	-20 − P_{12}	
P_{21}	+	-P_{22}	$\geq$	70	Problem 2
-P_{21}	+	-P_{22}	$\geq$	-70	
P_{21}			$\geq$	0	
-P_{21}			$\geq$	-50	
		P_{22}	$\geq$	40	
		-P_{22}	$\geq$	-90	

P_{31}			$\geq$	-30 + P_{21}	
-P_{31}			$\geq$	-30 − P_{21}	
		P_{32}	$\geq$	-20 + P_{22}	
		-P_{32}	$\geq$	-20 − P_{22}	
P_{31}	+	P_{32}	$\geq$	120	Problem 3
-P_{31}	+	-P_{32}	$\geq$	-120	
P_{31}			$\geq$	0	
-P_{31}			$\geq$	-50	
		P_{32}	$\geq$	40	
		-P_{32}	$\geq$	-90	

First we have a progressive routine, resolving the problem from 1 to 3. The solution for the problem 1 is $\frac{P_{11}}{P_{12}} = \frac{10}{90}$ with an objective function value of 220. With this solution from problem 1, problem 2 can be resolved.

P_{21}			$\geq$	-20	
-P_{21}			$\geq$	-40	
		-P_{22}	$\geq$	70	
		P_{22}	$\geq$	-110	
P_{21}	+	P_{22}	$\geq$	70	Problem 2
-P_{21}	+	-P_{22}	$\geq$	-70	
P_{21}			$\geq$	0	
-P_{21}			$\geq$	-50	
		P_{22}	$\geq$	40	
		-P_{22}	$\geq$	-90	

Its solution is $\begin{matrix} P_{21} \\ P_{22} \end{matrix} = \begin{matrix} 0 \\ 70 \end{matrix}$, which is used in the resolution of problem 3. The objective function in this problem has the value of 140.

P_{31}			$\geq$	-30	Problem 3
-P_{31}			$\geq$	-30	
		P_{32}	$\geq$	50	
		-P_{32}	$\geq$	-90	
P_{31}	$+$	P_{32}	$\geq$	90	
-P_{31}	$+$	-P_{32}	$\geq$	-90	
P_{31}			$\geq$	0	
-P_{31}			$\geq$	-50	
		P_{32}	$\geq$	40	
		-P_{32}	$\geq$	-90	

The solution from problem 3 is $\begin{matrix} P_{31} \\ P_{32} \end{matrix} = \begin{matrix} 30 \\ 60 \end{matrix}$ leading to an objective function value of 270. The total cost of operation is now of 630.

Once reached the problem 3, the progressive routine is terminated. The regressive routine starts from problem 3 to problem 1.

First, the dual from problem 3 is solved. The solution is $\pi_3 = [0\ 3\ 0\ 0\ 4\ 0\ 0\ 0\ 0\ 0]$, with $\alpha_3 = 270$ – the same objective function value of its primal, as it is supposed. A new constraint is then added to the problem 2, as explained in the previous section. The problem 2 becomes:

P_{21}				$\geq$	-20	Problem 2
-P_{21}				$\geq$	-40	
		-P_{22}		$\geq$	70	
		P_{22}		$\geq$	-110	
P_{21}	$+$	P_{22}		$\geq$	70	
-P_{21}	$+$	-P_{22}		$\geq$	-70	
P_{21}				$\geq$	0	
-P_{21}				$\geq$	-50	
		P_{22}		$\geq$	40	
		-P_{22}		$\geq$	-90	
$3P_{21}$		$+$	α_3	$\geq$	270	

The dual from problem 2 is resolved, which provides $\pi_2 = [0\ 0\ 4\ 0\ 0\ 2\ 0\ 0\ 0\ 1]$, with $\alpha_2 = 410$. A constraint is added to problem 1.

P_{11}	+	P_{12}			$\geq$	100	Problem 1
-P_{11}	+	-P_{12}			$\geq$	-100	
P_{11}					$\geq$	0	
-P_{11}					$\geq$	-50	
		P_{12}			$\geq$	40	
		-P_{12}			$\geq$	-90	
		-$4P_{12}$	+	α_2	$\geq$	50	

In this phase, a new progressive routine is in order. Therefore, problem 1 is resolved with its new constraint. Its solution is $\begin{matrix} P_{11} \\ P_{12} \end{matrix} = \begin{matrix} 50 \\ 50 \end{matrix}$. The objective function of this problem represents the total cost of operation, because it includes α_2, which includes α_3. The value of such objective function is 550, representing an improvement when compared to the 630 obtained at the end of the last progressive routine.

The same procedure made early is repeated until no constraints are added or no progress in the objective function is achieved.

3.3.3 Adapting the Dual Dynamic Programming to the UC Problem

The solutions evaluation procedure consists in calculating the optimal economic dispatch. To do so, a routine using Benders Decomposition was developed. Here, the procedure is described.

1. An initial dispatch solution is provided as an input to the Benders Decomposition function. This solution does not guarantee the respect of the ramp rate constraints. This initial solutions allows the iterative process to begin. The iterative process has two phases – progressive and regressive. The progressive phase starts at the first operation period and continues until the last. In the regressive phase, the reverse path is taken. The regressive process resolves the same problems that the progressive did, contemplating, when needed, the constructed constraints.
   Each phase follows the same algorithm structure, which is explained below.
2. Reminding:

$$
\begin{array}{lllll}
\text{Min:} & C_1^t X_1 + C_2^t X_2 & & & \\
\text{Subj:} & A_1 X_1 & & \geq b_1 & \\
 & & A_2 X_2 & \geq b_2 - E_2 X_1 &
\end{array}
$$

   For each of the operation periods the matrix ***A*** and ***E*** are constructed. They are matrix containing only the value 1 or 0, adapting to the current period unit commitment (***A***) and the past period unit commitment (***E***). The matrix ***b*** is also constructed for each operation period.

In the progressive process, the current period is considered master problem of the subsequent one(s). It is resolved considering the constraints added from its sub-problem.

$$\begin{aligned}
\text{Min:} \quad & C_1^t X_1 + \alpha(X_1) & & \\
\text{Subj:} \quad & A_1 X_1 & & \geq b_1 \\
& & \alpha & \geq (b_2 - E_2 X_1)^t * \pi^*
\end{aligned}$$

3. Having the problem structured, the solution is found through a linear optimization function, *linprog*. In the regressive process, this function also provides the "shadow prices", i.e., the dual problem solution, needed to the construction of the constraint to be added to the respective master problem.
4. This back and forward process continues until the best solution found, i.e., with lower operation costs, does not change for a determined number of iteration. 5 iterations showed to be enough.

One of the most critical problem on accommodating the wind power is the inherent variability. Consecutive periods often have significant amplitude on the wind power output levels. The capacity of the power system to deal with such difficulty is restrained by the ramping rates of the committed units. The developed Benders Decomposition routine, through the additional constraints that creates, is capable of finding the optimal dispatch solution that accommodates the mentioned variability. To do so, in the anteceding periods of the periods considered critical, the level of generation on the units with greater ramp rates is decreased and shifted to other units. Therefore, in the critical periods, the power system has more ramping capacity to cope with an abrupt fall of the wind power generation level. On the opposite side, when the critical period represents a sudden increase of wind power generation, the conventional power generation is shifted to the units that on the critical period are not committed.

3.3.4 Selecting the Optimization Framework

Two strategies were considered on the selection of the optimization framework: one using the *Matlab* conventional optimization tool box, and the other supported by a commercial solution.

The version of the developed algorithm using the Matlab optimization tool box needed approximately 1 hour and 12 minutes to produce a UC solution, after 10 DEEPSO generations, considering no wind power scenarios. Figure 1 presents a Matlab report on the spent time.

Profile Summary

Generated 09-Apr-2014 11:07:30 using cpu time.

Function Name	Calls	Total Time	Self Time*	Total Time Plot (dark band = self time)
main_rui	1	4344.496 s	0.075 s	
DEEPSO_rui	1	4344.415 s	0.166 s	
FITNESS_FUNCTION_rui	21	4343.331 s	1.173 s	
FunBenderNew2inverse2	229	4342.054 s	106.575 s	
linprog	161976	3910.535 s	50.802 s	
optim\private\simplex	161976	3796.198 s	56.589 s	
optim\private\simplexphaseone	161976	2545.185 s	681.543 s	
optim\private\simplexpiecewise	161976	1798.124 s	1798.124 s	
optim\private\simplexphasetwo	160245	930.575 s	639.414 s	
optimset	161976	324.944 s	116.169 s	

Figure 1 - *Matlab* Report - Conventional tool box version

As can be verified in figure 1, the optimization function, *linprog*, and its sub-functions are the principal factor that explains the expended time.

The incorporation of the commercial and more powerful optimization tool, *GUROBI* [38] permitted a reformulation of the optimization function *linprog*. Thus, the time performances were greatly improved. Figure 2 helps demonstrate the results.

Profile Summary

Generated 15-Apr-2014 11:42:43 using cpu time.

Function Name	Calls	Total Time	Self Time*	Total Time Plot (dark band = self time)
main_rui	1	535.594 s	0.062 s	
DEEPSO_rui	1	535.532 s	0.150 s	
FITNESS_FUNCTION_rui	21	534.513 s	1.129 s	
FunBenderNew2inverse2	225	533.302 s	125.770 s	
linprog	197928	407.532 s	44.422 s	
gurobi (MEX-file)	197928	340.947 s	340.947 s	

Figure 2 - *Matlab* Report - Commercial tool box version

With *GUROBI* it is only needed approximately 9 minutes to produce 10 DEEPSO generations, against the 1 hour and 12 minutes that was needed without it. Incorporating *GUROBI* the developed Benders Decomposition routine can be considered appropriate to a stochastic Unit Commitment problem. Thus, our work exploits the advantage of *GUROBI*.

3.4 Finding Representative Wind Power Scenarios

It is common to deliver the wind power forecast as point forecast, which represents a single value for each look-ahead time horizon. Decision makers in the operation of a power system must take into consideration the uncertainty of wind power. The most appropriate approach to consider the wind power uncertainty is by the representation of a set of scenarios. In order to calculate risks or conditional values at risk it is needed the description of the probability density function.

In 2007, *Pinson et al.* [39] proposed a method to generate scenarios of short-term wind power production that respect both the predictive distribution and the interdependence structure of prediction errors.

The scenarios data used in this work was created based on the referred technique. In order to reduce the number of scenarios, making the UC problem computational efficient, a methodology of finding representative wind power scenarios and their probabilities for stochastic models, proposed by *Sumaili et al.* [40] is used. This methodology is able to substitute a large scenario set by a smaller set of clusters, each one replaced by a representative scenario related to the probability of the cluster it represents. Thus, the computational effort associated to the stochastic programming algorithms can be reduced. This method produces not only a set of representative scenarios, but also orders them by their probability value. Therefore, it is possible to select a number of scenarios and understand whether the maximum level of risk defined is being satisfied or not.

3.5 Chapter’s Conclusion

A simple Unit Commitment problem structure was adopted, considering constraints like units’ minimum up and down times and ramping limits. The DEEPSO was shaped into the nature of our problem, being able to generate and evaluate in a proper manner the UC solutions. Benders Decomposition is used on the evaluation procedure. Through a commercial optimization tool, the running times are acceptable to the UC problem. The developed UC structure and computational functions are adequate to the study we intended to perform.

Chapter 4

Results on the Case Study

4.1 Description of the Power System

In this work, a simple example power system is used, composed by 10 generation units. Each unit has different capacities (Min and Max), ramp-rates ($R_k^{up}$and R_k^{dn}), and minimum up (T_k^{up}) and down (T_k^{dn}) times. Linear production costs are used, C_k. The information related to the power system is resumed on table 2.

Table 2 - Generator Data

Unit	Min (MW)	Max (MW)	C_k (€/MWh)	R_k^{up} (MW/h)	R_k^{dn} (MW/h)	T_0 (MW)
1	150	455	20,335	80	80	300
2	150	455	21,229	80	80	300
3	20	130	34,003	26	26	0
4	20	130	33,420	26	26	0
5	25	162	28,993	32.4	32.4	0
6	20	80	32,834	16	16	0
7	25	85	38,856	17	17	0
8	10	55	59,673	11	11	0
9	10	55	61,207	11	11	0
10	10	55	61,963	11	11	0

	T_k^{up} (h)	T_k^{dn} (h)	CC (€)	HC (€)	IS (h)	HS (h)
1	8	8	9000	4500	8	5
2	8	8	10000	5000	8	5
3	5	5	1100	550	-5	4
4	5	5	1120	560	-5	4
5	6	6	1800	900	-6	4
6	3	3	340	170	-3	2
7	3	3	520	260	-3	2
8	1	1	60	30	-1	0
9	1	1	60	30	-1	0
10	1	1	60	30	-1	0

The initial state of the generation units is symbolized by the column IS (h); positive values signify that the units are on the *on* status for these number of hours, negative values have the same logic but represent the *off* status. The initial power output is represented in T_0. Finally, the start costs are separated in Hot Start Cost, HC, and Cold Start Cost, CC.

In order to consider the possibility of load shedding, wind spilling and generation surplus, 3 artificial units were created with extremely high cost coefficients. The over inflating of the cost coefficients is due to the desire of avoiding UC solutions that permit such possibilities. In the attempt of selecting UC solutions that use at least 40% of the wind resources, the wind spilling is limited to 60% of the total wind power generation for each operational period. Table 3 presents the referred cost coefficients.

Table 3 - Artificial Units Cost Coefficients

Unit	C_k (€/MWh)
Load Shedding	10.000
Wind Spilling	1.000
Generation Surplus	10.000

For matter of modeling simplicity, as earlier referred, the electrical network was not represented in this study.

Table 4 contains information related to the level of load and reserve for all of the 24 periods.

Table 4 - Load and Spinning Reserve data

Period	Load (MW)	Spinning Reserve (MW)
1	700	70
2	750	75
3	850	85
4	950	95
5	1000	100
6	1100	110
7	1150	115
8	1200	120
9	1300	130
10	1400	140
11	1450	145
12	1500	150
13	1400	140
14	1300	130
15	1200	120
16	1050	105
17	1000	100
18	1100	110
19	1200	120
20	1400	140
21	1300	130
22	1100	110
23	900	90
24	800	80

The spinning reserve levels are assumed to be 10% of the system load levels. In this work, the spinning reserve is only considered to confirm the UC constraint 3.3. This means that, throughout the dispatch calculation, the effective level of spinning reserve is not controlled. To accommodate the wind power uncertainty and volatility the system's ramping capacity is often used to its limit. Therefore, even if the scheduled units in a particular operational period are not operating at their maximum power capacity, the system's level of spinning reserve might be compromised because it does not remain sufficient ramping capacity. A possible approach to contemplate this problem could be the ongoing control of the remaining spinning reserve level throughout the dispatch calculation, imputing inflated costs when the referred levels are not preserved.

4.2 Description of the Wind Power Scenarios

In the analysis, we used data from to two different days – *Day1* and *Day2*. For each day there is a point forecast, an actual measured value and a set of possible scenarios with their correspondent probability of occurrence. The scenarios were constructed according to the methodology presented in the section 3.4 – “Finding Representative Wind Power Scenarios”.

The total capacity of wind power considered in this study case is 700 MW.

Figures 3 and 4 illustrate the behavior inherent to the days considered, in what refers to the point forecast and the measured value.

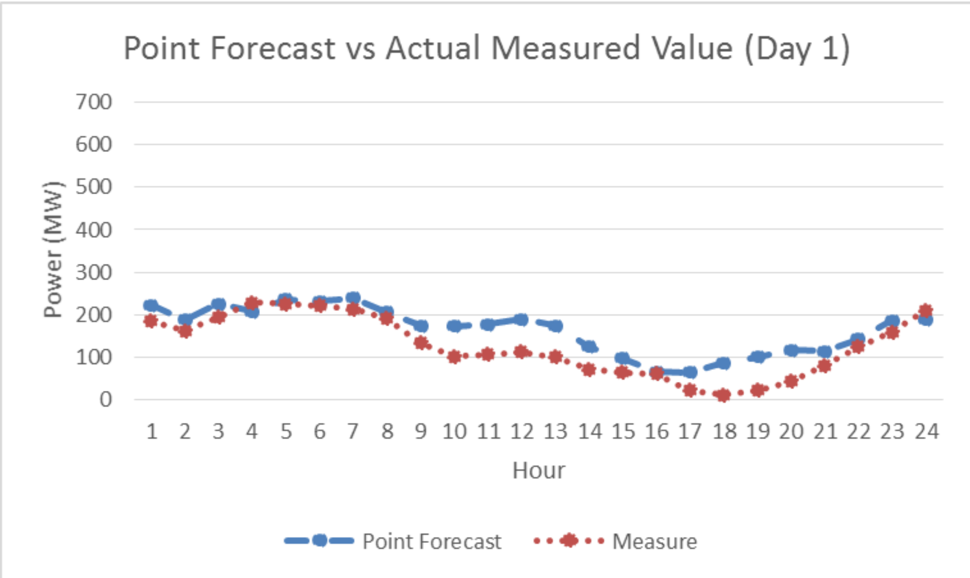

Figure 3 - Point Forecast versus the Actual Measure in the *Day1*

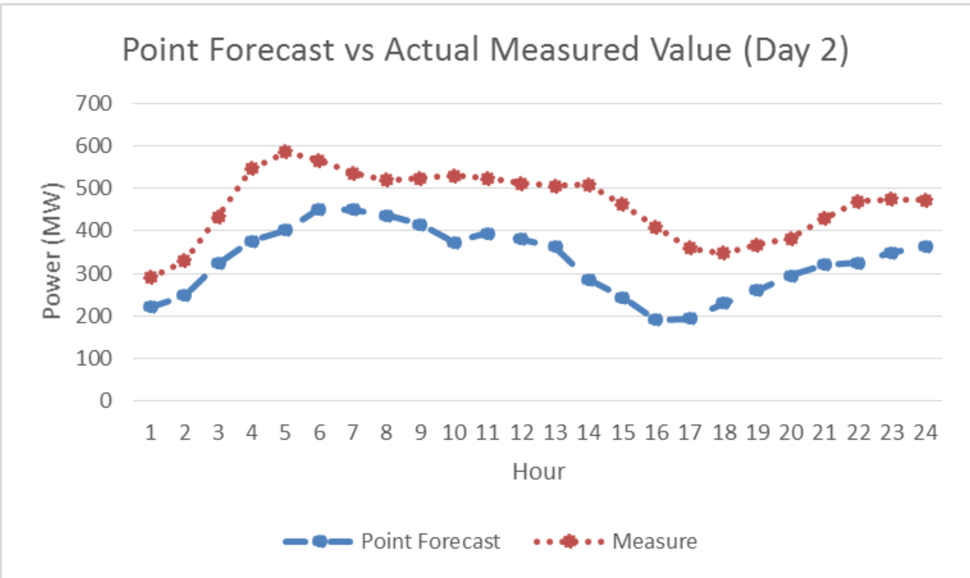

Figure 4 - Point Forecast versus the Actual Measure in the *Day2*

By observation of the last two figures it becomes clear that on the *Day2*, the error between the forecast and the actual measured value has a greater significance. The importance of this greater gap will be discussed later in this chapter.

An ideal stochastic method for calculating a UC solution should consider the complete set of possible wind power scenarios. Nevertheless, in order to achieve a method computationally efficient, we decided to consider a maximum of 5 wind power scenarios for each of the 2 stochastic approaches considered in this study - one uses the top 5 probable scenarios and the other uses the point forecast plus 4 extreme scenarios.

The following two figures represent the identified top 5 probable scenarios for the analysis of *Day1* and *Day2*.

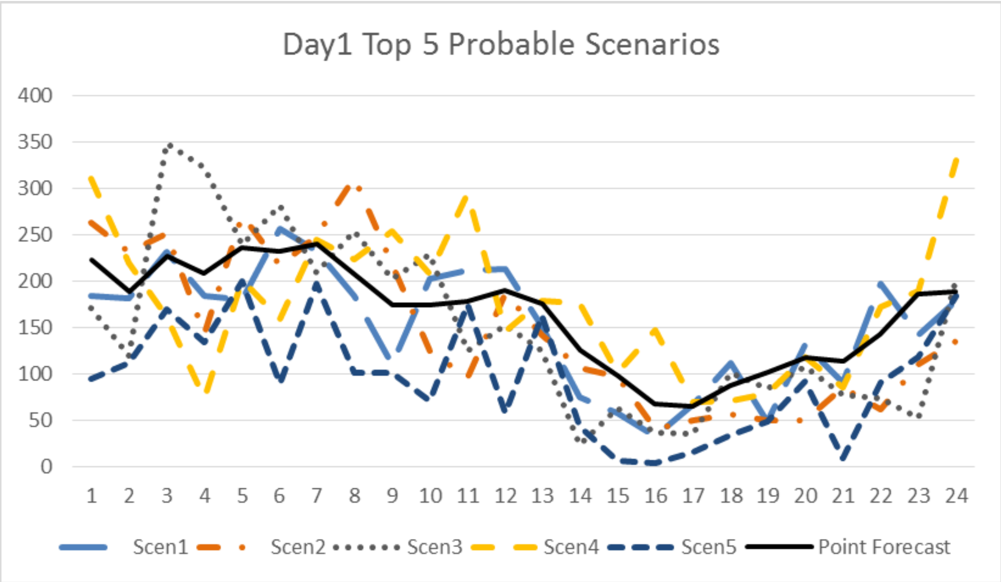

Figure 5 - Top 5 Probable Scenarios Day1

Horizontal axis: Period (hour) / Vertical axis: Power (MW)

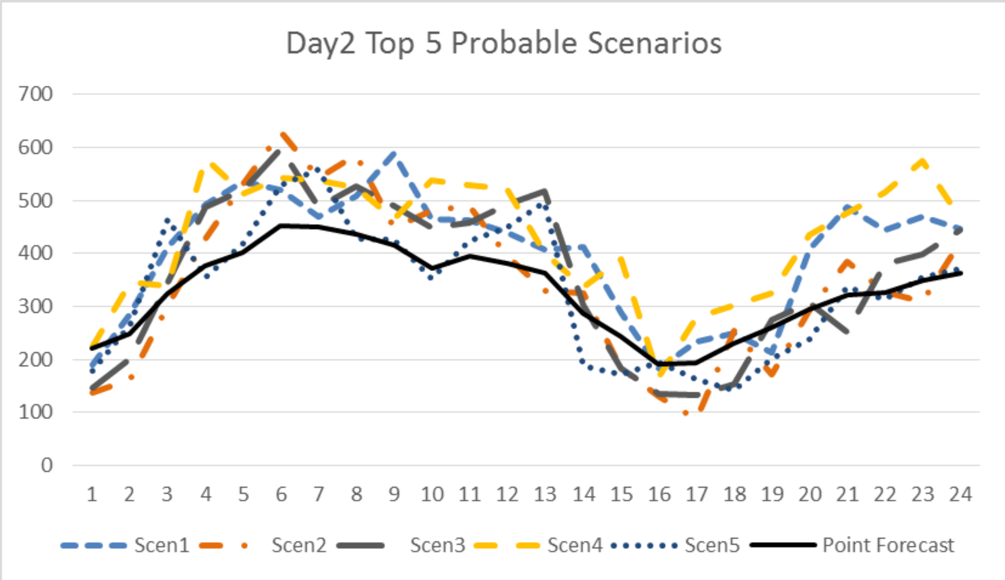

Figure 6 - Top 5 Probable Scenarios Day2

Horizontal axis: Period (hour) / Vertical axis: Power (MW)

Table 5 contains the associated probability for each of the 5 more probable scenarios represented in the last 2 figures.

Table 5 - Top 5 Probable Scenarios Probabilities

			Day1		
	Scenario1	**Scenario2**	**Scenario3**	**Scenario4**	**Scenario5**
Actual Probability	51%	12,2%	5,4%	3,6%	4,3%
Normalized Probability	67,55%	14,83%	7,15%	4,77%	5,70%

			Day2		
	Scenario1	**Scenario2**	**Scenario3**	**Scenario4**	**Scenario5**
Actual Probability	14,9%	8,7%	6,8%	4,1%	3,9%
Normalized Probability	38,80%	22,66%	17,71%	10,68%	10,16%

The selected scenarios represent, in the case of Day1, 76,5% of the universe of possibilities, while, in the case of Day2, it only represent 38,4%. Therefore, the analysis related to the Day2 implies a greater exposition to risk.

In our study we selected a set of extreme scenarios to evaluate the impact that their consideration could have on the search for a stochastic solution. It was considered, for each day, a set of scenarios composed by 2 scenarios of deficit of wind power and 2 scenarios of surplus, when compared to the expected value (point forecast). The selection of the mentioned extreme scenarios was based on the sum of the difference between hourly values of the point forecast and of the scenarios. The 2 higher values and the 2 lower ones were selected, establishing the described set of extreme scenarios.

Figures 7, 8, 9 and 10 illustrate the referred extreme scenarios. To improve the readability of those figures, each one only contains information of the point forecast, a scenario of deficit of wind power and another of surplus.

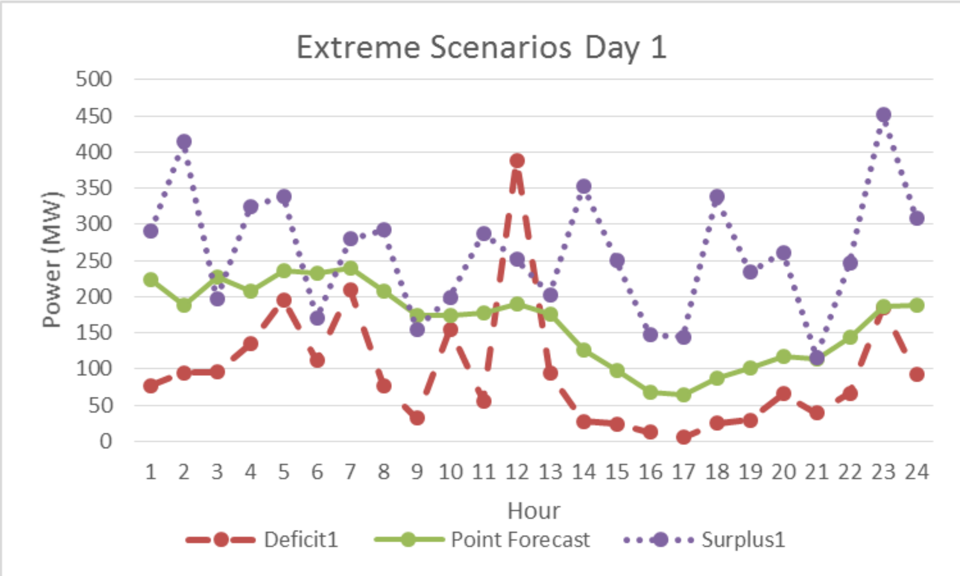

Figure 7 - Extreme Scenarios *Day1* - Deficit1 and Surplus1

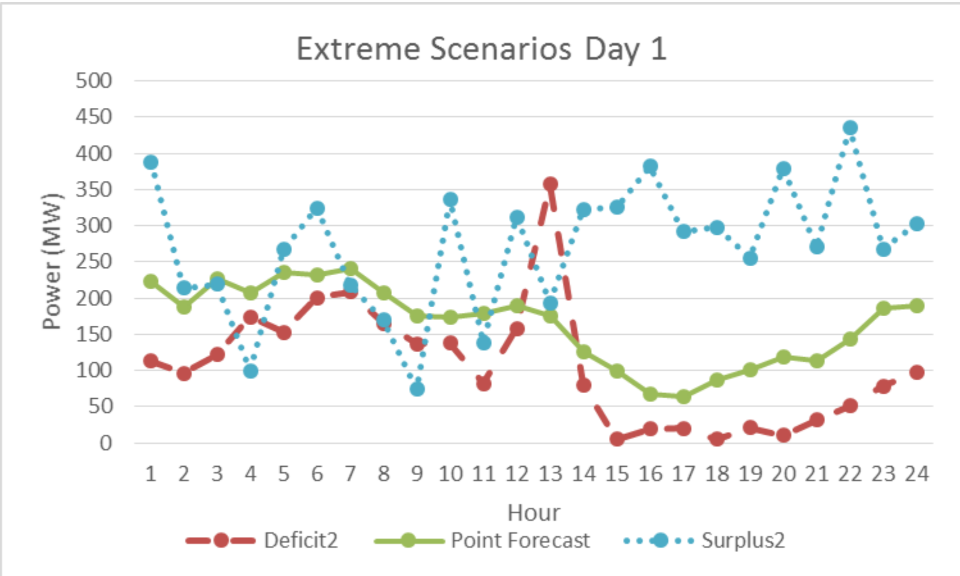

Figure 8 - Extreme Scenarios *Day1* - Deficit2 and Surplus2

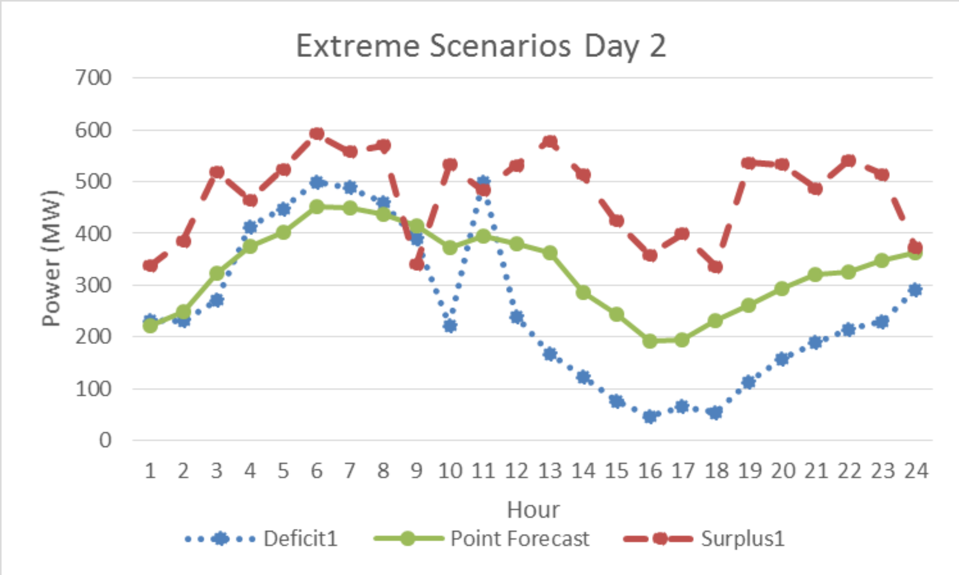

Figure 9 - Extreme Scenarios *Day2* - Deficit1 and Surplus1

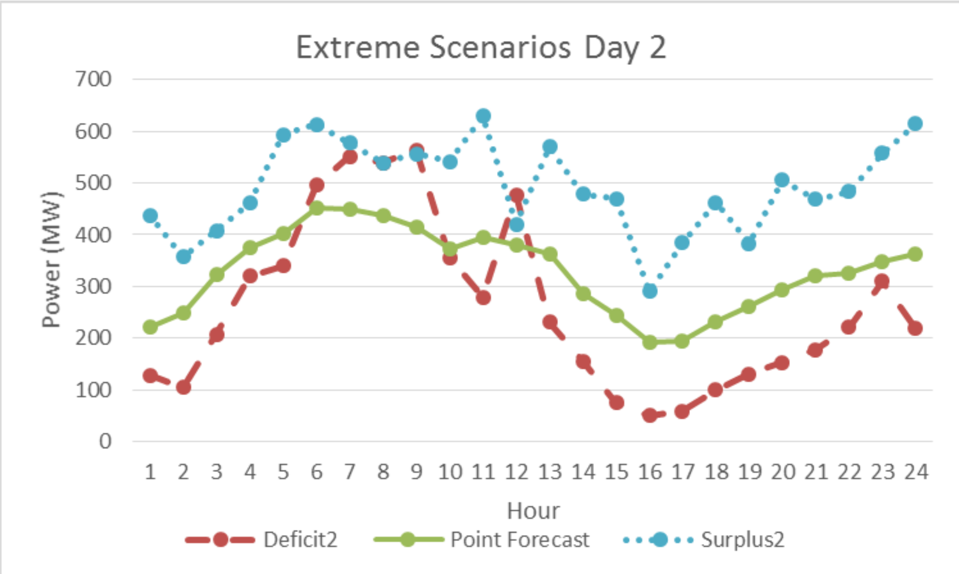

Figure 10 - Extreme Scenarios *Day2* - Deficit2 and Surplus2

In the methodology that uses these extreme scenarios in the search of a stochastic solution, which will be presented later in this chapter, we assigned 10% probability of occurrence for the extreme scenarios and 60% for the point forecast scenario. This balance of probabilities, assigning 10% to the extreme scenarios, has the objective of allowing an effective adaptation of the UC solutions to these scenarios.

4.3 Results and Discussion

In this section we present the results obtained during this work thesis and make a concise discussion of them. The analysis will be structured with the main objective of displaying a comparison between deterministic and stochastic solutions. Results from the data of the two different days will be also confronted in order to evidence the impact of the uncertainty in wind power.

Different studies were carried out for each day. The solutions were calculated based on two comparisons:

- Deterministic versus Stochastic using the top 5 probable scenarios;
- Deterministic versus Stochastic using the point forecast plus extreme scenarios.

The search for the optimal solutions was realized with 25-50 generations. Due to no sufficient tuning of the developed algorithm, combined with a relative small dimension of the DEEPSO population and low number of generation, result dispersion is expected. Thus, with the objective of having reliable results, the studies are based on the results from 5 different runs, and the average value is considered.

The evaluation of the solutions was made following two methods:

- Solution evaluation on the Actual Measured Value;
- Solution evaluation for all the days possible scenarios.

Once the data from *Day2* is considered to be more likely to produce significant results to our study[2], it will be initially analysed and then compared to the results from *Day1*. The costs presented refer to the final operation cost, including the corresponding penalties when applied.

4.3.1 Deterministic versus Stochastic using Top 5 Probable Scenarios

Below, the results from the analysis made by comparing the deterministic solution against the stochastic using the top 5 probable scenario are offered. In order to better assess the real value of introducing more than one scenario, the deterministic solution is searched based on the most probable scenario. In a latter section, a comparison between a stochastic UC solution using the top 5 probable scenarios and a deterministic one using the point forecast will be accessible.

Day2:

Table 6 contains the results from the analyses made to the *day2*, when comparing the optimal solutions on the actual measured values. The numeric results for the 5

[2] That belief comes by the greater discrepancy between the point forecast and the actual measured values, registered in *Day2*.

runs to the deterministic and stochastic approaches can be analysed in table 6. Information on the average and standard deviation is also given.

Table 6 - *Day2* Solutions Evaluation for Actual Measured Values - Deterministic vs Stochastic

Run	Deterministic	Stochastic
1	432.614,52 €	455.071,23 €
2	588.524,61 €	423.038,54 €
3	544.549,35 €	446.544,68 €
4	527.627,39 €	413.922,56 €
5	464.897,66 €	428.360,07 €
Average	511.642,71 €	433.387,42 €
Standard deviation	62.609,38	16.989,37

The performance that each solution had when confronted to all possible scenarios was studied. Table 7 presents the produced results. The values on each run refer to the expected cost considering all scenarios weighted with the respective probability of occurrence.

Table 7 - Solutions Evaluation on All Scenarios - Deterministic vs Stochastic

Run	Deterministic	Stochastic
1	781.850,49 €	690.873,45 €
2	854.234,27 €	591.933,93 €
3	883.521,36 €	607.825,53 €
4	752.747,81 €	695.399,13 €
5	858.561,67 €	581.012,67 €
Average	826.183,12 €	633.408,94 €
Standard deviation	55.859,28	55.373,75

The expected operational cost is inferior for the stochastic approach. Both in table 6 and in table 7, the minimum solution was obtained in the stochastic method and the maximum in the deterministic. The average values in both tables show the advantage of a stochastic UC calculation.

For a more detailed analysis, figure 11 represents a chart constructed with the accumulated probability of each solution, i.e. stochastic or deterministic, being inferior than a certain final operational cost.

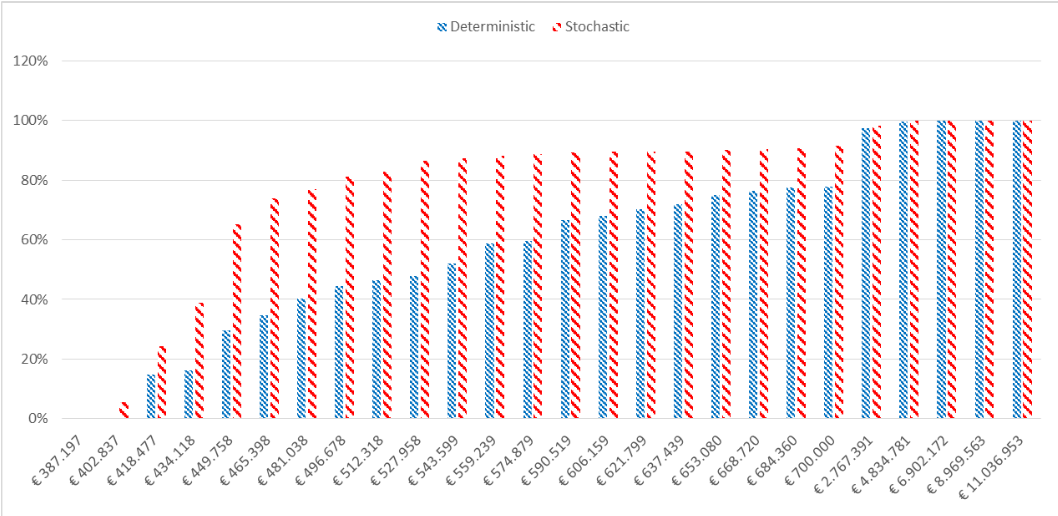

Figure 11 - Accumulated probabilities - Deterministic versus Stochastic

Horizontal axis: Operational Costs / Vertical axis: Probability

From the analysis of figure 11, some statements can be made. For instance, for the *Day2*, the stochastic solution has a 65% probability of having a final cost under 449.758€ against the 30% of the deterministic one. On the other hand, the stochastic solution has a 19% probability of being superior to 496.678€, against to the 56% in the case of the deterministic solution. Detailed information on the data label from figure 11 can be found in table 30, in the Appendix A.

It is clear that, for a day where the wind power point forecast carries a significant error when compared to the actual measured value, a stochastic solution is more robust and reliable than a deterministic one, leading to lower operation costs. In a risk analysis point of view, for the studied data, a stochastic solution is always desirable when compared to a deterministic solution.

Day1:

The same type of analysis presented for the *Day2* will be provided for the *Day1*. Thus, table 8 compares the results obtained from deterministic and stochastic solutions. Each solution selected is evaluated considering the wind power output that was measured that day.

Table 8 - *Day1* Solutions Evaluation for Actual Measured Values - Deterministic vs Stochastic

Run	Deterministic	Stochastic
1	551.521,24 €	431.738,27 €
2	493.896,46 €	410.550,44 €
3	571.070,34 €	436.105,98 €
4	465.845,71 €	406.129,75 €
5	451.955,98 €	409.417,83 €
Average	506.857,95 €	418.788,46 €
Standard deviation	52.398,17	13.995,63

It is clear that stochastic solutions had a better performance than the deterministic ones. Table 9 presents the results from the evaluation of the solutions in all possible scenarios.

Table 9 - Solutions Evaluation on All Scenarios - Deterministic vs Stochastic

Run	Deterministic	Stochastic
1	1.184.678,14 €	836.006,73 €
2	1.319.824.24 €	763.140,05 €
3	998.956,86 €	738.967,03 €
4	1.207.603,68 €	770.336,70 €
5	1.549.287,47 €	838.521,86 €
Average	1.252.070,08 €	789.394,48 €
Standard deviation	202.184,35	45.226,16

For all the 5 runs, the expected operation costs obtained from the stochastic solutions are inferior to the produced by the deterministic solutions. Again, the minimum values are present in the stochastic method, and the maximum in the deterministic. All this supports the idea that a stochastic approach is more robust than a deterministic.

The chart in figure 12 is similar to the represented in figure 11.

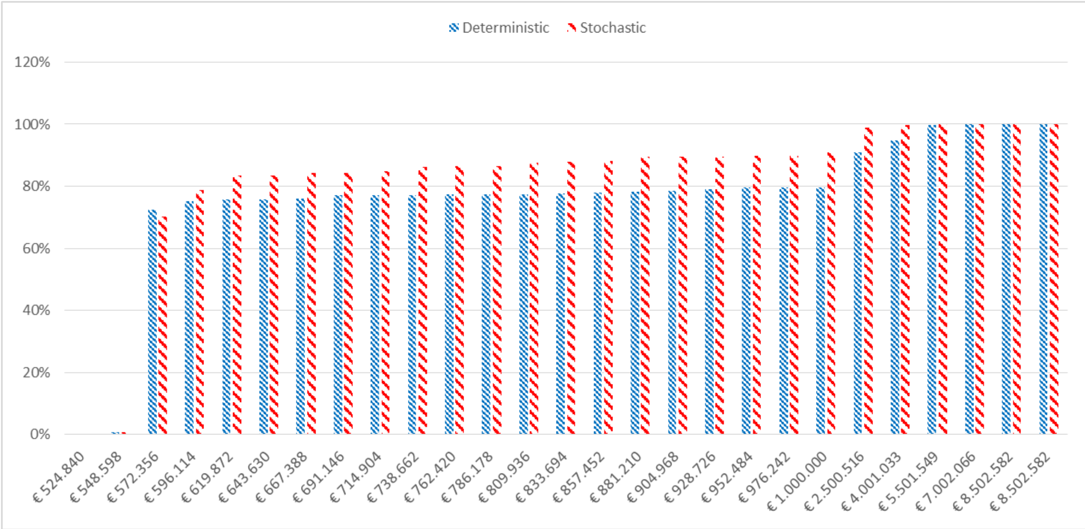

Figure 12 - Accumulated probabilities - Deterministic versus Stochastic

Horizontal axis: Operational Costs / Vertical axis: Probability

For matter of readability, no data label was included in the last chart. That data can be consulted in table 31, in the Appendix A. For the majority of the operation costs considered, the stochastic approach has a greater probability of producing inferior operational costs.

The stochastic approach has produced better results than the deterministic one through all the analysis presented so far, and for both of the studied days.

Table 10 presents the expected values of Load Shedding, Spilled Wind and Generation Surplus for both days studied, and from deterministic and stochastic solutions. The values represent the sum of the average of each scenario for the 5 runs, weighted with the respective probability of happing.

Table 10 - Load Shedding, Spilled Wind and Generation Surplus - Deterministic versus Stochastic using Top 5 Probable Scenarios

	Day2		*Day1*	
	Deterministic	**Stochastic**	**Deterministic**	**Stochastic**
Load Shedding (MWh)	15,64	10,36	39,46	13,74
Spilled Wind (MWh)	93,46	16,45	11,38	9,12
Generation Surplus (MWh)	16,69	0,92	2,38	1,39

Once again, the stochastic approach produces preferable results than the deterministic one. For all the parameters evaluated the stochastic approach presents lower levels.

The following two tables, table 11 and 12, show an evaluation of the deterministic and stochastic solutions when under the wind power output conditions considered in the extreme scenarios previously introduced.

Table 11 - *Day2* Extreme Scenarios Evaluation

	Day2			
	Deficit1		**Deficit2**	
	Deterministic	**Stochastic**	**Deterministic**	**Stochastic**
Load Shedding (MWh)	0	0	79,02	35,05
Spilled Wind (MWh)	239,93	74,07	0	0
Generation Surplus (MWh)	0	0	0	0
	Surplus1		**Surplus2**	
	Deterministic	**Stochastic**	**Deterministic**	**Stochastic**
Load Shedding (MWh)	0	0	177,79	0
Spilled Wind (MWh)	246,65	125,01	315,6	145,3
Generation Surplus (MWh)	0	0	77,78	72,78

Table 12 - *Day1* Extreme Scenarios Evaluation

	Day1			
	Deficit1		**Deficit2**	
	Deterministic	**Stochastic**	**Deterministic**	**Stochastic**
Load Shedding (MWh)	0	0	54,67	0
Spilled Wind (MWh)	0	0	0	0
Generation Surplus (MWh)	0	0	0	0
	Surplus1		**Surplus2**	
	Deterministic	**Stochastic**	**Deterministic**	**Stochastic**
Load Shedding (MWh)	0	0	290,89	104,94
Spilled Wind (MWh)	200,67	401,13	100	97,52
Generation Surplus (MWh)	120,43	115,21	22,52	0

The results confirm the robustness that a stochastic solution has when compared to a deterministic one. The results from the stochastic strategy for *Day2* are preferable in all the analyzed scenarios. The same can be said for *Day1*, with the exception of the scenario “Surplus1”, where the stochastic solutions reveals higher levels of spilled wind. As expected, the data from *Day2* produced more significant results to investigate the importance of consider a stochastic approach.

Analyzing the results associated to the extreme scenario “Surplus2”, where it occurs an excess of wind power generation relatively to the point forecast, there are expected significant levels of load shedding. These surprising results have its explanation on the extreme wind power variation in subsequent operational periods, which troubles the system’s operation, namely because of the limited ramping capacity of the thermal units. For instance, at a particular operational period with high level of wind power generation, the conventional units operate with low output. If in the subsequent operational period an increase of load demand occurs combined with a pronounced reduction in the wind power generation, the system’s ramping up capacity has to compensate both events. Therefore, it might be needed to proceed to load shedding. Also, for the *Day2*, in the extreme scenario “Deficit1” it is expected to occur wind spilling. Again, the system’s limited ramping capacity is the main responsible. An inverse argument to the one stated before can be made. In an operational period of low wind power generation, the conventional units have to operate at a significant output levels. If in the subsequent period the load demand decreases and the wind power generation suddenly increases, the system’s ramping down capacity might not be enough to ensure the power balance.

4.3.2 Deterministic versus Stochastic using the Point Forecast plus Extreme Scenarios

In this section the results presented are obtained using a different strategy in the stochastic search. Instead of using the top 5 more probable scenarios, it is used the point forecast plus 4 extreme scenarios – chosen in such a way that deficit and surplus of wind power are represented. The search for the deterministic solutions is based on the point forecast values, instead of the most probable scenario used in the previous strategy.

The same analysis’ structure from the last section is used on this one.

Day2:

Table 13 contains information related to the confrontation between the established deterministic and stochastic solutions and the Actual Measured Values.

Table 13 – *Day2* Solutions Evaluation for Actual Measured Values – Deterministic vs Stochastic

Run	Deterministic	Stochastic
1	474.041,52 €	568.217,42 €
2	427.629,84 €	597.404,30 €
3	532.030,45 €	515.340,14 €
4	449.055,12 €	497.516,58 €
5	461.963,45 €	576.768,15 €
Average	476.938,67 €	551.049,32 €
Standard deviation	32.234,61	42.561,38

In this case, the deterministic approach led to favourable results, when the solutions are evaluated for the measured values of wind power generation. Here, the solution with the minimum operational cost comes from the deterministic method, and the one with the maximum from the stochastic. Complementarily, the following table shows the results that deterministic and stochastic solutions had when evaluated for all possible scenarios.

Table 14 – *Day2* Solutions Evaluation on All Scenarios – Deterministic vs Stochastic

Run	Deterministic	Stochastic
1	943.803,67 €	758.114,26 €
2	1.135.662,13 €	772.965,17 €
3	844.778,95 €	919.263,26 €
4	943.211,32 €	963.151,41 €
5	839.570,95 €	832.791,94 €
Average	941.405,40 €	849.257,21 €
Standard deviation	119.845,33	89.821,15

The difference between the average values in this case is less significant than the registered in table 7, when the top 5 scenarios were used on the search of stochastic solutions. Either way, the average of these stochastic solutions is inferior to the deterministic, and the minimum expected value belongs to a stochastic solution and the maximum to a deterministic.

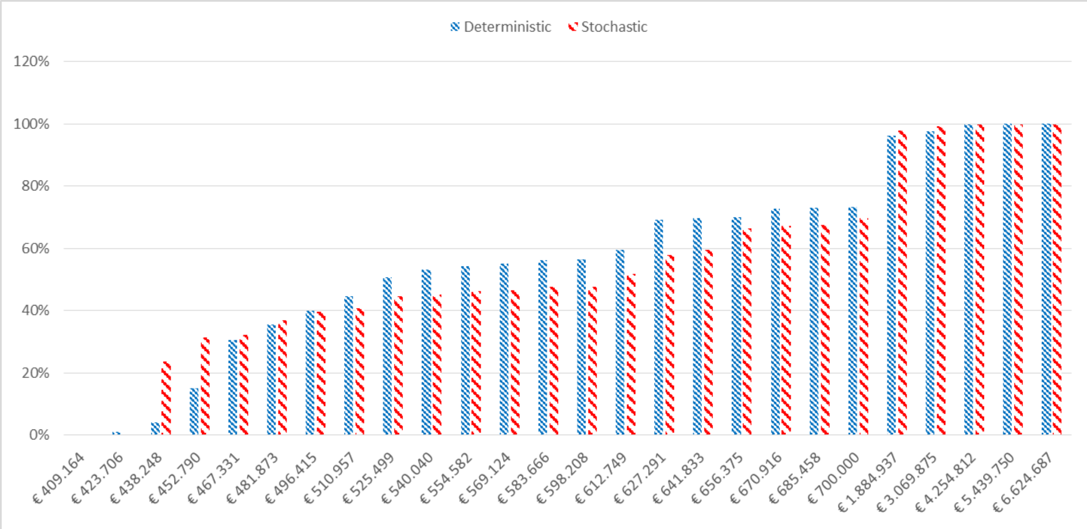

Figure 13 - Accumulated probabilities - Deterministic versus Stochastic

Horizontal axis: Operational Costs / Vertical axis: Probability

This chart is similar to the one presented in figure 11. Comparing the two of them, it is evident that the benefit of using stochastic search has lower significance. In fact, if it can be said that the stochastic solution leads to operation costs inferior to 452.790€ in 31% of the cases against the 15% of the deterministic, it is also true that there are 41% chances that the operation costs would be superior to 641.833€ with a stochastic solution and only 30% with a deterministic one. Data label information is present in table 32, in the Appendix A.

Day1:

Results related to the study carried out for the data of *Day1* will be presented in this section. Table 15 holds the results from the deterministic and stochastic solutions evaluated considering the actual measured values for *Day1*.

Table 15 - *Day1* Solutions Evaluation for Actual Measured Values - Deterministic vs Stochastic

Run	Deterministic	Stochastic
1	588.459,32 €	589.260,16 €
2	586.341,19 €	588.275,73 €
3	589.753,65 €	584.168,73 €
4	584.935,24 €	589.052,02 €
5	582.644,01 €	600.465,87 €
Average	586.426,68 €	590.244,50 €
Standard deviation	2.816,94	6.075,74

As registered for the *Day2*, the results on the table 15 show that the deterministic solution would represent lower operational costs for the measured conditions of wind power generation.

Table 16 presents the results obtained when the selected solutions were evaluated for all possible scenarios. Once again, in this strategy, the deterministic approach produces better results.

Table 16 - *Day1* Solutions Evaluation on All Scenarios - Deterministic vs Stochastic

Run	Deterministic	Stochastic
1	1.125.075,79 €	1.060.759,26 €
2	813.749,44 €	1.122.415,10 €
3	913.729,99 €	1.124.094,91 €
4	833.761,18 €	931.221,19 €
5	868.331,36 €	941.721,13 €
Average	910.929,55 €	1.036.042,32 €
Standard deviation	125.578,65	94.483,33

In addition, the following chart contains the accumulated probabilities that the solutions from deterministic and stochastic methods have of being under determined operation costs. In the Appendix A, table 33 contains the data label information of the chart below.

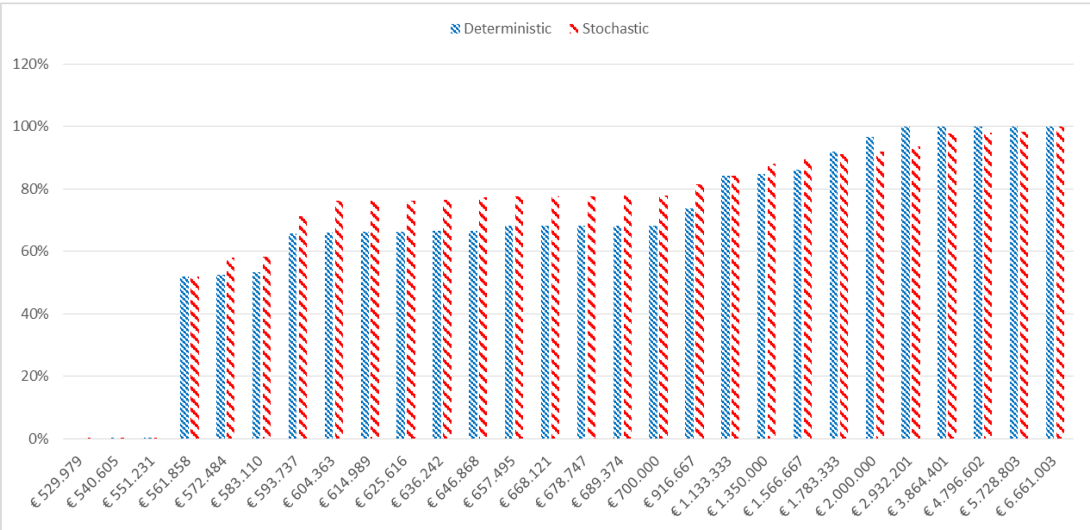

Figure 14 - Accumulated probabilities - Deterministic versus Stochastic

Horizontal axis: Operational Costs / Vertical axis: Probability

From the analysis of figure 14 and figure 12 it can be understood that the use of the point forecast plus the 4 extreme scenarios on the search of stochastic solutions leads to poorer results than those obtained in the last section, when compared to deterministic solutions. The last chart was constructed with information of "run 5". As it can be seen in table 16, the deterministic solution has a smaller expected final operation cost. The obtained results are ambiguous. The stochastic solution has a 76% chance of leading to operation costs under 604.363€, against the 66% of the deterministic one. On the other hand, the deterministic strategy does not produces results superior to 2.932.201€, while the stochastic strategy has 6% chance of being above that value. In the Appendix A, table 33 offers the complete information on the last chart accumulated probabilities.

Table 17 is analogous to table 10 and contains the expected values of Load Shedding, Spilled Wind and Generation Surplus for both studied days, and from deterministic and stochastic solutions, when using the point forecast and extreme scenarios to search for a stochastic solution.

Table 17 – Load Shedding, Spilled Wind and Generation Surplus - Deterministic versus Stochastic using Point Forecast plus Extreme Scenarios

	Day2		***Day1***	
	Deterministic	**Stochastic**	**Deterministic**	**Stochastic**
Load Shedding (MWh)	20,32	20,02	25,39	32,24
Spilled Wind (MWh)	96,63	105,78	20,32	16,45
Generation Surplus (MWh)	9,63	8,36	2,12	3,42

From the analysis of table 17 it can be concluded that, to the operation days considered it is not possible to identify the better approach. As similar to the later analysis in this section, the deterministic UC solution presents, in some cases, better results than the stochastic, and in other cases worst results. Comparing the results in the previous table to those registered in table 10, it is evident that the stochastic strategy of using the top 5 more probable scenarios is preferable to the one used on this section.

Table 18 and 19 show an evaluation of the deterministic and stochastic solutions when under the wind power output conditions considered in the extreme scenarios previously introduced.

Table 18 - *Day2* Extreme Scenarios Evaluation

	Day2			
	Deficit1		Deficit2	
	Deterministic	Stochastic	Deterministic	Stochastic
Load Shedding (MWh)	181,15	302,37	113,93	68,23
Spilled Wind (MWh)	0	0	0	0
Generation Surplus (MWh)	0	0	0	0
	Surplus1		Surplus2	
	Deterministic	Stochastic	Deterministic	Stochastic
Load Shedding (MWh)	0	179,53	0	0
Spilled Wind (MWh)	305,97	378,76	211,65	187,01
Generation Surplus (MWh)	52,78	72,78	0	0

Table 19 - *Day1* Extreme Scenarios Evaluation

	Day1			
	Deficit1		Deficit2	
	Deterministic	Stochastic	Deterministic	Stochastic
Load Shedding (MWh)	0	245,53	181,27	0
Spilled Wind (MWh)	0	0	0	0
Generation Surplus (MWh)	0	0	0	0
	Surplus1		Surplus2	
	Deterministic	Stochastic	Deterministic	Stochastic
Load Shedding (MWh)	150,66	503,83	111,26	6,17
Spilled Wind (MWh)	100,26	100	465,54	343,31
Generation Surplus (MWh)	52,52	42,52	89,37	160,21

The results confirm that this stochastic approach cannot be considered neither preferable nor inferior to the deterministic one. The levels of load shedding, spilled wind and generation surplus are, in some cases, inferior in the deterministic approach, and superior in the others.

Comparing the results from the stochastic approach in these tables to the correspondent in tables 11 and 12, the benefit of using the top 5 probable scenarios comes clear.

As mentioned and explained in the previous section, even in scenarios of wind power surplus, load shedding might occur.

4.3.3 Evaluation on Extreme Scenarios

In this section we expose the results from the evaluation of the deterministic and stochastic solutions on a set of selected extreme scenarios. This set was created by the selection of the scenarios that had higher values on the sum of the absolute values of the difference between its hourly values and the point forecast. A set of extreme scenarios was created for each day. The deterministic solution was based on the point forecast, for both the table that follow.

For *Day1* 17 extreme scenarios were selected, accumulating a probability of 2,1% of the entire universe of possibilities; *Day2* produced 30 extreme scenarios that represent 6,6% of all possible scenarios.

This evaluation on extreme scenarios has the main objective of verifying which one of the stochastic approaches adapts properly to these unseen conditions.

Having proceeded to the evaluation on all the identified extreme scenarios, the following tables contain the expected values of load shedding, spilled wind and generation surplus using the strategies presented in 4.3.1 and 4.3.2.

Table 20 - Evaluation on Extreme Scenarios - Deterministic vs Stochastic Top 5 Probable Scenarios

	Day2		***Day1***	
	Deterministic	**Stochastic**	**Deterministic**	**Stochastic**
Load Shedding (MWh)	11,91	8,686	67,97	72,035
Spilled Wind (MWh)	222,22	70,113	88,08	64,713
Generation Surplus (MWh)	25,09	4,476	21,82	23,817

Table 21 - Evaluation on Extreme Scenarios - Deterministic vs Stochastic Point Forecast plus Extreme Scenarios

	Day2		***Day1***	
	Deterministic	**Stochastic**	**Deterministic**	**Stochastic**
Load Shedding (MWh)	11,91	6,19	67,97	58,61
Spilled Wind (MWh)	222,22	258,51	88,08	91,39
Generation Surplus (MWh)	25,09	17,92	21,82	28,18

Analyzing table 20 and 21 we conclude that the stochastic approach of using the top 5 probable scenarios produces preferable results. In fact, for *Day2*, which is the day where the point forecast is more distinct from the registered wind power values, this stochastic approach led to inferior levels of load shedding, spilled wind and generation surplus when compared to the deterministic approach.

As observed in the earlier sections, in the previous tables, the stochastic approach that uses the point forecast plus 4 extreme scenarios does not produce consistently better results than those achieved with the deterministic strategy.

Comparing the 2 stochastic strategies, the one using the top 5 probable scenarios presents lower levels of spilled wind and generation surplus, for the 2 days. The point forecast plus extreme scenarios stochastic approach led to inferior levels of load shedding. The better results on the levels of load shedding obtained by the latter strategy are not as significant as the ones obtained by the top 5 probable approach on the levels of spilled wind and generation surplus. Thus, we conclude that the approach that uses the more probable scenarios instead of the more extreme, adapts properly to this set of extreme scenarios.

4.3.4 Final Unit Commitment Solutions

The Unit Commitment solutions presented next were calculated after 100 DEEPSO generations. The comparison between the UC stochastic solutions of the top 5 more probable scenarios and the point forecast plus extreme scenarios is presented below. Results from the deterministic UC solution using the point forecast are also present in this section.

Day2:

The UC solutions calculated for the *Day2* are presented next.

Table 22 – *Day2* Final Stochastic Unit Commitment Solution, Top 5 Probable Scenarios

	Stochastic UC – Top 5 Probable Scenarios									
	Unit1	**Unit2**	**Unit3**	**Unit4**	**Unit5**	**Unit6**	**Unit7**	**Unit8**	**Unit9**	**Unit10**
t_1	1	1	0	1	0	0	1	1	0	0
t_2	1	1	0	1	1	0	1	1	0	0
t_3	1	1	0	1	1	0	1	0	1	0
t_4	1	1	1	1	1	0	0	1	0	0
t_5	1	1	1	1	1	1	0	0	1	0
t_6	1	1	1	1	1	1	0	0	0	1
t_7	1	1	1	1	1	1	0	1	1	1
t_8	1	1	1	1	1	1	1	0	0	1
t_9	1	1	1	1	1	1	1	1	0	1
t_{10}	1	1	1	1	1	1	1	1	1	1
t_{11}	1	1	1	1	1	1	1	1	0	1
t_{12}	1	1	1	1	1	1	1	1	1	1
t_{13}	1	1	1	1	1	1	1	1	0	1
t_{14}	1	1	1	1	1	1	1	1	0	0
t_{15}	1	1	1	1	1	1	1	1	0	0
t_{16}	1	1	1	1	1	1	1	0	1	0
t_{17}	1	1	1	1	1	1	1	1	1	1
t_{18}	1	1	1	1	1	1	1	0	0	0
t_{19}	1	1	1	1	1	1	1	0	0	1
t_{20}	1	1	1	1	1	1	1	1	1	0
t_{21}	1	1	1	1	1	1	1	1	1	1
t_{22}	1	1	1	1	1	0	1	1	0	0
t_{23}	1	0	1	1	1	0	1	1	1	0
t_{24}	1	0	1	0	1	0	0	1	1	1

Table 23 - *Day2* Final Stochastic Unit Commitment Solution, Point Forecast plus Extreme Scenarios

	Stochastic UC - Point Forecast plus Extreme Scenarios									
	Unit1	**Unit2**	**Unit3**	**Unit4**	**Unit5**	**Unit6**	**Unit7**	**Unit8**	**Unit9**	**Unit10**
t_1	1	1	1	0	1	1	0	0	0	0
t_2	1	1	1	1	1	1	0	0	0	0
t_3	1	1	1	1	1	1	1	0	1	0
t_4	1	1	1	1	1	1	1	0	0	1
t_5	1	1	1	1	1	1	1	1	1	0
t_6	1	1	1	1	1	1	1	1	0	1
t_7	1	1	1	1	1	1	1	0	1	1
t_8	1	1	1	1	1	1	1	0	1	1
t_9	1	1	1	1	1	1	1	1	0	1
t_{10}	1	1	1	1	1	1	1	1	1	1
t_{11}	1	1	1	1	1	1	1	1	1	1
t_{12}	1	1	1	1	1	1	1	1	1	1
t_{13}	1	1	1	1	1	1	1	0	1	1
t_{14}	1	1	1	1	1	1	1	0	1	1
t_{15}	1	1	1	1	1	1	1	1	0	0
t_{16}	1	1	1	1	1	1	1	1	0	1
t_{17}	1	1	1	1	1	1	1	0	1	1
t_{18}	1	1	1	1	1	1	1	1	0	0
t_{19}	1	1	1	1	1	1	1	0	1	0
t_{20}	1	1	1	1	1	1	1	1	1	1
t_{21}	1	1	1	1	1	1	1	0	1	1
t_{22}	1	1	1	1	1	1	1	0	0	0
t_{23}	1	1	1	1	1	0	1	0	0	0
t_{24}	1	1	0	0	0	0	0	1	1	0

Table 24 - *Day2* Final Deterministic Unit Commitment Solution, Point Forecast

	Deterministic UC - Point Forecast									
	Unit1	**Unit2**	**Unit3**	**Unit4**	**Unit5**	**Unit6**	**Unit7**	**Unit8**	**Unit9**	**Unit10**
t_1	1	1	0	1	1	0	1	0	1	0
t_2	1	1	1	1	1	1	1	1	1	0
t_3	1	1	1	1	1	1	1	0	0	1
t_4	1	1	1	1	1	1	1	0	0	0
t_5	1	1	1	1	1	1	1	0	0	1
t_6	1	1	1	1	1	1	1	0	0	0
t_7	1	1	1	1	1	1	1	0	0	0
t_8	1	1	1	1	1	1	1	0	0	0
t_9	1	1	1	1	1	1	1	0	0	1
t_{10}	1	1	1	1	1	1	1	0	0	1
t_{11}	1	1	1	1	1	1	1	1	0	1
t_{12}	1	1	1	1	1	1	1	1	1	1
t_{13}	1	1	1	1	1	1	1	0	1	1
t_{14}	1	1	1	1	1	1	1	0	1	0
t_{15}	1	1	1	1	1	1	1	0	0	0
t_{16}	1	1	1	1	1	1	1	1	1	0
t_{17}	1	1	1	1	1	1	1	0	0	1
t_{18}	1	1	1	1	1	1	1	0	0	0
t_{19}	1	1	1	1	1	1	1	0	1	0
t_{20}	1	1	1	1	1	1	1	0	1	0
t_{21}	1	1	1	1	1	1	1	1	0	1
t_{22}	1	1	1	1	1	1	1	0	0	0
t_{23}	1	1	1	1	1	1	1	0	1	0
t_{24}	1	0	1	0	1	1	0	1	0	0

Comparing the 3 UC solutions, the main difference between them is the schedule of the last 3 units (units that have superior cost coefficients). For most of the operation periods, the number of these units that are scheduled to operate is greater in the stochastic solutions. As the stochastic methods have to adapt to several scenarios, they need an extra ramping capacity compared to what happens for the deterministic method. In spite of superior cost coefficients, this peaking units allow the stochastic UC solutions to adapt better to unseen scenarios, preventing them of the possibility of load shedding, spilled wind and generation surplus.

Figure 15 represents a histogram which compares the number of the possible scenarios that would be between determined operational costs, for each of the 3 approaches.

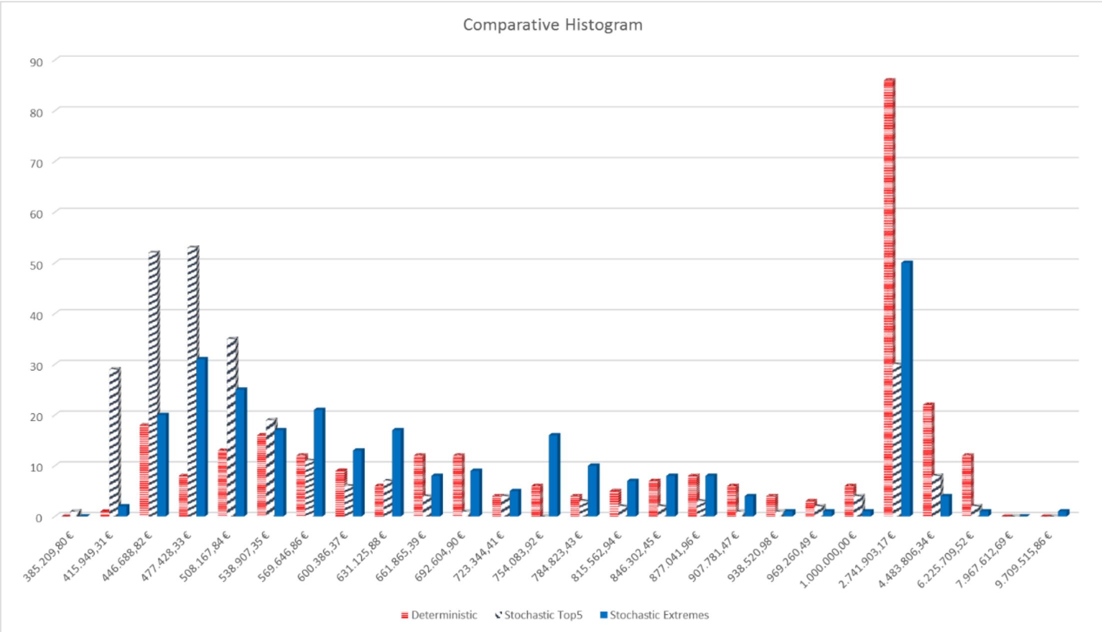

Figure 15 - Comparative Histogram - All approaches, Final UC Solutions

Horizontal axis: Operational Costs / Vertical axis: Number of Scenarios

The stochastic solutions, mainly the one using the top 5 probable scenarios, have more scenarios in the intervals of lower operational costs than the deterministic. For the intervals of superior operational costs the deterministic solution accounts for more scenarios. As each scenario has a related probability, the last histogram could lead to mistaking conclusions. Thus, figure 16 presents the accumulated probabilities that each method has on producing operational results under certain value. Table 34 in Appendix A contains the data label from the following chart.

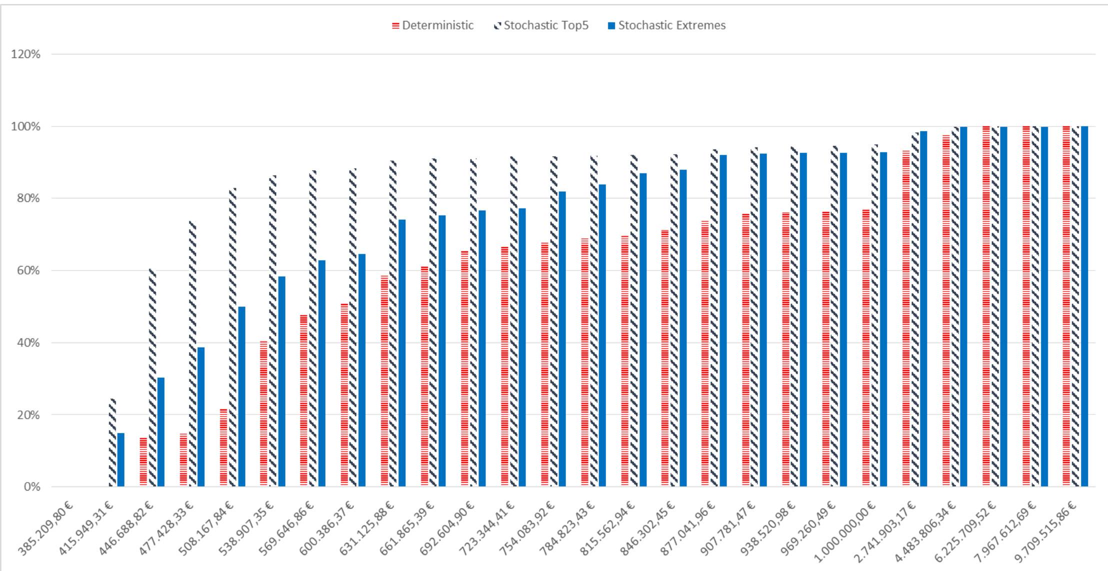

Figure 16 - Accumulated Probabilities - All Approaches, Final Solutions

Horizontal axis: Operational Costs / Vertical axis: Probability

From the analysis of figure 16, the supremacy of the stochastic solutions is perfectly evident. The stochastic methods have always higher probability of producing operational costs inferior to the determined values. Once again, the stochastic approach that considers the top 5 probable scenarios is preferable to the one using the point forecast plus 4 extreme scenarios.

Table 25 presents the expected values of load shedding, spilled wind and generation surplus for each of the 3 strategies adopted.

Table 25 - *Day2* Load Shedding, Spilled Wind and Generation Surplus - All Approaches

	Day2		
	Deterministic	**Stochastic Top5**	**Stochastic Extremes**
Load Shedding (MWh)	40,10	10,47	11,30
Spilled Wind (MWh)	117,18	16,05	97,98
Generation Surplus (MWh)	14,48	0,68	8,99

In line with the previous analysis, the stochastic approaches led to preferable results. Inferior levels of load shedding, spilled wind and generation surplus were registered for the stochastic methods, particularly for the one using the top 5 more probable scenarios.

Day1:

Here, the selected UC solutions for *Day1* are presented.

Table 26 – *Day1* Final Stochastic Unit Commitment Solution, Top 5 Probable Scenarios

	Stochastic UC – Top 5 Probable Scenarios									
	Unit1	**Unit2**	**Unit3**	**Unit4**	**Unit5**	**Unit6**	**Unit7**	**Unit8**	**Unit9**	**Unit10**
t_1	1	1	0	1	0	0	0	0	0	0
t_2	1	1	1	1	1	1	1	1	1	0
t_3	1	1	1	1	1	1	1	0	0	1
t_4	1	1	1	1	1	1	1	0	0	1
t_5	1	1	1	1	1	1	1	0	1	0
t_6	1	1	1	1	1	1	1	1	1	1
t_7	1	1	1	1	1	1	1	1	1	1
t_8	1	1	1	1	1	1	1	1	0	1
t_9	1	1	1	1	1	1	1	0	1	0
t_{10}	1	1	1	1	1	1	1	0	1	1
t_{11}	1	1	1	1	1	1	1	1	1	0
t_{12}	1	1	1	1	1	1	1	1	1	1
t_{13}	1	1	1	1	1	1	1	0	1	1
t_{14}	1	1	1	1	1	1	1	1	1	1
t_{15}	1	1	1	1	1	1	1	1	0	0
t_{16}	1	1	1	1	1	1	1	1	0	1
t_{17}	1	1	1	1	1	1	1	0	1	1
t_{18}	1	1	1	1	1	1	1	1	0	1
t_{19}	1	1	1	1	1	1	1	0	1	0
t_{20}	1	1	1	1	1	1	1	1	1	1
t_{21}	1	1	1	1	1	1	1	1	0	0
t_{22}	1	1	1	1	1	1	1	0	1	0
t_{23}	1	1	1	1	1	1	1	0	1	0
t_{24}	1	0	1	1	1	1	0	1	1	0

Table 27 - *Day1* Final Stochastic Unit Commitment Solution, Point Forecast plus Extreme Scenarios

	Stochastic UC - Point Forecast plus Extreme Scenarios									
	Unit1	Unit2	Unit3	Unit4	Unit5	Unit6	Unit7	Unit8	Unit9	Unit10
t_1	1	1	1	0	1	0	1	0	0	1
t_2	1	1	1	1	1	0	1	1	0	0
t_3	1	1	1	1	1	1	1	0	1	1
t_4	1	1	1	1	1	1	1	0	0	1
t_5	1	1	1	1	1	1	1	0	0	1
t_6	1	1	1	1	1	1	1	0	1	1
t_7	1	1	1	1	1	1	1	1	1	0
t_8	1	1	1	1	1	1	1	1	1	0
t_9	1	1	1	1	1	1	1	0	1	1
t_{10}	1	1	1	1	1	1	1	1	0	1
t_{11}	1	1	1	1	1	1	1	1	1	0
t_{12}	1	1	1	1	1	1	1	1	1	1
t_{13}	1	1	1	1	1	1	1	1	1	1
t_{14}	1	1	1	1	1	1	1	1	1	1
t_{15}	1	1	1	1	1	1	1	0	0	1
t_{16}	1	1	1	1	1	1	1	1	0	1
t_{17}	1	1	1	1	1	1	1	0	0	1
t_{18}	1	1	1	1	1	1	1	0	1	1
t_{19}	1	1	1	1	1	1	1	0	1	0
t_{20}	1	1	1	1	1	1	1	1	1	1
t_{21}	1	1	1	1	1	1	1	1	0	1
t_{22}	1	1	1	1	1	1	1	0	0	0
t_{23}	1	1	1	1	1	1	1	1	1	0
t_{24}	1	1	0	0	0	0	0	1	1	1

Table 28 - *Day1* Final Deterministic Unit Commitment Solution, Point Forecast

	Deterministic UC - Point Forecast									
	Unit1	**Unit2**	**Unit3**	**Unit4**	**Unit5**	**Unit6**	**Unit7**	**Unit8**	**Unit9**	**Unit10**
t_1	1	1	1	1	1	1	0	0	0	0
t_2	1	1	1	1	1	1	0	0	0	0
t_3	1	1	1	1	1	1	0	0	0	0
t_4	1	1	1	1	1	1	1	0	0	0
t_5	1	1	1	1	1	1	1	0	1	1
t_6	1	1	1	1	1	1	1	0	1	0
t_7	1	1	1	1	1	1	1	0	0	1
t_8	1	1	1	1	1	1	1	0	0	1
t_9	1	1	1	1	1	1	1	0	0	1
t_{10}	1	1	1	1	1	1	1	1	1	1
t_{11}	1	1	1	1	1	1	1	1	1	0
t_{12}	1	1	1	1	1	1	1	1	1	1
t_{13}	1	1	1	1	1	1	1	0	1	0
t_{14}	1	1	1	1	1	1	1	0	1	1
t_{15}	1	1	1	1	1	1	1	1	1	0
t_{16}	1	1	1	1	1	1	1	0	1	0
t_{17}	1	1	1	1	1	1	1	1	0	1
t_{18}	1	1	1	1	1	1	1	0	0	0
t_{19}	1	1	1	1	1	1	1	0	1	0
t_{20}	1	1	1	1	1	1	1	1	1	1
t_{21}	1	1	1	1	1	1	1	0	1	0
t_{22}	1	1	1	1	1	1	1	0	0	1
t_{23}	1	1	1	1	1	1	1	0	0	0
t_{24}	1	1	1	0	0	0	0	0	1	0

As observed for *Day2*, the schedule of the last 3 units is the main dissimilarity in the final Unit Commitment solutions. Again, the stochastic UC solutions present more of these peak units scheduled than the deterministic. Thus, more ramping capability is assured, allowing a more robust UC solution. Figure 17 is similar to figure 15, and consists on a histogram that compares the number of the possible scenarios that are between determined operational costs, for each of the 3 approaches.

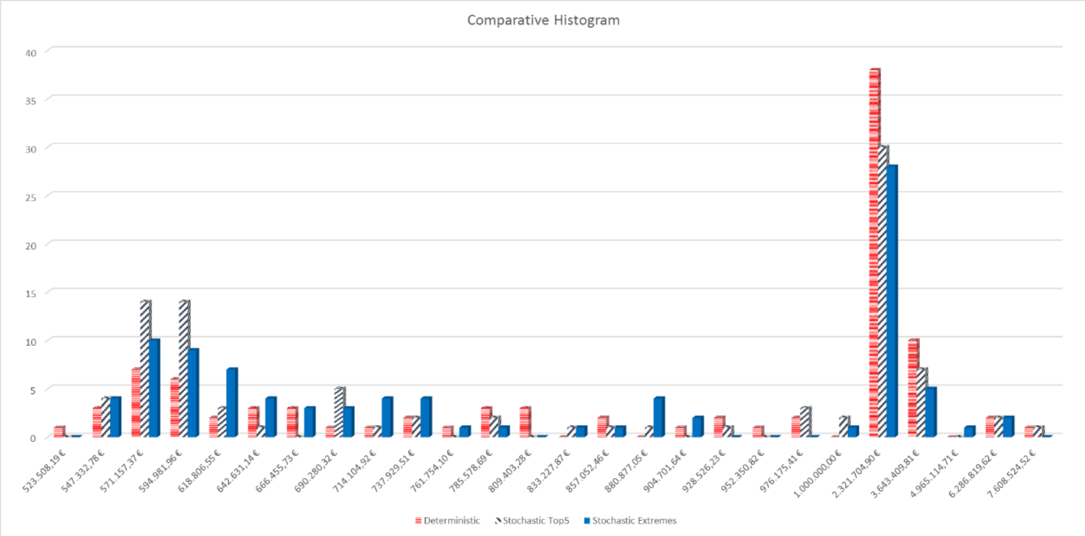

Figure 17 - Comparative Histogram - All approaches, Final UC Solutions

Horizontal axis: Operational Costs / Vertical axis: Number of Scenarios

Analyzing the previous figure it can be observed that for the lower operational costs there are more stochastic scenarios than deterministic. On the other hand, for the superior operational costs, the deterministic approach accounts for more scenarios.

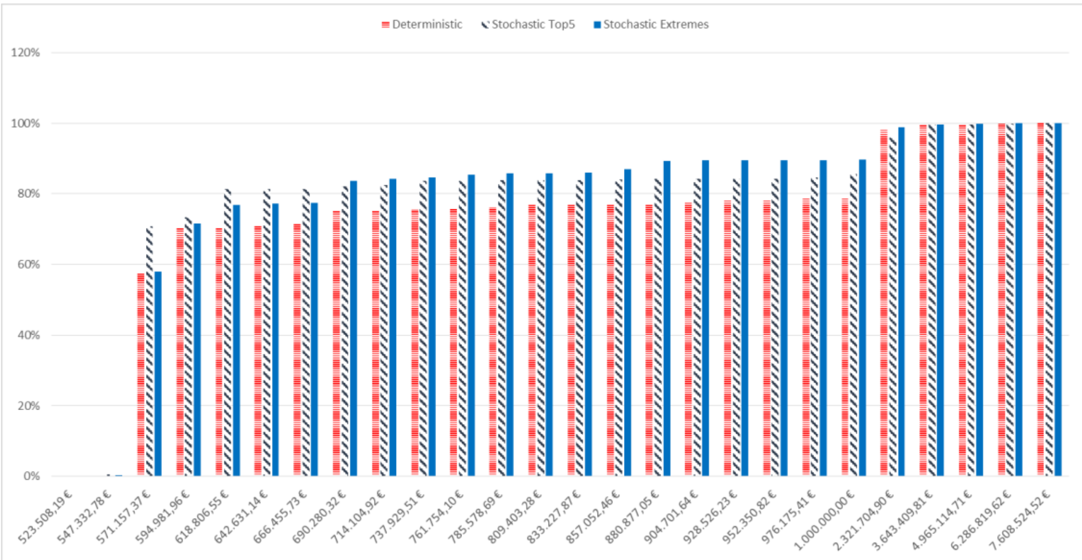

Figure 18 - Accumulated Probabilities - All Approaches, Final Solutions

Horizontal axis: Operational Costs / Vertical axis: Probability

Figure 18 shows that, for the majority of the intervals considered, the stochastic approaches have more probability of producing results under the determined values of operational costs. Comparing to the results on figure 16, the supremacy of the stochastic strategies is less significant. Also, the stochastic approach that considers the point forecast plus 4 extreme scenarios presents better results than the other stochastic one for operational costs superior to 666.455€.

Table 29 - *Day1* Load Shedding, Spilled Wind and Generation Surplus - All Approaches

	Day1		
	Deterministic	**Stochastic Top5**	**Stochastic Extremes**
Load Shedding (MWh)	20,15	17,81	13,93
Spilled Wind (MWh)	17,73	8,68	14,44
Generation Surplus (MWh)	3,29	1,09	2,68

Table 29 contains the expected values of load shedding, spilled wind and generation surplus for all the 3 approaches. Again, the stochastic methods are preferable to the deterministic. The levels of spilled wind in this case are significant lower than the registered in table 25. This can be explained by the inferior wind power generation of *Day1*, and also because of the more difference between the forecasts and actual measured values for *Day2*.

4.4 Chapter's Conclusion

The study presented in this chapter confirms the benefits of considering a stochastic approach on the Unit Commitment problem. The stochastic strategy of using the top 5 probable scenarios proved to be the best approach.

Chapter 5

Conclusion

The increasing share of renewable energy, namely wind power generation, brings new challenges and concerns to power systems operators. They have to guarantee the power demand and generation balance. For systems with high presence of wind power generation, the maintenance of this balance can be problematic. Periods with high levels of wind power generation combined with low demand create over-generation that causes difficulties to the system operation. As consequence, wind curtailments are expected, representing a waste of natural resources.

Studies refer that good wind forecasting has an important influence on the reduction of the Unit Commitment costs. Another solution suggested is the aggregation of wind plants over wider geographical areas providing a mechanism capable of reducing wind plant variability. Recent studies indicate that taking into account the stochastic nature of the wind in the Unit Commitment procedure, more robust schedules could be produced. The ramping capacity of the power systems is pointed as being a crucial factor on the accommodation of wind power generation.

In this work we propose a computational stochastic method of calculating a Unit Commitment solution. A variation of EPSO, called DEEPSO, is used to create new UC solutions through the calculation process. A routine using Benders Decomposition was developed in order to evaluate the generated UC solution, calculating an optimal economic dispatch. The implemented stochastic UC algorithm takes about 2 hours to find a final solution, after 100 DEEPSO generations and considering 5 different wind power scenarios. As the Unit Commitment is a day-ahead procedure, this is an acceptable time, once it refers to a personal computer with a 2.67GHz processor.

The impact that the wind power forecasting has on the UC problem was evaluated by introducing wind power output scenarios. Performances of the deterministic and stochastic solutions are compared based on the actual measured values of wind power generation and based on a risk evaluation that considers all possible wind power scenarios. Two stochastic approaches were considered. One using the top 5 more probable scenarios, and the other using the point forecast plus 4 extreme scenarios.

The results indicate that the stochastic Unit Commitment is more robust than a deterministic one. The stochastic approach that considers the top 5 probable scenarios produced the best results. It proved to be preferable to the deterministic method. For the majority of the cases, this stochastic method of calculating the UC presented inferior expected operational costs, load shedding, spilled wind, and generation surplus levels. The stochastic approach that uses the point forecast plus 4 extreme scenarios led to poorer results than the other stochastic method. No supremacy over the deterministic method could be recognized for this stochastic approach.

With the study carried out and with the obtained results the advantage of adopting a stochastic method of calculating the Unit Commitment was clearly demonstrated. A stochastic UC solution adapts better to extreme and unseen wind power scenarios, which facilitates the system operation and leads to lower operational costs. As levels of load shedding, spilled wind, and generation surplus are inferior in a stochastic approach (and consequent reserve requirements also inferior), along with less costly system operation, we conclude that the systems operators should embrace a stochastic method of calculating the units schedule.

The developed UC calculation tool, combining the DEEPSO with the Benders decomposition, showed its viability. This combination is expected to present great performances with the increasing of the complexity of the power systems analyzed. Benders Decomposition technique is recognized to be much faster than the conventional simplex formulations, especially for large scale problems. In this work we attempted to prove the feasibility of this type of algorithm structure. In what concerns its efficiency, much can still be done. First, coding optimization is needed. Taking advantage of the Benders Decomposition routine that was developed, post-optimization is possible. As the domain of the dual problem is fixed, past solutions can be used as start points, reducing the computing time. Moreover, parallel computing is a possibility, decreasing dramatically the computational time. With the use of more than one computer, the DEEPSO population can be distributed, and the computing time divided by all the computers. Implementing all this features, we could increase the number of generation on the DEEPSO algorithm, which can increase the efficiency of the developed tool. Also, quadratic generation cost functions could be linearized through the piecewise technique, which implies the increase of variables in the Benders Decomposition routine.

More exhaustive studies are expected in future works. A medium-term collaboration with systems operators would be of great value, permitting the access of real operational data and assessing in a more realistic manner the benefit of considering a stochastic Unit Commitment. A more profound study that considers the electrical grid and the respective power flow constraints could help to expose and confirm the supremacy of the stochastic method over the deterministic. More detailed reserve constraints should be considered in future works. Namely, the reserve levels throughout the dispatch calculation should be controlled, as its reduction causes a decrease in the system reliability. Thus, dispatch solutions that maintain the specified levels of spinning reserve should be favored against others that do not.

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Appendixes

Appendix A - Tables

Table 30 - Data from *Day2* accumulated probabilities – Deterministic versus Stochastic using top 5 probable scenarios

	% under certain value	
	Deterministic	Stochastic
€ 387.197	0%	0%
€ 402.837	0%	6%
€ 418.837	15%	24%
€ 434.118	16%	39%
€ 449.758	30%	65%
€ 465.398	35%	74%
€ 481.038	40%	77%
€ 496.678	44%	81%
€ 512.318	46%	83%
€ 527.958	48%	87%
€ 543.599	52%	87%
€ 559.239	59%	88%
€ 574.879	60%	89%
€ 590.519	67%	89%
€ 606.159	68%	90%
€ 621.799	70%	90%
€ 637.439	72%	90%
€ 653.080	75%	90%
€ 668.720	77%	91%
€ 684.360	77%	91%
€ 700.000	78%	92%
€ 2.767.391	97%	98%
€ 4.834.781	100%	100%
€ 6.902.172	100%	100%
€ 8.969.563	100%	100%
€ 11.036.953	100%	100%

Table 31 – Data from *Day1* accumulated probabilities – Deterministic versus Stochastic using top 5 probable scenarios

	% under certain value	
	Deterministic	Stochastic
€ 524.840	0%	0%
€ 548.598	1%	1%
€ 572.356	72%	70%
€ 596.114	75%	79%
€ 619.872	76%	83%
€ 643.630	76%	84%
€ 667.388	76%	84%
€ 691.146	77%	84%
€ 714.904	77%	85%
€ 738.662	77%	86%
€ 762.420	77%	86%
€ 786.178	77%	87%
€ 809.936	77%	88%
€ 833.694	78%	88%
€ 857.452	78%	88%
€ 881.210	78%	90%
€ 904.968	79%	90%
€ 928.726	79%	90%
€ 952.484	80%	90%
€ 976.242	80%	90%
€ 1.000.000	80%	91%
€ 2.500.516	91%	99%
€ 4.001.033	95%	100%
€ 5.501.549	100%	100%
€ 7.002.066	100%	100%
€ 8.502.582	100%	100%
€ 8.502.582	100%	100%

Table 32 - Data from *Day2* accumulated probabilities – Deterministic versus Stochastic using Point Forecast plus Extreme Scenarios

	% under certain value	
	Deterministic	Stochastic
€ 409.164	0%	0%
€ 423.706	1%	0%
€ 438.248	4%	24%
€ 452.790	15%	31%
€ 467.331	31%	32%
€ 481.873	36%	37%
€ 496.415	40%	40%
€ 510.957	45%	41%
€ 525.499	51%	45%
€ 540.040	53%	45%
€ 554.582	54%	46%
€ 569.124	55%	47%
€ 583.666	56%	48%
€ 598.208	57%	48%
€ 612.749	60%	52%
€ 627.291	69%	58%
€ 641.833	70%	59%
€ 656.375	70%	66%
€ 670.916	73%	67%
€ 685.458	73%	68%
€ 700.000	73%	70%
€ 1.884.937	96%	98%
€ 3.069.875	98%	99%
€ 4.254.812	100%	100%
€ 5.439.750	100%	100%
€ 6.624.687	100%	100%

Table 33- Data from *Day1* accumulated probabilities - Deterministic versus Stochastic using Point Forecast plus Extreme Scenarios

		% under certain value	
		Deterministic	Stochastic
€	**529.979**	0%	0%
€	**540.605**	0%	0%
€	**551.231**	0%	0%
€	**561.858**	52%	52%
€	**572.484**	52%	58%
€	**583.110**	53%	58%
€	**593.737**	66%	71%
€	**604.363**	66%	76%
€	**614.989**	66%	76%
€	**625.616**	66%	76%
€	**636.242**	67%	76%
€	**646.868**	67%	77%
€	**657.495**	68%	78%
€	**668.121**	68%	78%
€	**678.747**	68%	78%
€	**689.374**	68%	78%
€	**700.000**	68%	78%
€	**916.667**	74%	81%
€	**1.133.333**	84%	84%
€	**1.350.000**	85%	88%
€	**1.566.667**	86%	89%
€	**1.783.333**	92%	91%
€	**2.000.000**	97%	92%
€	**2.932.201**	100%	94%
€	**3.864.401**	100%	98%
€	**4.796.602**	100%	98%
€	**5.728.803**	100%	98%
€	**6.661.003**	100%	100%

Table 34 - Data from *Day2* accumulated probabilities - All Approaches

		% under certain value		
		Deterministic	Stochastic Top 5	Stochastic Extremes
€	**385.209**	0%	0%	0%
€	**415.949**	0%	25%	15%
€	**446.688**	14%	60%	30%
€	**477.428**	15%	74%	39%
€	**508.167**	22%	83%	50%
€	**538.907**	41%	86%	58%
€	**569.646**	48%	88%	63%
€	**600.386**	51%	88%	65%
€	**631.865**	59%	91%	74%
€	**661.865**	61%	91%	75%
€	**692.604**	65%	91%	77%
€	**723.344**	67%	92%	77%
€	**754.083**	68%	92%	82%
€	**784.823**	69%	92%	84%
€	**815.562**	70%	92%	87%
€	**846.302**	71%	92%	88%
€	**877.041**	74%	94%	92%
€	**907.781**	76%	94%	93%
€	**938.520**	76%	94%	93%
€	**969.260**	76%	95%	93%
€	**1.000.000**	77%	95%	93%
€	**2.741.903**	94%	98%	99%
€	**4.483.806**	98%	100%	100%
€	**6.225.709**	100%	100%	100%
€	**7.967.612**	100%	100%	100%
€	**9.709.515**	100%	100%	100%

Table 35 - Data from *Day1* accumulated probabilities - All Approaches

		% under certain value		
		Deterministic	**Stochastic Top 5**	**Stochastic Extremes**
€	**523.508**	0%	0%	0%
€	**547.332**	0%	1%	0%
€	**571.157**	58%	71%	58%
€	**594.981**	70%	73%	72%
€	**618.806**	71%	81%	77%
€	**642.631**	71%	81%	77%
€	**666.455**	72%	81%	78%
€	**690.280**	75%	82%	84%
€	**714.104**	75%	82%	84%
€	**737.929**	76%	84%	85%
€	**761.754**	76%	84%	86%
€	**785.578**	76%	84%	86%
€	**809.403**	77%	84%	86%
€	**833.227**	77%	84%	86%
€	**857.052**	77%	84%	87%
€	**880.877**	77%	84%	89%
€	**904.701**	78%	84%	90%
€	**928.526**	78%	84%	90%
€	**952.350**	78%	84%	90%
€	**976.175**	79%	85%	90%
€	**1.000.000**	79%	86%	90%
€	**2.321.704**	98%	96%	99%
€	**3.643.409**	100%	100%	100%
€	**4.965.114**	100%	100%	100%
€	**6.286.819**	100%	100%	100%
€	**7.608.524**	100%	100%	100%

Appendix B - Publications

B.1 “Coping with Wind Power Uncertainty in Unit Commitment: a Robust Approach using the New Hybrid Metaheuristic DEEPSO”

The following abstract was submitted to the “*MedPower 2014*” and its acceptance still holds confirmation.

Coping with Wind Power Uncertainty in Unit Commitment: a Robust Approach using the New Hybrid Metaheuristic DEEPSO

Rui Pinto, Vladimiro Miranda, *Fellow, IEEE*,
Leonel Carvalho, *Member, IEEE*, Jean Sumaili, *Member, IEEE*

I. Extended Abstract

THE increasing share of wind power in thermal-dominated generation systems is seen as a threat not only to system reliability but also to its cost-effective operation. The decision to start or shut down thermal units for the next operating hours must take into account the inherent uncertainty of wind power forecasts.

The error inherent to wind power forecasting can make the power operation costly prohibitive and/or unreliable. For example, if wind power is less than its forecast, the system operator will need to start back up thermal units at increased generation costs and risk load curtailment. On the other hand, if the wind power is greater than its forecast, the system operator might need to decrease the production of the generators and risk wind spill. Even if the wind could be accurately forecasted, there would still be hours where wind power is not used at its maximum output due to insufficient ramping capabilities. Robust unit commitment schedules are therefore necessary not only to keep the operation costs low but also to avoid unwanted actions such as wind spillage and load curtailment.

The unit commitment model addressed in this paper consists on the minimization of the total operation costs over a commitment period taking into account technical constraints of the generating units such as ramping rates and minimum up and down times. Wind power spillage is also considered as well as load curtailment.

In addition, this paper evaluates the impact on the total operational costs of using a stochastic unit commitment approach instead of the traditional deterministic approach. The stochastic approach consists on using several wind power scenarios to devise a robust commitment plan for the generation units whereas the deterministic approach relies solely on the point forecasts. The scenarios are built from the wind power point forecasts taking into account the temporal dependency between errors. The method used to obtain scenarios from wind power point forecasts is detailed in [1]. Furthermore, clustering techniques are used to find a set of most representative scenarios and underlying probabilities [2] for decreasing the computational effort.

The generation of unit commitment solutions is guaranteed by a new hybrid metaheuristic DEEPSO [3], which is combination of the DE-EA-PSO algorithms, where EA stands for Differential Evolution, EA for Evolutionary Programming and PSO for Particle Swarm Optimization.

The generation of new unit commitment solutions in DEEPSO includes a simple correction algorithm to make sure that the generating units' constraints, like minimum up and minimum down time, as well as minimum spinning reserve are verified at all times. The evaluation of solutions consists on the computation of the optimal economic dispatch for all the operating periods taking into account the ramping capabilities of generating units. Benders Decomposition [4] and Dual Dynamic Programming [5] are used for the calculation of the optimal economic dispatch.

Stochastic and deterministic unit commitment solutions are compared by obtaining the operational costs of these solutions for the actual wind power realizations. Furthermore, the set of representative scenarios is also used to make a probabilistic analysis on the wind power spillage and load curtailment risks.

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