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A Multiple Criteria Utility-based Approach for the Unit Commitment with Wind Power and Pumped Storage Hydro

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Abstract

The integration of wind power in electricity generation brings new challenges to unit commitment due to the random nature of wind speed. For this particular optimisation problem, wind uncertainty has been handled in practice by means of conservative stochastic scenario-based optimisation models, or through additional operating reserve settings. However, generation companies may have different attitudes towards operating costs, load curtailment, or waste of wind energy, when considering the risk caused by wind power variability. Therefore, alternative and possibly more adequate approaches should be explored.

This work is divided in two main parts. Firstly we survey the main formulations presented in the literature for the integration of wind power in the unit commitment problem (UCP) and present an alternative model for the wind-thermal unit commitment. We make use of the utility theory concepts to develop a multi-criteria stochastic model. The objectives considered are the minimisation of costs, load curtailment and waste of wind energy. Those are represented by individual utility functions and aggregated in a single additive utility function. This last function is adequately linearised leading to a mixed-integer linear program (MILP) model that can be tackled by general-purpose solvers in order to find the most preferred solution.

In the second part we discuss the integration of pumped-storage hydro (PSH) units in the UCP with large wind penetration. Those units can provide extra flexibility by using wind energy to pump and store water in the form of potential energy that can be generated after during peak load periods. PSH units are added to the first model, yielding a MILP model with wind-hydro-thermal coordination. Results showed that the proposed methodology is able to reflect the risk profiles of decision makers for both models. By including PSH units, the results are significantly improved.

Keywords

Unit commitment, Economic dispatch, Wind uncertainty, Stochastic optimisation, Multi-criteria decision making, Utility theory, Pumped storage hydro.

Resumo

A integração de energia eólica nos sistemas de geração de energia elétrica introduz novos desafios no problema do *Unit Commitment*. A elevada aleatoriedade associada à velocidade do vento tem sido tratada essencialmente através de modelos de otimização estocásticos baseados em cenários, normalmente conservadores, ou através da definição de níveis de reserva adicionais que permitam fazer face aos possíveis desvios em relação às previsões de produção eólica. No entanto, as empresas geradoras de energia apresentam diferentes atitudes perante riscos como o corte de carga, a não satisfação dos níveis de reserva requeridos ou o desperdício de eólica.

Na primeira parte deste trabalho é efetuado um estudo do estado da arte das formulações para o problema do Unit Commitment com integração de energia eólica e é proposto um modelo estocástico multi-objectivo alternativo. São considerados como objectivos a minimizar os custos operacionais, do corte de carga e do desperdício de energia eólica. Estes objectivos são representados individualmente através de uma função de utilidade não-linear genérica que são agregadas numa função de utilidade aditiva, que é linearizada originando um problema de programação linear inteira mista. Este problema pode ser resolvido por *solvers* de otimização genéricos de forma a encontrar a solução preferida de um determinado agente de decisão, considerando a sua atitude perante o risco.

Numa segunda parte são adicionadas ao modelo termico-eólico as unidades hidroelétricas de geração de energia com sistemas de bombagem e armazenamento. Pretende-se explorar a capacidade destas unidades em utilizar energia eólica para bombar água que fica armazenada em forma de energia potencial, podendo posteriormente ser gerada em períodos de maior procura de energia. Testes realizados demonstram que a abordagem multi-critério proposta reflete as diferentes atitudes do decisor em ambos os modelos. Considerando unidades hídricas com bombagem os resultados são melhorados significativamente.

Palavras-chave

Unit commitment, Pré-despacho, Incerteza eólica, Optimização estocástica, Apoio à decisão multi-critério, Teoria da utilidade, Central hidroelétrica com bombagem.

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Glossary

DA	**D**ay **A**head
DM	**D**ecision **M**aker
ED	**E**conomic **D**ispatch
EENS	**E**xpected **E**nergy **N**ot **S**erved
ENS	**E**nergy **N**ot **S**erved
EXS	**E**nergy e**X**cess **S**erved
GENCO	**G**eneration **C**ompany
ISO	**I**ndependent **S**ystem **O**perator
MADM	**M**ulti-**A**ttribute **D**ecision **M**aking
MAUT	**M**ulti-**A**ttribute **U**tility **T**heory
MCDM	**M**ulti-**C**riteria **D**ecision **M**aking
MILP	**M**ixed-**I**nteger **L**inear **P**rogramming
MIP	**M**ixed-**I**nteger **P**rogramming
MOCO	**M**ulti-**O**bjective **C**ombinatorial **O**ptimisation
MOO	**M**ulti-**O**bjective **O**ptimisation
PSH	**P**umped **S**torage **H**ydro
RAC	**R**eliability **A**ssessment **C**ommitment
RNS	**R**eserve **N**ot **S**erved
RT	**R**eal **T**ime
UCP	**U**nit **C**ommitment **P**roblem
WPF	**W**ind **P**ower **F**orecasts
WHTUCP	**W**ind-**H**ydro-**T**hermal **U**nit **C**ommitment **P**roblem

WTUCP	**W**ind-**T**hermal **U**nit **C**ommitment **P**roblem

Chapter 1

Introduction

This document aims at partially fulfilling the requirements for the degree of Master's in Electrical and Computers Engineering (profile of Systems and Industrial Planning). A preliminary work and report, academically valued in 12 European Credit Transfer and Accumulation (ECTS), were developed and evaluated in March in the Institute of Engineering, Polytechnic of Porto, Portugal. That first part was developed under a research project – COORDINATOR: algoritmos híbridos para uma gestão efectiva da produção de energia, em sistemas hidro-térmicos com recursos eólicos – funded by *Fundação para a Ciência e a Tecnologia*, in partnership with INESC Porto. This final document includes in the previous document a research work academically valued in 30 ECTS, developed in the University of Bremen, Germany, under the ERASMUS internship exchange program.

1.1 Scope and Research Question

In power systems operations, the short-term scheduling of power generation units (also known as Unit Commitment Problem) is done in two stages, where decisions taken in a first stage influence a second one. The first stage is the unit commitment, that is performed several hours before the operating day (usually 24 hours) and consists on deciding which power generating units must be committed/decommitted in the day-ahead to meet the load. Due to technical limitations of most thermal units, that do not provide enough operational flexibility, the pre-planned states cannot be changed in the day-ahead operation. The second stage is the economic dispatch, that is taken minutes before the implementation and consists on deciding the most economic production level for the committed units, which is influenced by the commitment decisions. This second stage is also used to deal with uncertainties by allowing to adjust the production levels of thermal units according to the real wind values verified in each time period in the intra-day perspective.

The Unit Commitment Problem (UCP) is a mixed-integer non-linear combinatorial optimisation problem: it deals with integer variables, such as the units status, and with non-linear functions (thermal generation cost functions), falling in the class of NP-hard problems. In its standard format the problem handles only thermal power generators, but several extensions have been proposed to incorporate hydro units. More recently, not only due to the continuous increase of fuel costs but also for environmental concerns, there is a trend to take advantage and include as much renewable energy as possible in electricity generation. Those sources of energy are generally cheaper and have lower environmental impact. Among the renewable sources of energy, wind energy is the one that is growing the most throughout the world. However, due to the stochastic behavior of the wind speed, the wind power production is highly uncertain. The need for accurate forecasting tools for the wind speed arises, but even the best tools available are unable to avoid the uncertainty associated with the wind power production. The UCP becomes more complicated with the large penetration of wind energy sources, since the wind units are non-dispatchable and their production levels depend on the random wind speed.

The uncertainty inherent to the wind energy may have different impacts in the context of the UCP with wind integration. An unexpected downward deviation in the wind power production may erupt into load demand or reserve curtailments, due to the ramping-up limitations of the thermal units. On the other hand, a big upward deviation in the supply of wind power may lead to an unwanted waste of renewable and clean energy, when the thermal committed units cannot be decommitted or do not have enough downward ramping capabilities. These wind curtailments may happen mostly at night, when the wind is usually stronger while the load demand is lower.

In general, power systems operations are subject to other sources of uncertainty besides those brought up by the renewable sources of energy. These include load demand deviations or forced outages of the equipments. The wind uncertainty have been tackled by means of providing additional operating reserve, or by considering stochastic programs where the reserve is committed implicitly. These approaches appear mostly in conservative environments. They try to avoid load or reserve curtailments by finding schedules that cover the possible deviations from the wind power forecasting over a set of predetermined scenarios, assuming an aversion attitude from the decision makers towards risk of curtailments and usually leading to higher operating costs. Some approaches aim at penalising the amount of energy/reserve not served in the objective function. However, generation companies (GENCOs) and/or system operators (ISOs) may have different attitudes towards risk caused by the wind power integration in the UCP. Some may prefer to risk load demand curtailments if that means a relevant enough reduction in operating costs, and others may prefer to pay to avoid the possibility of not serving demanded energy. These risk profiles may also change over time due to economical or political issues.

In this way, the large penetration of wind farms in power systems with thermal units introduces the question of how should the thermal UCP be adapted to incorporate the high variability of wind speed. There is the need for innovate approaches that can balance the unexpected surpluses or deficits of wind power according to the preferences of decision makers during their operations in power systems.

Generation technologies have appeared to help to accommodate as many wind energy as possible into power systems. From those technologies, hydro units with pumping and energy storage capacities have proved to be an interesting solution due to its flexibility of operation, by using surpluses of energy generated by wind to pump and store water that can be used to produce electric energy during peak load periods. The impact of using those facilities in a multi-criteria approach for the UCP with large wind integration is then a topic of interest, particularly if the GENCO wants to analyze the possibility of investments in pumped storage hydro units.

1.2 Objectives

This work focuses on the day-ahead short-term UCP with wind integration that can be either undertaken by ISOs in decentralised markets or by GENCOs in centralised non-competitive environments. The ambit of our work falls in two main areas: 1) power systems and 2) multi-criteria decision making.

A few contributions are expected in the power systems area. We intend to describe the thermal UCP and the main steps involved in the short-term operation of power systems. We also briefly describe the impact of the integration of wind power in the thermal UCP and survey the main stochastic formulations that have been presented in the literature so far. Making use of the survey, we aim at proposing and describing an alternative stochastic WTUCP model based on the model presented in [7], that proved to be effective to achieve the optimal solution for small and large-scale thermal UCP. Firstly, we integrate the wind power in a scenario-based approach that aims at minimising expected costs represented by three components: operating costs, energy not served (or load curtailment) and waste of wind energy (or energy excess served).

We will develop a multi-objective optimisation model for the WTUCP to handle the impact of wind uncertainty in power systems operations. Operating costs, load curtailment and waste of wind energy are assumed to be targets to minimise by ISOs or GENCOs. These objectives are represented by an individual non-linear utility function proposed in [8] that should appropriately represent the satisfaction level of the decision maker towards the feasible levels for operating costs, load curtailment and waste of wind energy. The individual utility functions are linearised by a fixed number of segments. The linearised utility functions are aggregated in one single additive utility function, the objective function of the model, assuming that utility independence and additive independence between criteria hold.

The final stochastic multi-objective model for solving the WTUCP with this new approach allows to integrate the ISOs or GENCOs preferences and profile characteristics for finding the most preferred solution following the maximum expected utility paradigm.

In a second stage, hydro units with pumping and storage capacities are included in the model, yielding a model with wind-hydro-thermal coordination. We aim at finding the impact of including those units when comparing to the results found by solving the wind-thermal model.

1.3 Outline

This work is organised in eight chapters. This chapter presents the scope, relevance and main goals of this work. Chapter 2 contains a brief introductory explanation of the thermal UCP and states the impact of wind integration. Chapter 3 reviews the current research in integrating wind into the UCP and proposes an alternative stochastic model to solve the wind-thermal unit commitment problem. Chapter 4 reviews multi-attribute decision making theory, in particular utility theory. Chapter 5 describes a new utility-based approach developed to solve the wind-thermal UCP problem and presents the simulations and results obtained for three different decision maker profiles. Chapter 6 provides an introduction about pumped storage hydro units and reviews the literature on the integration of those units into the UCP. Chapter 7 describes the proposed approach and mathematical modeling for the integration of pumped storage hydro units in the previous wind-thermal UCP model, and presents the simulations and results obtained with the wind-hydro-thermal model. Finally, chapter 8 provides final conclusions of this work and refers to possible future work.

Chapter 2

Wind-Thermal Unit Commitment Problem

2.1 Unit Commitment - Problem Description

The unit commitment problem is a hard combinatorial optimisation problem whose objective is to determine a schedule to a set of power generating units, which must be commited/decommited over a planning horizon, in such a way that total costs are minimised. Typically, the pre-dispatch problem, necessary to evaluate the scheduling decisions, is a subproblem of the UCP. The pre-dispatch problem determines the production levels at which the commited units must operate in order to meet the forecasted system demand and reserve requirements, while satisfying a set of operational constraints and minimising the overall operating costs. Later, in a shorter period basis (5 to 15 minutes ahead of real dispatch) optimal production levels are determined for the units that were set to ON by the UCP. This optimisation problem is known as Economic Dispatch (ED). In a real power system, both GENCOs and consumers are located in different places, so the network is composed by several buses and nodes. However, in the UCP a simplification takes place: GENCOs and consumers are considered to be connected through a single bus, as shown in Figure 2.1.

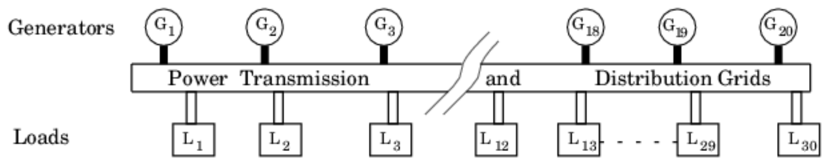


FIGURE 2.1: Single bus power system [1]

The UCP typically refers to a short-term scheduling, usually from 1 day to 2 weeks split in periods of one hour and takes place on a day-ahead (DA) stage, rather than real-time (RT) stages. More extended planning horizons can be considered, yielding the mid-term and long-term UCP, up to one year. Those problems are outside the scope of this work.

In centralised non-competitive environments, the UCP is of major practical importance for GENCOs, who are looking for economic schedules that can meet the load and reserve requirements, satisfying the constraints at minimum operating costs. The fact of having the monopoly of the energy production and distribution allows these companies to set a price that provides them the required profit.

Some decentralised (competitive) markets have a similar structure to the centralised ones, and the UCP is centrally carried out by the ISO on a daily basis. However, rather than minimising the operating costs, the goal is about maximising profit.

In electricity market operations three stages are usually carried out by the ISOs: 1) the DA stage, where the market prices are defined by solving the UCP according to the supply and demand bids. 2) the reliability assessment commitment (RAC) stage, where the commitment status of some units is revised closer to real-time, in order to address the updated information about some uncertain variables such as the load demand, units outages, availability of renewable energy or other financial issues about the market. The commitment of fast-start units may change in this stage; 3) the real-time market. Here the status of the power generating units is fixed and the ED model determines the optimal production level assigned to each committed unit. The ISO takes now into account the verified real values of the previously considered uncertain parameters.

2.1.1 Objective and Constraints

There are different mathematical models to solve the thermal UCP problem. Different assumptions and constraints may be considered, depending on the environment of operation (centralised or decentralised), characteristics of the power generating units or features of the power system. A general structure for the thermal UCP is shown in Figure 2.2.

Objective function:

Minimise (Production costs + start-up costs + shut-down costs)

Subject to:

$$\begin{cases} \text{System constraints} \begin{cases} \text{Load requirements} \\ \text{Reserve requirements} \end{cases} \\ \text{Technical constraints} \begin{cases} \text{Minimum up and down times} \\ \text{Generation limits and ramps} \end{cases} \\ \text{Network constraints} \end{cases}$$

FIGURE 2.2: A generalised structure for the thermal UCP

The objective function corresponds to the minimisation of fuel costs for producing electric energy, plus start-up and shut-down costs of thermal units over the planning horizon. The set of constraints include system constraints, technical constraints and network constraints.

System operation constraints are related to load and spinning reserve requirements satisfaction. The total thermal generation must meet the load demand, and enough reserve levels provided by upward capabilities of thermal units must meet some pre-defined requirements.

Technical constraints are related to limitations of thermal units. Those constraints are usually divided in two groups: 1) minimum number of consecutive time periods that the thermal units must be kept ON/OFF; 2) generation limitations: include the feasible maximum and minimum production level of each thermal unit as well as ramp constrains. Ramp constraints limit the maximum increase or decrease rate of generated power between consecutive periods, due to technical restrictions of thermal units.

Network constraints are responsible for the reliability and stability of the system. A more detailed explanation of the UCP objective and constraints and a mathematical formulation are provided in section 3.2.

2.2 Unit Commitment Problem with Wind Integration

The expansion of wind power plants all over the world has experienced a big capacity growth rate in the last decade, more accentuated in the countries located in Europe and North America. Despite the predictable decrease of the growth rate, the installed capacity will continue growing up achieving almost 500 GW of installed capacity by the end of 2016 [9]. This fact creates new challenges for the UCP, for both GENCOs and ISOs.

As known, the wind power production depends on the wind speed, which depends on some complex factors such as the climate or geodesy. Thus, it is very hard to predict the speed of the wind and give accurate wind power forecasts (WPF), necessary to calculate the available wind power at each hour of the day-after. The wind may verify rapid and unpredictable changes on its speed in small time periods bringing uncertainty, and consequently risk, to the decision.

For the thermal UCP, the main sources of uncertainty considered are the load demand and forced outages of units. However, errors considering the predicted and realised values inherent to these sources are usually low. In this way, it is legitimate that these parameters are usually considered as known with certainty (inputs) when solving the UCP. When the wind power production is considered such simplification is not reasonable. The high deviations between the forecasted and realised values may cause high load/reserve curtailment values or even deteriorate the security of the whole system. For these reasons, additional supporting methods that take into account the wind uncertainty, have to be used when wind is included in the UCP.

Previous studies show that the accuracy of the WPF has a significant impact in the UCP and ED decisions, since more accurate forecasts would provide better and more economic schedules [2, 10–14]. This may be related either to the reserve levels defined that depend on the WPF errors [15] or to the less conservatism of the solutions obtained , since more accurate WPF means less risk deviations (scenarios) from the inputs considered [10–12, 16].

Nevertheless, the importance of accurate WPF might depend on the power system considered. For instance, Ummels *et al.* performed in [17] a simulation for the Wind-Thermal Unit Commitment Problem (WTUCP) in the Dutch system, using an auto-regressive moving average process for the WPF considered. They surprisingly concluded that for the Dutch system the wind power limited predictability does not require additional reserve levels. They also concluded that the wind power variability does not have a significant effect on the system costs, curtailments, waste of energy or emissions. However we should keep in mind that these results might be related to the specific characteristics of the power system.

The interests related to the accuracy of the forecasts may vary among groups, inside the power system. For example, ISOs are more concerned with the accuracy related to possible rapid changes between time periods, the so-called ramp events, in order to maintain the reliability and stability of the system. On the other hand, GENCOs might be more concerned in accurate WPF for the overall planning period, in order to find good schedules and minimise the operating costs using all the available resources in the most economic manner.

The problem has been tackled in two ways: deterministic and stochastic approaches. In the deterministic models only one wind scenario is considered and the uncertainty of the wind power is not included. Concerning the stochastic models, some authors include the wind uncertainty assessing probabilities to the possible wind power outcomes. Some optimise the expected value of a number of possible pre-estimated scenarios, others developed rigid models that cover all possible deviations between scenarios, while others consider probability distributions for the wind production input. There are other models that are adjusted in an intra-day perspective according to the more accurate forecasts that are provided. A few multi-criteria approaches can also be found in the literature [18–21].

In this chapter, we survey the main formulations presented in the literature focusing on stochastic models. We will start by introducing models previously proposed in the literature, followed by a proposal of a complete model that is adapted from the work presented by Viana and Pedroso in [7].

Chapter 3

Formulations for the Short-term Wind-Thermal Unit Commitment Problem

Notation

Constants

- T – length of the planning horizon.
- U – number of thermal units.
- W – number of wind units.
- S – number of scenarios.
- $\mathcal{T} = \{1, \ldots, T\}$ – set of planning periods.
- $\mathcal{U} = \{1, \ldots, U\}$ – set of thermal units.
- $\mathcal{W} = \{1, \ldots, W\}$ – set of wind units.
- $\mathcal{S} = \{1, \ldots, S\}$ – set of scenarios.

- $P_u^{\min}, P_u^{\max}$ – minimum and maximum production levels of thermal unit u.
- $T_u^{\text{on}}, T_u^{\text{off}}$ – minimum number of consecutive periods thermal unit u must be kept switched on/off.
- $r_u^{\text{up}}, r_u^{\text{down}}$ – maximum up/down rates of thermal unit u.
- C^{ens} – cost of energy not served.
- C^{rns} – cost of reserve not served.
- C^{exs} – cost of waste of energy.
- D_t – system load requirements in period t.
- R_{ts} – spinning reserve requirements, in percentage, in period t, for scenario s.
- a_u, b_u, c_u – fuel cost parameters for thermal unit u.
- $a_u^{\text{hot}}, a_u^{\text{cold}}$ – hot and cold start up costs for thermal unit u.
- t_u^{cold} – number of periods after which start up of thermal unit u is evaluated as cold.
- y_u^{prev} – initial state of thermal unit u (1 if on, 0 if off).
- t_u^{prev} – number of consecutive periods thermal unit u has been on or off prior to the first period of the planning horizon.
- $prob_s$ – probability of occurrence of scenario s.
- pw_t^{Exp} – expected wind power production forecast in period t.
- pw_t^{Upd} – updated wind power production forecast in period t.
- FW_{wt} – wind generation of wind unit w in period t.

Variables

- Decision variables:
  - y_{ut} – 1 if thermal unit u is ON in period t, 0 otherwise.
  - p_{uts} – production level of thermal unit u, in period t, for scenario s.
  - pw_{wts} – wind generation (used to serve the load demand) of wind unit w, in period t, for scenario s.
  - cw_{wts} – curtailed wind generation of wind unit w, in period t, for scenario s.
  - ens_{ts} – energy not served in period t for scenario s.
  - rns_{ts} – reserve not served in period t for scenario s.
  - exs_{ts} – energy excess served in period t for scenario s.
  - p_{ut}^{Day} – day-ahead scheduled power generation for thermal unit u in period t.
  - p_{uts}^{up} – up regulation of the production level of thermal unit u, in period t, scenario s.
  - p_{uts}^{down} – down regulation of the production level of thermal unit u, in period t, scenario s.
- Auxiliary variables:
  - $x_{ut}^{\text{on}}, x_{ut}^{\text{off}}$ – 1 if thermal unit u is started/switched OFF in period t, 0 otherwise.
  - s_{ut}^{hot} – 1 if thermal unit u has a hot start in period t, 0 otherwise.
  - s_{ut}^{cold} – 1 if thermal unit u has a cold start in period t, 0 otherwise.
  - p_{uts}^{max} – maximum production levels of unit u in period t, scenario s (due to ramp constraints).
- Production costs
  - $F(p_{uts})$ – fuel cost of unit u in period t, scenario s.
  - $S(x_{ut}^{\text{off}}, y_{ut})$ – start-up cost of unit u in period t.
  - H_{ut} – shut down cost of unit u in period t.

3.1 Stochastic Formulations for the Wind-Thermal Unit Commitment Problem

The aim of this section is to explain how wind power production can be included in the formulation of the thermal UCP, and compare formulations previously proposed.

Several works presented in the literature show that by neglecting uncertainty and using deterministic values for the wind power generation more expensive schedules are obtained [2, 10, 14, 22–25]. Therefore, several stochastic approaches were developed where the uncertainty of the wind energy is included in the model using the available WPF. These forecasts are usually integrated in the models in two different ways: using cumulative distribution functions of the forecasted wind power, or using a set of generated scenarios. The former may be used to obtain cumulative probabilities to be inserted as parameters in the model [15]. The latter may be integrated using multiple pre-defined scenarios for the whole set of periods [10], or using a scenario tree tool where the number of scenarios increases with the length of the planning period [2, 12–14]. These topics are discussed later.

Some approaches assume that the WPF errors follow a normal distribution. However, those errors do not really follow that kind of distribution [26]. Thus the best way for integration of the errors of the WPF in the WTUCP is still an ongoing discussion.

In this chapter we will describe the objective function and the system constraints of the WTUCP. The remaining technical constraints are introduced in the section 3.2 since they are related to the unit states variables, independent of the scenarios and not relevant in this section. The load is considered as a stochastic parameter, since it is not possible to know with certainty the value of demand in each period of the following day. However, as the relative error observed in the real-time compared with the forecasted values is not relevant, it is commonly considered as a known parameter. Reserve is used to cover some deviations. The spinning reserve may be defined in several ways. Power system operators or energy markets have their own rules and/or practices to define the spinning reserve. The simplest approach is to define a fixed percentage of the load. The purpose of the reserve is to cover generator outages and/or load deviations.

3.1.1 Common Stochastic Formulation

A common practice in the context of the WTUCP is to introduce probabilities in a scenario-based approach. A scenario represents a possible wind realisation in each of the planning periods and it is assumed that only one of the generated scenarios will occur in the following day. This is a strong assumption since it is known that it is very unlikely that the wind realisations for each hour of the planning horizon will follow only one of the S scenarios considered. Nevertheless, this approach allows us to integrate the possible deviations around the forecasted wind speed values. The generation of scenarios should ensure a temporal relation between consecutive periods. This means that the generated values of wind power production for each period should be related to the previous and the following ones, and not be independently generated.

Ideally, a different schedule should be obtained for each scenario so that the decision maker (DM) gets an overview of the possible events and chooses one of the possible scenario-indexed schedules, knowing the negative impact on his objective if each of the other possible scenarios occurs [19]. He/she can, following this procedure, implement a solution according to his/her preferences and attitude towards the risk. However, this methodology seems to be not practical for real and large-scale applications, due to the high computational time needed to solve each single (scenario indexed) problem. Therefore, the most common practice is to develop a model that leads to a schedule that is feasible for all possible scenarios (but not necessarily optimal if each scenario is analysed separately).

Wang *et al.* followed this approach firstly in [23] and later expanded it in [10, 22, 27]. They integrated the wind energy characteristics in the thermal UCP model proposed by Carrion and Arroyo [28] to prove the importance of moving from deterministic to stochastic programming models, when considering the WTUCP.

Since the model represents a stochastic scenario-based approach, the objective is to minimise the expected operating costs, taking into account the probability of each scenario. All the variables, excluding the binary variables y_{ut}, x_{ut}^{on} and x_{ut}^{off}, are indexed by scenario, and constraints force that the commitment to be found is the same for all the possible wind realisations. An economic pre-dispatch is intrinsically run for each scenario. A general version of the objective of this formulation is presented in (3.1). The value of the objective function obtained is only an indicator of the expected costs for the obtained commitment, since the real costs to be observed would be different from this expected value. Note that only the continuous variables p_{uts} are indexed by scenario.

$$\min \sum_{s\in\mathcal{S}} prob_s \sum_{t\in\mathcal{T}} \sum_{u\in\mathcal{U}} (F(p_{uts}) + S(x_{ut}^{\text{off}}, y_{ut}) + H_{ut}). \tag{3.1}$$

The traditional deterministic UCP formulation coincides with the stochastic one by considering only one scenario with probability equal to one. In deterministic approaches, the only scenario considered for the wind production input comes from the forecasted wind power or the expected value of a number of generated scenarios.

To reduce the conservatism of the deterministic model, which assumes that load and reserve have to be served, it is common to introduce some flexibility in the formulation by including other indicators such as the possibility of load or reserve curtailment [10, 12]. The curtailment events are introduced to give more flexibility to the model, accommodating big deviations that can be verified between different scenarios. Energy not served (ENS) or load curtailment events can occur in scenarios where the sum of available wind power is not enough to meet the load. These events may occur when the available production cannot absorb such variations. It is also possible to have reserve curtailment, yielding to the so-called reserve not served (RNS) values. The RNS values may be divided in spinning and replacement reserve slacks, or only as a single operating reserve, as discussed later. Both components ENS and RNS commonly have an associated cost per MW, represented by C^{ens} and C^{rns}, respectively. These costs may, for instance, be deducted from the current penalties applied by some system operators in some regulated markets to services not served [10].

After integrating these components, the objective function is now to minimise the sum of the expected production and start-up and shut-down costs, plus the expected costs of energy and reserve curtailments, as shown in (3.2).

$$\min \sum_{s \in \mathcal{S}} prob_s \sum_{t \in \mathcal{T}} \sum_{u \in \mathcal{U}} (F(p_{uts}) + C^{ens} ens_{ts} + C^{rns} rns_{ts}) + \sum_{t \in \mathcal{T}} \sum_{u \in \mathcal{U}} (S(x_{ut}^{\text{off}}, y_{ut}) + H_{ut}) \tag{3.2}$$

Note that for reserve to be curtailed ahead of load, the C^{ens} penalty value should be bigger than the C^{rns} penalty.

Concerning wind uncertainty, opposite events may also occur. An unforeseen upward wind realisation may occur in several scenarios, yielding a waste of wind energy or energy excess served (EXS), when the committed thermal units are operating in their feasible minimum. This wind power surplus happens mostly at night, when wind is usually stronger and the system load is low. The wind energy may be then spilled in order to maintain the normal operation of the slow-start units, such as coal and nuclear, due to the physical constraints of those units, and simultaneously ensure the reliability and stability of the system due to ramp and/or inertia technical and network constraints.

In this formulation the integer variables and the technical constraints related to the thermal units remain independent of the scenarios. This means that the start-up and shut-down constraints, as well as the minimum on and minimum off time constraints, described further in the section 3.2, are the same for all scenarios. The system constraints (see (3.3)-(3.5)) must be satisfied for each scenario. Constraints (3.3) state that the total energy production provided by the thermal and wind units meets the load demand with possibility of load curtailment. Constraints (3.4) ensure the reserve satisfaction if not curtailed. Note that $p_{ut}^{\max}$ is considered instead of $P_u^{\max}$, due to the technical ramp limits of the thermal units, further detailed in the section 3.2. Constraints (3.5) state that the wind production plus the wind curtailment meet the available wind power and constraints (3.6) compute the waste of energy per scenario per period.

$$\sum_{u \in \mathcal{U}} p_{uts} + \sum_{w \in \mathcal{W}} pw_{wts} = D_t - ens_{ts}, \quad \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{3.3}$$

$$\sum_{u \in \mathcal{U}} (p^{\max}_{uts} - p_{uts}) \geq D_t.R_t - rns_{ts}, \quad \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{3.4}$$

$$pw_{wts} + cw_{wts} = FW_{wt}, \quad \forall w \in \mathcal{W}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{3.5}$$

$$\sum_{w \in \mathcal{W}} cw_{wts} = exs_{ts}, \quad \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{3.6}$$

Note that the EXS value for each period/scenario is given by the sum of the curtailed wind energy on each unit w (3.6). Constraints (3.3)-(3.4) could be developed without any of ENS and RNS values in conjunction with objective (3.1), as done by Wang, Shahidehpour and Z. Liin [29]. The authors developed a deterministic formulation considering the expected wind generation as a known parameter in the objective function shown in (3.1) to determine the unit commitment. They also added constraints to ensure that each scenario dispatch remains within a feasible range from the dispatch previously determined. They used Bender's decomposition to solve the problem adding cuts iteratively until a feasible solution is found. However, this model demonstrates to be too conservative and it may become difficult to find feasible solutions, since the decision space would become very restricted.

Following the scenario-based approaches, Zhang, Zechun and Liangzhong presented in [30] a robust stochastic WTUCP to deal with the spinning reserve requirements from one hour to the next, in order to cover wind power variations between scenarios. The authors preferred to consider only three scenarios whose discrete probabilities are deducted from the continuous CDF of the WPF. To reflect their concerns in the presented formulation two additional constraints would be needed, (3.7) for upward dispatches and (3.8) for downward dispatch of thermal units.

$$\begin{gathered}\sum_{u \in \mathcal{U}} (p^{\max}_{u,t+1,f} - p_{u,t+1,f}) \geq \sum_{w \in \mathcal{W}} (pw_{wte} - pw_{w,t+1,f}), \\ \text{for } \ t = 1 \ldots T-1, \forall e, f \in \mathcal{S}, e \neq f\end{gathered} \tag{3.7}$$

$$\sum_{u\in\mathcal{U}}(\min(p_{u,t+1,f}-P_u^{\min},r_u^{\text{down}})\geq\sum_{w\in\mathcal{W}}(pw_{w,t+1,f}-pw_{wte}), \\ \text{for } t=1\dots T-1,\forall e,f\in\mathcal{S},e\neq f \tag{3.8}$$

The consideration of these new constraints would cover the risk introduced by the wind speed variations between periods. The number of scenarios should be small to ensure the computational efficiency of the model. The authors did not consider ENS or RNS values in constraints (3.3)-(3.5). So the problem, with this additional constraints, besides being non-flexible and very exigent for the solver to find a feasible solution is also too conservative and results in high operational costs.

3.1.2 Stochastic Formulation Updating Data in a Rolling Manner

The commitment decision is usually made in a day-ahead perspective, in a short term horizon, typically for 24 hours. However, more updated information becomes available during the day, which should be taken into account, especially in systems with large wind penetration. In this way, commitment and dispatch decisions should be allowed to be changed in an intra-day perspective, in order to incorporate the updated forecasts, changing the day-ahead decisions in a rolling plan manner. For system operations with large-scale wind power, more accurate near real-time wind power measurements and continuous re-calculation are essential in the context of the UCP and ED [17]. This logic is used in the Wind Power Integration in the Liberalised Electricity Markets (WILMAR) project, presented by Meibom *et al.* in [2, 12–14].

WILMAR is a project initially developed to study the changes in Nordic system energy markets due to the large amount of wind power. The first approach was initially presented by Barth *et al.* in [14]. The authors presented a model that does not correspond to an unit commitment model, but rather to a planning tool that aims to optimise a given input schedule for 5 different markets. In their previous work an economic dispatch is run for each of the planning periods. The goal of the primary versions of WILMAR was to figure out the impacts of the integration of large amounts of wind power in electricity markets, finding optimal production levels for given commitments, evaluating variations in prices and system costs.

Further, WTUCP algorithms were developed in the context of the WILMAR project. Tuohy *et al.* extended the previous work in [2, 12, 13, 31] considering unit commitment variables and integrating system, technical and network constraints. The aim was to analyse the impact of stochastic wind and load on the unit commitment and dispatch of power systems with high levels of wind power. The model calculates the UC and ED decisions in a day-ahead rolling plan approach, using multiple scenarios in a multi-stage scenario tree. The commitment decisions are divided in stages, typically about 1, 3 or 6 hours long each. In the first stage there is only one root node where the wind power production and load are assumed to be known with certainty, yielding the "here-and-now" decisions. In the following stages different paths with a given probability of occurrence are generated by a scenario tree tool, finding a commitment for each scenario path. Each UCP run finds a schedule based on the forecasted information for the lacking planning periods, starting at noon and finishing at the end of the following day (36h). An illustration of the rolling planning and decision structure considering 3 hours long stages can be seen in Figure 3.1.

The more distant from the decision stage are the planning periods, more uncertainty exists, and consequently more scenarios are needed. As more accurate WPF are available, more schedules are able to be found at more realistic levels. The commitment decisions from past stages are inputs to the model in order to find the solutions for the subsequent periods. In this way, the length of the forecast horizon which the system is optimised over is reduced for subsequent planning periods. In Figure 3.1 we can see that at each 3 hours (starting at 12 AM and finishing at midnight of the following day) the planning period considered in the model is reduced. The wind power production is assumed to be known for the first 3 hours, five scenarios are generated for the following 3 hours, and for the remaining periods ten scenarios are used. For more information on the UC model of the WILMAR project the reader is addressed to [12].

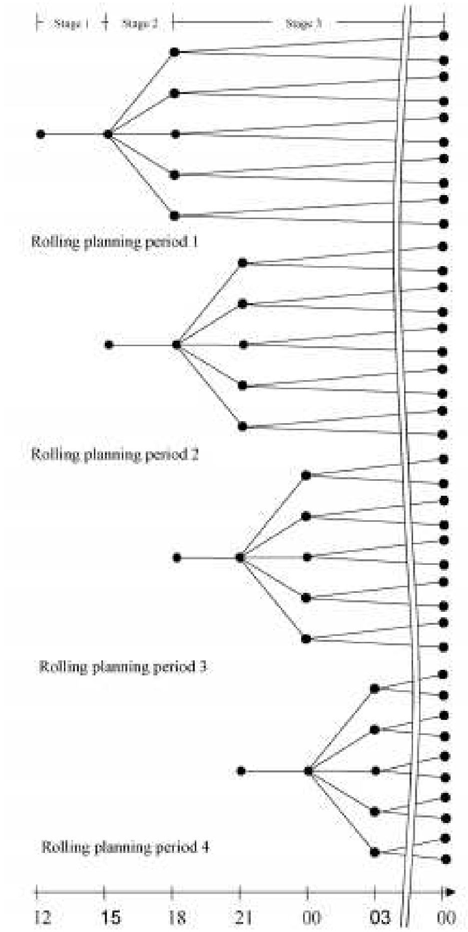


FIGURE 3.1: Rolling planning with scenario trees [2]

In terms of objective function, it aims to minimise the expected operating and start-up and shut-down costs as well as the load and reserve curtailments, as shown in (3.9).

$$\begin{aligned}\min \sum_{s \in \mathcal{S}} prob_s \sum_{t \in \mathcal{T}} \sum_{u \in \mathcal{U}} (F(p_{ut}^{\text{Day}} + p_{uts}^{\text{up}} - p_{uts}^{\text{down}}) + C^{ens} ens_{ts}^{int} + C^{rns^{spin}} rns_{ts}^{spin} \\ + C^{rns^{rep}} rns_{ts}^{rep}) + \sum_{t \in \mathcal{T}} C^{ens} ens_t^{day} + \sum_{t \in \mathcal{T}} \sum_{u \in \mathcal{U}} (S(x_{ut}^{\text{off}}, y_{ut}) + H_{ut}).\end{aligned} \tag{3.9}$$

The scenarios of the scenario tree tool and the respective probabilities are then used. Penalties are applied to avoid load and reserve curtailments. In terms of reserve, it is divided into spinning and replacement reserve, with different penalties, $C^{rns^{spin}}$ for the spinning reserve and $C^{rns^{rep}}$ for the replacement, according to the Irish code. Both are treated in an intra-day manner and indexed by scenario. In terms of load curtailment, it is divided into the day-ahead (ens_t^{day}) as an expected value for ENS, and intra-day (ens_{ts}^{int}), indexed by scenario for the intra-day load curtailment verified in each scenario. Both have the same associated cost (C^{ens}).

Each day at 12 AM a day-ahead constraint is added into the model in order to set the day-ahead prices, since they typically must be defined and provided to the ISO from 12h to 36h before the operating day. The expected ENS value is minimised in this step by adding the respective penalty cost to the objective function. Constraint (3.10) is added to model the ENS at the day-ahead stage. Deterministic values for wind and load (average value of the forecasted scenarios) are used to find the commitment that satisfies the constraints at minimum cost.

$$\sum_{u \in \mathcal{U}} p_{ut}^{\text{Day}} + \sum_{w \in \mathcal{W}} pw_{wt}^{\text{Exp}} = D_t - ens_t^{day}, \quad \forall t \in \mathcal{T} \tag{3.10}$$

The UC model considers a fixed production level per period for each thermal unit for the rolling plan horizon at the day-ahead stage. However, up and down regulations in relation to the predefined level are considered in the intra-day operations, in order to integrate the updated data of the WPF.

In the intra-day perspective, and considering the deviations related to each scenario, constraints (3.11) are added to the model. Here, pw_{wt}^{Exp} is the expected wind power for each time period, introduced as a parameter.

$$\sum_{u \in \mathcal{U}} (p_{uts}^{\text{up}} - p_{uts}^{\text{down}}) - \sum_{w \in \mathcal{W}} cw_{wts} = \sum_{w \in \mathcal{W}} (pw_{wt}^{\text{Exp}} - pw_{wts}^{\text{Upd}}) - ens_{ts}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{3.11}$$

As we can see, the deviations between the wind generation in each scenario are covered by the up or down regulations (auxiliary variables), deducing then the wind curtailment. Load curtailment provides the necessary flexibility into the model.

Additional constraints to define the various reserves considered are also provided in the referred paper.

The main conclusions of the WILMAR project developments, concerning the WTUCP formulations, are that the stochastic optimisation is able to reduce the cost and produce better performing schedules than the traditional deterministic approach. Rescheduling more often means that more reliable and economic solutions are achieved. The uncertainty is minimised because more wind and load forecasts are being updated, particularly when fast-start units are available. Their flexibility allows to cover some of the variability of wind power output. Additional storage of electricity did not appear to bring any extra benefits in their study. The accuracy of the WPF has an important role on planning decisions when integrating wind energy, since more economic schedules may be obtained if the WPF are more accurate.

A limitation of the model is that it is necessary to assume perfect forecasts for the first stage, whose associated errors may have a big influence in the following commitment stages. Furthermore, the model does not consider network constraints that are particularly important for some markets. The model is still mainly a planning tool and is not being used by real-time market operators.

3.1.3 Other Formulations for the UCP with Wind Integration

In [11], Jiang, Wang and Guan presented a robust optimisation model for the thermal UCP in the day-ahead market. The objective is to minimise the total cost under the worst wind power scenario, applying a Bender's decomposition algorithm to obtain a solution. Pumped storage hydro units are included in the model. The wind power is represented with an uncertainty set that captures the ramp events and includes the worst-case scenario, protecting it in terms of incremental costs. The conservatism of the model is controlled by a variable managed by the DM, however it can be hard for him/her to define this value and the solution may easily be conservative.

A model developed for the day-ahead wind-thermal UCP for the system operators in deregulated power systems is presented by Xie *et al.* in [15]. The model does not follow a scenario-based approach, and considers the Expected Energy Not Served (EENS) as a function of WPF uncertainty and thermal generators outages. The EEES, related to a possible waste of wind energy, is a function of wind uncertainties, that are expressed in terms of the unit commitment variables and consequently define the spinning reserve levels to set. Specialised formulations for these two indicators are presented, which are initially non-linear and depend on the cumulative probability based on the forecasted wind power. In order to integrate the EENS and EEES indicators, two steps are required. Firstly the stochastic variables EENS and EEES are set to be under a defined threshold value at all time periods. However, besides the loss of flexibility, there is some difficulty inherent to the definition of the ceilings, that can turn the model less flexible and introduce extra conservatism. The cost may increase exponentially if the EENS threshold is set too low or, on the other hand, huge amounts of ENS may be introduced if the threshold is set too high. A cost-benefit variable is created and added to the objective function to balance EENS and EEES values with the reserve amount. With this cost-benefit balance, the spinning reserve determination can balance the least EENS and EEES in each time period. However, the difficulty of setting the thresholds as well as the penalty values is still a drawback.

Botterud *et al.* [16] improved the study described in section 3.1.1 and integrated demand dispatch to the model presented in [10]. They considered a flexible load demand in the intra-day market that responds to the prices practiced in each of the planning periods. Flexible load demand can help with the integration of wind power when there is a surplus in the production, since the price practiced in the market decreases. Instead of a scenario-based approach, the authors developed a deterministic model that considers the wind generation as the 50% quantile of the WPF. The wind uncertainty is integrated by setting the reserve with a level equal to the difference between the 1% and 50% quantiles of the WPF. The model is prepared for the 3 stages of operation (DA, RAC and RT) which are solved based on the supply and demand bids that are previously known and remain always the same. The updated WPF are available at each stage. Within a case study for the electricity market of Illinois the authors conclude that the flexibility from the demand dispatch improves the ability to handle wind power uncertainty. A dynamic spinning reserve adjusted depending on the level of uncertainty of the WPF leads to more efficient schedules of resources compared with the traditional fixed reserves.

Ruiz, Philbrick and Sauer [24] presented a day-ahead scheduling approach using a stochastic model based on scenarios that represent three uncertainty sources: generation outages, load and wind power. The model is divided in two stages. The first before the scenario realisation when the commitment decisions are taken for the slow-start units. The second for the ED and commitment of fast-start units after verifying which scenario has been realised. The work combines two strategies to accommodate the wind power uncertainty: the scenario analysis and a dynamic reserve level definition. The aim is to obtain robust solutions. Numerical results obtained through a case study on Public Service Company system, Colorado, showed that the most significant difference between stochastic and deterministic policies is in the wind power curtailment. Thus, the stochastic approaches revealed to be very appropriate for the systems with large amounts of installed wind generation with high uncertainty and without too many flexible units such as the thermal fast-start and pumped storage hydro units.

Abreu *et al.* [32] presented a UCP model for competitive environments with the objective of maximising the profit of GENCOs and setting the prices for the energy, the so-called price-based UCP. They considered only wind and cascaded hydro units, exploring the coordination between them (wind power surplus can be used to store water in cascaded hydro units). The errors inherent to the WPF are integrated using scenarios managed through a Monte Carlo simulation. The model provides also an assessment of risk to define the estimated pay-off concerning the market uncertainties. The risk is related to the differences between the targeted and the real price, and the objective is to calculate an expected payoff that satisfies the GENCO and simultaneously maintains the expected downside risk below a certain threshold. The main conclusions are that the coordination between wind and hydro units would lower the wind curtailment and increase the expected payoff of the GENCO. The stochastic approach would lower the expected risk of the GENCO comparing with the deterministic one and in uncoordinated cases would result in higher payoffs.

3.2 Wind-Thermal Unit Commitment Problem - A Newly Proposed Formulation

This section aims at proposing a mixed-integer programming (MIP) model for the short-term WTUCP, and at presenting a brief explanation of the model objective and constraints. The model presented in [7] proved to be efficient to achieve the optimal solution for small and large-scale applications for the UCP with thermal units. In this section it is adapted to develop a model with wind energy production integration in a stochastic way, in a scenario-based approach. The main characteristics found in the literature, such as load curtailment, reserve curtailment and waste of energy are also included and modeled to provide flexibility.

The presented model can be used either by GENCOs or by ISOs (that centrally manage the system), and provides a day-ahead scheduling. The ON/OFF states cannot be changed once the commitment decision is done. A pre-dispatch is implicit in the model, needed to evaluate a unit commitment solution. However, it should also be considered that other EDs are run frequently in a intra-day perspective, in order to cover deviations caused by load uncertainty and unit forced outages.

3.2.1 Objective function

The objective is to minimise the total expected production costs over the planning horizon. Those costs include fuel, start-up and shut-down costs, plus the costs of load and reserve curtailments and waste of energy, as shown in (3.12). Other objectives, such as maximising the profit, may be considered for liberalised markets [32, 33].

$$\min \sum_{s\in\mathcal{S}} prob_s \sum_{t\in\mathcal{T}} \sum_{u\in\mathcal{U}} (F(p_{uts}) + C^{ens}ens_{ts} + C^{rns}rns_{ts}$$
$$+C^{exs}exs_{ts}) + \sum_{t\in\mathcal{T}} \sum_{u\in\mathcal{U}} (S(x_{ut}^{\text{off}}, y_{ut}) + H_{ut}). \tag{3.12}$$

The fuel costs represented by $F(p_{uts})$ refer to the thermal units, since the wind power production is considered at no costs. The fuel consumption of thermal units is not represented by a linear function of the generated power. $F(p_{ut})$ can be represented by the equation (3.13).

$$F(p_{uts}) = \begin{cases} c_u p_{uts}^2 + b_u p_{uts} + a_u + |e_u sin(f_u(P^{\min} - p_{uts}))| & \text{if } y_{ut} = 1, \\ 0 & \text{otherwise.} \end{cases} \tag{3.13}$$

where a, b, c, e, f are parameters of the fuel cost function. This function takes into account the valve-point loading effect represented by the absolute component of the function and the parameters e and f. This effect is defined by a set of valve points. The area between consecutive points is concave, as shown in the continuous line of Figure 3.2, for 5 valve points.

However, being non-continuous and non-convex, this type of function becomes very hard to optimise, due to the considerable decrease of efficiency of MIP solvers to handle non-continuous and non-convex functions.

Thus, a quadratic approximated function is generally used (see equation 3.14). The shape of the quadratic cost function is depicted in Figure 3.2 in dashed line.

$$F(p_{uts}) = \begin{cases} c_u p_{uts}^2 + b_u p_{uts} + a_u & \text{if } y_{ut} = 1, \\ 0 & \text{otherwise.} \end{cases} \tag{3.14}$$

This simplified cost function still brings several optimisation challenges as there are not efficient solvers for quadratic programming. Therefore, many researchers linearised the

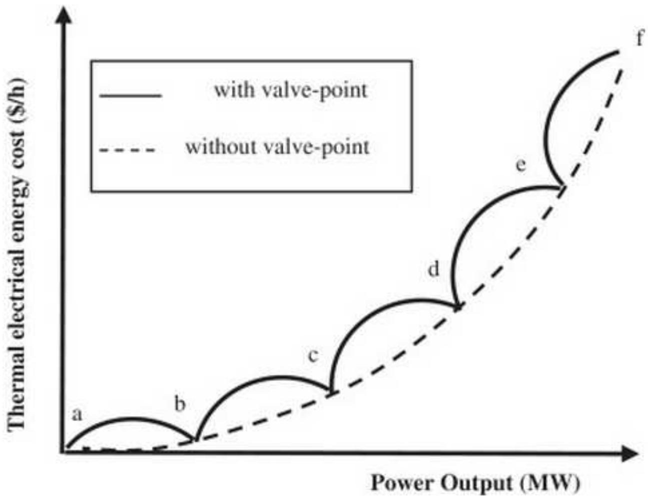


FIGURE 3.2: Common shape of the fuel cost function when considering the valve-point loading effect [3]

cost function, used meta-heuristics/evolutionary programming algorithms or hybridised heuristic-based methods with MIP solvers, in order to achieve better computational performances. In all of these cases they accept the risk of finding a sub-optimal solution. More recently, Viana and Pedroso [7] proposed an iterative linear model that converges to global optimality.

In order to take advantage of the efficiency of MILP solvers, in this work a linear lower approximation of the quadratic fuel cost function (3.14) is performed. The function $F(p)$ is approximated by a set of linear functions defined by the tangent lines to $F(p)$ in a pre-defined set of production levels p, so-called breakpoints. The first linear function is tangent to $F(p)$ at the minimum feasible power $(P^{\min}, F(P^{\min}))$ and the last linear function is tangent to $F(p)$ at the maximum feasible power $(P^{\max}, F(P^{\max}))$. All the additional production levels p defined to set the tangent lines to $F(p)$ are equidistant between the interval $[P^{\min}, P^{\max}]$. The total number of segments approximating $F(p)$ is defined by the user. Figure 3.3 shows an example of a lower linear approximation of $F(p)$ by 4 segments (red lines).

Shut-down costs H_{ut} are commonly assumed to be zero and start-up costs can come from hot or cold start-ups, depending on the number of consecutive periods that the unit was

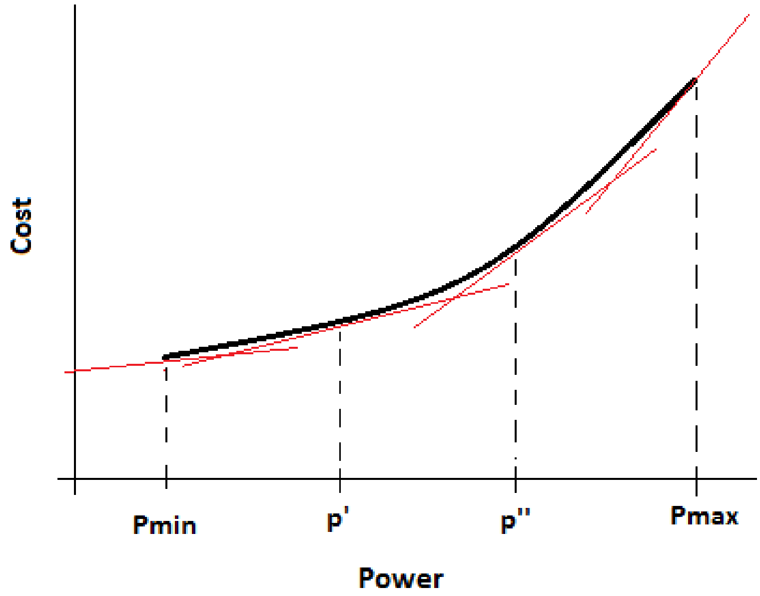


FIGURE 3.3: Lower approximation of the quadratic cost function by 4 linear functions

OFF before start-up. These costs can be modeled as:

$$S\left(x_{ut}^{\text{off}}, y_{ut}\right) = a_u^{\text{hot}} s_{ut}^{\text{hot}} + a_u^{\text{cold}} s_{ut}^{\text{cold}}. \tag{3.15}$$

where s_{ut}^{hot} and s_{ut}^{cold} are binary variables and the constants a_u^{hot} and a_u^{cold} are set as follows:

$$\begin{cases} a_u^{\text{hot}} & \text{if } \gamma_{ut}^{\text{off}} \leq t_u^{\text{cold}}, \\ a_u^{\text{cold}} & \text{otherwise,} \end{cases} \tag{3.16}$$

with γ_{ut}^{off} as the number of consecutive periods that thermal unit u was OFF before period t.

3.2.2 System constraints

The system constraints remain the same as those described in section 3.1.1. Only a fixed spinning reserve level, which will be used to cover load deviations and forced outages of the generating units, will be considered in this study. Non-spinning and replacement reserves are excluded. However, by integrating ramp constraints (described later) the maximum feasible generation in consecutive periods may differ and variables $p^{\max}_{ut}$ should be considered instead of constant $P^{\max}_u$. Those variables are used when setting the reserve constraints, as shown in (3.18). As we can see, the load is satisfied by the thermal plus the wind productions. Only thermal units can provide reserve, since wind power production level is dispatchable.

Some flexibility is introduced in the model by allowing wind power production to be curtailed, if necessary, as shown in (3.19). The wind energy produced plus the wind energy curtailed meet the wind generation for each unit and period.

$$\sum_{u\in\mathcal{U}} p_{uts} + \sum_{w\in\mathcal{W}} pw_{wts} = D_t - ens_{ts}, \quad \forall t\in\mathcal{T}, \forall s\in\mathcal{S} \tag{3.17}$$

$$\sum_{u\in\mathcal{U}} (p^{\max}_{uts} - p_{uts}) \geq D_t.R_t - rns_{ts}, \quad \forall t\in\mathcal{T}, \forall s\in\mathcal{S} \tag{3.18}$$

$$pw_{wts} + cw_{wts} = FW_{wt}, \quad \forall w\in\mathcal{W}, \forall t\in\mathcal{T}, \forall s\in\mathcal{S} \tag{3.19}$$

$$\sum_{w\in\mathcal{W}} cw_{wts} = exs_{ts}, \quad \forall t\in\mathcal{T}, \forall s\in\mathcal{S} \tag{3.20}$$

with:

$$\begin{aligned}
p^{\max}_{uts} &\leq y_{ut}P^{\max}_u, \\
&\qquad \forall u\in\mathcal{U},\ \text{for}\ t=2\ldots T, \forall s\in\mathcal{S}, \\
p^{\max}_{uts} &\leq p_{u,t-1,s} + y_{u,t-1}r^{\text{up}}_u + (y_{ut}-y_{u,t-1})st^{\text{up}}_u + P^{\max}_u(1-y_{ut}), \\
&\qquad \forall u\in\mathcal{U},\ \text{for}\ t=2\ldots T, \forall s\in\mathcal{S}, \\
p^{\max}_{uts} &\leq (y_{ut}-y_{u,t+1})st^{\text{down}}_u + P^{\max}_u y_{u,t+1}, \\
&\qquad \forall u\in\mathcal{U},\ \text{for}\ t=1\ldots T-1, \forall s\in\mathcal{S}.
\end{aligned}$$

3.2.3 Technical constraints

Technical constraints represent limitations related to the thermal units technical characteristics when setting their state and/or production levels.

Minimum up and down times

Each unit must be ON/OFF for at least a minimum consecutive number of periods (T_u^{on} / T_u^{off}) after it is set to ON/OFF.

The first period is modeled in a different way because of the initial state of the units. The constraints for this period only consider the input data and may be represented by (3.21) and (3.22), where θ_u^{on} in (3.21) represents the $\max(0, T_u^{\text{on}} - t_u^{\text{prev}})$, while θ_u^{off} in (3.22) represents the $\max(0, T_u^{\text{off}} - t_u^{\text{prev}})$.

$$y_{ut} = 1, \quad \forall u \in \mathcal{U} : y_u^{\text{prev}} = 1, \text{ for } t = 0, \ldots, \theta_u^{\text{on}}, \tag{3.21}$$

$$y_{ut} = 0, \quad \forall u \in \mathcal{U} : y_u^{\text{prev}} = 0, \text{ for } t = 0, \ldots, \theta_u^{\text{off}}. \tag{3.22}$$

Constraints (3.23) and (3.24) aim to do the same for the remaining planning periods, where τ_{ut}^{on} and τ_{ut}^{off} stand for $\max(t - T_u^{\text{on}} + 1, 1)$ and $\max(t - T_u^{\text{off}} + 1, 1)$, respectively.

$$\sum_{i=\tau_{ut}^{\text{on}}}^{t} x_{ui}^{\text{on}} \leq y_{ut}, \qquad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}, \tag{3.23}$$

$$\sum_{i=\tau_{ut}^{\text{off}}}^{t} x_{ui}^{\text{off}} \leq 1 - y_{ut}, \quad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}. \tag{3.24}$$

Generation limits and ramps

It is sporadically assumed that the dynamics of the generating plants does not pose restrictions (other than on maximum and minimum power levels) on the amount of power generated at each time period of the time horizon. Unfortunately, this is not realistic for large units or for relatively short time periods (e.g., 15 min), when ramp constraints need to be considered. These constraints limit the maximum increase or decrease of generated power from one time period to the next, reflecting the thermal and mechanical inertia that has to be overtaken for the unit in order to increase or decrease its output. To formulate these restrictions, constraints (3.25) and (3.26) are added, allowing to model, respectively, the maximum up and down rates for each unit in consecutive periods of time. In (3.27) we can see the restriction of the capacity limits of each thermal unit. Concerning wind units the respective constraint is not needed since the wind power available that is considered reflects this restriction.

$$p_{uts} - p_{u,t-1,s} \leq r_u^{\text{up}}, \qquad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S}, \tag{3.25}$$

$$p_{u,t-1,s} - p_{uts} \leq r_u^{\text{down}}, \qquad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S}. \tag{3.26}$$

$$P_u^{\text{min}} y_{ut} \leq p_{uts} \leq P_u^{\text{max}} y_{ut}, \quad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S}. \tag{3.27}$$

3.2.4 Auxiliary constraints

This section is presented only to provide the auxiliary constraints that support the computation of the auxiliary variables, in order to complete the model formulation and its full understanding.

Setting and computation of variables s_{ut}^{hot} and s_{ut}^{cold}

Constraints (3.28) state that every time a unit is switched ON, a start-up cost will be incurred.

$$s_{ut}^{\text{hot}} + s_{ut}^{\text{cold}} = x_{ut}^{\text{on}}, \quad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}. \tag{3.28}$$

To determine whether a unit has a cold or a hot start, constraints (3.29) apply. It will be a cold start if the unit remained OFF for more than t_u^{cold} periods of time, and a hot start otherwise.

$$y_{ut} - \sum_{i=t-t_u^{\text{cold}}-1}^{t-1} y_{ui} \leq s_{ut}^{\text{cold}}, \quad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}. \tag{3.29}$$

Setting and computation of variables x_{ut}^{on} and x_{ut}^{off}

Constraints (3.30) and (3.31) relate switch-on and switch-off variables with the y_{ut} variables.

$$y_{ut} - y_{u,t-1} \leq x_{ut}^{\text{on}}, \qquad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}, \tag{3.30}$$

$$x_{ut}^{\text{off}} = x_{ut}^{\text{on}} + y_{u,t-1} - y_{ut}, \quad \forall u \in \mathcal{U}, \forall t \in \mathcal{T}. \tag{3.31}$$

Relaxation of integrality constraints on variables x_{ut}^{on} and x_{ut}^{off}

Constraints (3.28) and (3.31) allow to relax a row of variables x_{ut}^{on} and x_{ut}^{off}. In fact, if s_{ut}^{hot} and s_{ut}^{cold} are defined as binary variables, using (3.28), x_{ut}^{on} will also always be 0 or 1 and, since y_{ut} is binary, using (3.31) x_{ut}^{off} will always be set to 0 or 1, for feasible y_{ut}.

Chapter 4

Multi-criteria Decision Making

4.1 Multi-attribute Decision Making and Multi-Objective Optimisation

In mathematical optimisation of a single criterion, the aim is to find out the best solution for that criterion from a set of feasible alternatives. Using some computational tools the best solution is found and implemented. Therefore, unless there are alternative optimal solutions, there is not in general a decision process involved in the selection of the solution to implement. However, frequently the DM wishes to optimise not only one but multiple objectives simultaneously. This is the context in which the multi-criteria decision methodologies fall and the subject of this work.

In multiple criteria decision making (MCDM), there are two or more objectives to optimise. Those objectives are conflicting, i.e., there is not a solution which optimises them all simultaneously, and multiple "optimal" solutions (called non-dominated solutions) can be found. Therefore, an intermediate selection process is required before solution implementation - the subjectivity of the DM should be integrated in this intermediate process in order to choose and implement not the (single) optimal solution that in general does not exist, but the preferred solution or alternative. The interest for MCDM has continually grown up in the last decades, as proved by the several books and surveys in the literature [34–38].

MCDM can be divided in two sub-areas: multi-attribute decision making (MADM) and multi-objective optimisation (MOO). The differences between these two groups is discussed in this chapter. Focus to MOO is given for a better understanding of the MOO methodology applied in this work.

4.1.1 Multi-attribute Decision Making

In MADM the aim is to order, group or select one alternative out of a discrete and finite set of non-dominated solutions which are mutually exclusive alternatives. There are several techniques to solve multi-attribute problems. These techniques are divided in two main categories: non-compensatory and compensatory approaches. The former do not permit trade-offs between attributes, so an unfavorable value in one attribute cannot be offset by a favorable in some other. It includes methods such as *maximin*, *maximax*, conjunctive or disjunctive constraint method or the lexicographic method. Those methods are described in greater detail in [39].

The compensatory methods, on the contrary, allow trade-offs between attributes. In those methods, changes in one attribute can be compensated by changes in any of the other attributes. These methods include scoring models such as the analytic hierarchy process (AHP) [40] or the simple additive weighting (SAW) [41] and compromising models as the technique for order preference by similarity to an ideal solution (TOPSIS) [41] or linear programming for multidimensional analysis of preference (LINMAP) [42]. Also the concordance models such as PROMETHEE [43] or the elimination and choice translation reality (ELECTREE) [44] methods take part and are widely used. Multi-attribute value theory (MAVT) is also included in the set of compensatory methods [39, 45].

4.1.2 Multi-objective Optimisation

In MOO the problem is represented as a mathematical problem integrating the constraints and objective function(s). If the problem is of combinatorial nature, we lay in the framework of Multi-objective Combinatorial Optimisation (MOCO). In order to find out a (reduced or whole) set of trade-off solutions, an optimisation procedure must be used. At the end a MADM technique may be applied to choose a solution from the set of solutions found by the MOO technique.

As mentioned, a MOO problem is mathematically represented as a typical optimisation problem, but with more than a single objective. The objectives are usually conflicting. It means that there is not one optimal solution simultaneously optimising all the criteria, but several good solutions exist. They have been and will be referred in this text as non-dominated or trade-off solutions. The objective functions can be either maximised or minimised. A set of constraints and bounds define the solution space. Without loss of generality, in (4.1) a MOO problem is represented considering n objective functions to minimise.

$$
\begin{aligned}
\text{minimise} \quad & F_1(x), F_2(x), ..., F_n(x) \\
\\
\text{subject to} \quad & g_j(x) \leq 0, \forall j \in 1...\mathcal{J} \\
& h_k(x) = 0, \forall k \in 1...\mathcal{K}
\end{aligned}
\tag{4.1}
$$

4.1.2.1 Basic Concepts

In this section the basic concepts related with MOO necessary for a better understanding of the work developed in this document are presented. For a more detailed explanation of the theory related with MCDM, we refer to [38, 46].

Please note that we give the same meaning to attribute, criterion or objective, in this document.

Firstly we should formally introduce the concept of dominance. A solution A dominates another solution B if A is no worse than B in all objectives and is strictly better than B in at least one of the objectives. Other dominance-related concepts are worth being introduced:

- *Dominated solution*: A solution is dominated if there exists another solution that is better in at least one criterion and not worse in the remaining criteria.
- *Non-dominated solution or Pareto optimal solution*: A solution in non-dominated if it is not dominated by any other feasible solution. In this way, none of the objective functions of a non-dominated solution can be improved in value without impairment in some of the other objective values. Without any preference information about the criteria, we cannot say that one solution is better than another solution if both are non-dominated.
- *Non-dominated set, Pareto front or Pareto optimal set*: Represents the set of non-dominated solutions.
- *Trade-off*: Relation between values of attributes that means the necessary amount to loose in an attribute to gain in another attribute.
- *Convex dominance*: A non-dominated solution is convexly dominated if there is a convex combination of other solutions that dominates that solution.

4.1.2.2 Approaches and Methods for Multi-objective Optimisation

The techniques associated to MOO can be classified according to the role of the decision maker and the stage in the decision making process at which his/her preferences are articulated. These preferences can be indicated by asking the DM for his/her opinion about the attributes (relative importance, aspiration levels, ...) or about the alternatives (satisfaction level, comparison between pairs, ...).

Depending on how and when the DM is asked to provide information on his preferences, the methodologies used can be divided in four groups:

- *no articulation of preference information*: in these techniques the subjectivity of the DM is not required, and is not included in the final selection. The techniques are mostly used when the DM cannot define what he/she prefers. This is the case of the MinMax formulation [47].

- *a priori aggregation of preference information*: the preferences are integrated in the formulation of the problem, so the DM participates on it, leading to the preferred solution. Those methods are usually performed by associating weights to each objective and aggregating the objectives resulting on a single objective function. Examples for this type of techniques are the weighted sum [48], goal programming [49], lexicographic method [50] or the exponential weighted criterion [51]. The value theory and the utility theory [45] are also applied in some MOO problems, as an aggregation method with pre-articulation of preferences.

- *progressive or interactive articulation of preference information*: the DM actively takes part in an iterative solution process and specifies the preferential information gradually, until an acceptable solution is found. This group includes techniques such as the STEM [52] or the method of Steuer [53].

- *a posteriori articulation of preference information*: in these methods the set of non-dominated solutions is firstly generated and then presented to the DM, who is supposed to select the most satisfactory solution. A MADM technique from the section 4.1.1 can be used for that purpose. There are two goals to achieve within this approach: 1) obtain a good approximation of the non-dominated set; 2) the set of solutions should be maximally-spread over the Pareto frontier.

  MOO techniques following this approach are, for instance, the ϵ-constraint method [34, 35, 37] and the normal boundary (NBI) method [54]. There are some multi-objective meta-heuristics based on simulated annealing [46, 55], tabu search [56] or evolutionary optimisation [57] such as NSGA [58], NSGA-II [59], the niched Pareto multi-objective optimisation [60] or the SPEA [61] and SPEA2 [62] that also follow an *a posteriori* articulation of preferences.

Some reviews on multi-objective optimisation techniques can be found in the literature [35, 36, 36].

4.2 Utility Theory

In the multi-criteria decision making field, multi-attribute value theory (MAVT) is often applied to sort and select alternatives. This approach is linked to situations in contexts of certainty, in which the alternatives are previously known [45]. In environments of very high uncertainty, where decisions about future and uncertain outcomes are taken, one DM may give different levels of importance for the feasible levels assigned to one or more criteria. This means that a DM may have different attitude, such as aversion or proneness, towards risk. In this way, in problems in which the possible solutions are not previously known, just like in the WTUCP, the multi-attribute utility theory (MAUT) is more appropriate than MAVT. This theory will be briefly reviewed in this chapter. The concept of utility has a long and complex history, and its origin cannot be exactly defined but may be traced back to the era of Aristotle. The utility theory is mostly used in the field of economics [63]. Even among economists, there is still no consensus about the precise definition of the term utility. However, it holds that an item or service's utility is a measure of satisfaction that the consumer will derive from the consumption of that particular good or service.

Generalising, the so-called utility is a measure of desirability or satisfaction that provides a uniform scale to compare different alternatives. On the other hand, a utility function is a device that quantifies the preferences of a decision maker by assigning a numerical index to varying levels of satisfaction of a criterion. It allows to model an individual's attitude towards risk inherent to the future possible outcomes. The decision falls down in the concept of choosing the alternative with the greatest expected utility.

4.2.1 The Unidimensional Utility Theory

The unidimensional utility theory allows to model the satisfaction level of a DM among a set of possible outcomes for a single criterion. The DM cannot express exactly what is the consequence of each alternative, but he can assign probabilities of occurrence of each possible outcome. This leads to the use of the expected utility theory [64, 65], that allows to evaluate an alternative which utility is the sum of the utilities of the possible outcomes weighted by the probability of occurrence of each outcome.

Therefore, the expected utility EU_j for an alternative j can be defined as:

$$EU_j = \sum_{m \in \mathcal{M}} prob_{(m|j)} U_m \tag{4.2}$$

where $prob_{(m|j)}$ is the probability of the outcome m if alternative j is chosen and U_m the measured utility of the outcome m. With this method it is possible to set the action that yields to the maximum expected utility as the preferred action.

The utility of an outcome x is denoted by $u(x)$. Utility functions are so constructed such that $u(x) < u(x')$, if and only if x is less preferred when compared to x'. In the same way, $u(x) = u(x')$ if and only if $x \sim x'$, i.e. x is indifferent to x'. In other words, the utility function is a representation of some level of performance measured in its natural units into an equivalent level of decision-maker satisfaction, denoted as utility. Utility values are commonly defined in the range [0,1], although it is not a necessary condition. The utility function is only used for the purpose of comparing and/or ranking alternatives, and the utility values have no other practical interest.

DM's are typically characterised by three types of risk attitudes: risk averse, risk neutral and risk prone. Figure 4.1 synthesises the typical shapes of the utility functions supposing a single criterion to minimise and utility measurements that are monotonically decreasing. As we can see, the DM's risk attitude is reflected in the shape of the utility curve which reflects the DM's preference attitudes with the increase of the outcome level of some criteria. The utility function for each attribute is quantified by means of interactions based on lottery questions between the analyst and the DM. The different risk attitudes are characterized, for instance, by the identified certainty equivalents that DM is willing to choose for a set of given lotteries.

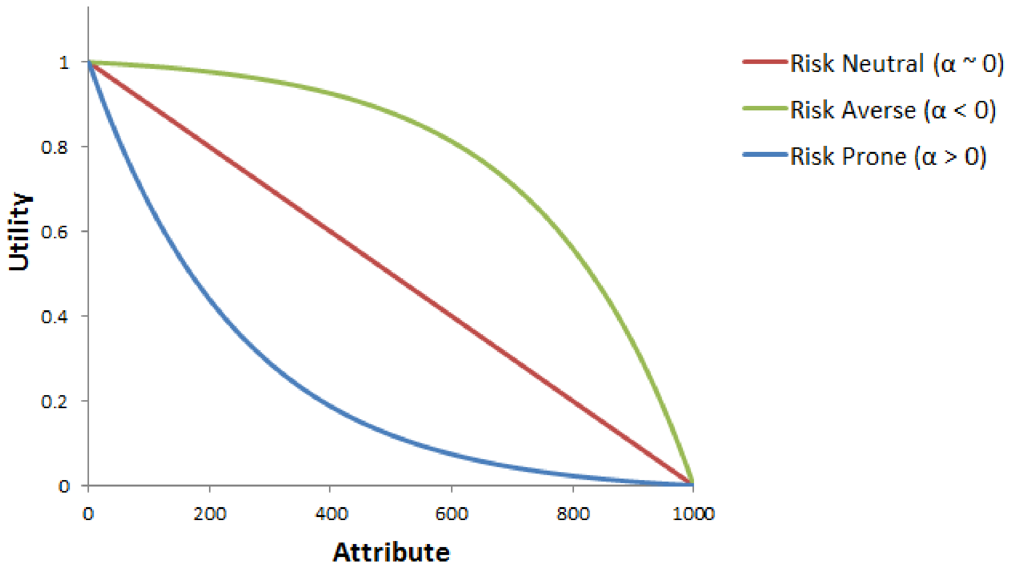


FIGURE 4.1: Graphical representation of risk attitudes for a criterion to minimise

A risk prone DM presents an high rate decrease of satisfaction for low values of the outcome and his/her utility varies at a low rate for high values of the outcome. He/she is more interested in the possibility of obtaining low values of the outcome than to avoid high values. Considering a decision between playing a lottery or accept a certain amount in a minimisation problem, the risk prone DM would play the lottery, even if it has a greater expected value, if the lottery offers the possibility of obtaining low values for the outcome. On the other hand, a risk averse DM verifies a low rate decrease of utility for low values and a higher growth rate only for high values of the possible outcomes, since he/she is more interested in avoiding high values for the objective that he/she aims to minimise. This DM would accept a certain amount that is higher than the expected value of a lottery, if that lottery offers the possibility of occurrence of an undesired high value for the outcome.

The risk-neutral, or "risk indifferent", decides exclusively through the expected value paradigm, and his/her behavior is represented by a linear function. Thus, maximising the utility is the same as maximising the expected value. Although it is uncommon, note that a DM may also be neither risk-averse nor risk-prone and his/her marginal utility may not be monotonically increasing or decreasing.

Once the proper utility function for the DM is constructed, the most preferred solution can be obtained without his/her interference [66]. There are several works presented in the literature to assess a single-criterion utility function of a DM [45, 67–69]. There are two main approaches: using the certainty equivalents, or using probabilities based on lottery elicitation. It is also possible to approximate the DM preferences to some specific nonlinear functions such as exponential or logarithmic [45, 69].

4.2.2 The Multi-attribute Utility Theory

In order to make use of the utility theory in MCDM problems, it is necessary to aggregate the individual utility function of each criterion, described in section 4.2.1, in a single utility function. The resulting multi-attribute utility function allows to evaluate and rank solutions for a typical multi-criteria problem. Although the MAUT is used in general when the alternatives, or actions, as well as the possible outcomes and respective probabilities for each action are previously known, in the context of this work the MAUT concepts will be used within a MOO problem. It means that the feasible alternatives are not previously known. The aim will be to find the most preferred solution from the DM perspective for the UCP considering the MAUT paradigm.

Consider that we have n attributes and x_i denotes a level for solution $x = (x_1, x_2, \ldots, x_i, \ldots, x_n)$ in the i-th attribute. Then, the aim is to assess an utility function $u(x) = u(x_1, x_2, ..., x_n)$ over the n attributes. In order to aggregate the utility values for the different criterion levels in a single utility measurement, the individual utility values must be normalised. This normalisation usually takes place within the interval $[0, 1]$.

In the context of MAUT there is a property that has to be verified. The attributes must be mutually utility independent [45]. This means that the conditional preferences, i.e. the utility function of one attribute, do not change if there is a change in the utility values of any of the remaining attributes. So, the utility function of each criterion must remain the same independently of the shape of the utility functions for the remaining criteria.

The most common way to evaluate the utility of a multi-criteria solution is, due to its simplicity, through an additive utility function, as shown in equation (4.3).

$$U(x_1, x_2, ..., x_n) = k_1.u_1(x_1) + k_2.u_2(x_2) + ... + k_n.u_n(x_n) \tag{4.3}$$

where U represents the overall utility of the solution and the values k_i represent positive scaling constants that allow to sum the separate contributions of the attributes in order to have a unique utility value [45]. Thus,

$$k_1 + k_2 + ... + k_n = 1 \tag{4.4}$$

Note that this scaling constants are not weights directly defined by the DM that measure the relative importance between criteria. They are components that allow to harmonise the utility values for the set of criteria in a single overall utility value, which allows to evaluate a solution according to the DM preferences over all criteria simultaneously. Therefore, the value of the scaling constants depend on the ranges defined by the DM in which the possible values for the individual utility functions can vary, as discussed later and shown in Annex B. There are several works that propose methods for estimating these k_i's [45, 69, 70]. Those methods are commonly based on indifference judgments performed between an analyst and the DM.

An additive utility function only represents the preferences of a DM over a set of attributes if the attributes are also additive independent. This means that the conditional preferences of one attribute or a set of attributes do not change if there is a change in the values of any of the remaining attributes. For more information about these conditions we address the reader to [45].

Chapter 5

A Multiple Criteria Utility-based Approach for the Wind-Thermal Unit Commitment

Notation

Constants

- k^{cost} – scaling constant for the operating costs in the additive utility function.
- k^{ens} – scaling constant for the energy not served in the additive utility function.
- k^{exs} – scaling constant for the energy excess served in the additive utility function.
- α^{cost} – parameter for the shape of the operating costs utility function.
- α^{ens} – parameter for the shape of the energy not served utility function.
- α^{exs} – parameter for the shape of the energy excess served utility function.

Variables

- Decision variables:
  - u_s^{cost} – utility of the operating costs for the planning horizon, for scenario s.
  - u_s^{ens} – utility of the energy not served for the planning horizon, for scenario s.
  - u_s^{exs} – utility of the energy excess served for the planning horizon, for scenario s.

5.1 The Utility-based Approach for the WTUCP

In this section, a MAUT-based approach is developed to solve the multi-objective WTUCP, at the day-ahead stage. The aim is to develop a MOCO model with *a priori* aggregation of preference information that can represent the DM attitude towards risk associated to the random behavior of the wind speed. The model is based in MAUT concepts and allows to find the most preferred solution in the DM day-ahead perspective, assuming that the individual utility functions and scaling constants are properly assessed.

In order to integrate the wind power variability, we propose a stochastic programming model based in scenarios. When the model is run at the day-ahead stage, it is assumed that one of the considered set of scenarios will occur. The probability and the hourly wind power of each scenario is previously known, as presented in the work proposed by Boterrud *et al.* in [10]. Important criteria concerning the GENCO's or ISO's operations are identified, all to be minimised. Reviewing the literature, in the multi-objective WTUCP we find objectives such as the operating costs (fuel and start-up), wind curtailment, reserve curtailment, waste of wind energy or CO_2 emissions [18–21, 32]. In this work, three objectives are considered:

- *Operating costs*: The operating costs will be given by the sum of fuel costs and start-up costs. Shut-down costs are assumed to be zero.

- *Energy not served*: Energy not served or load curtailment events can occur in scenarios where the sum of available wind power is not enough to meet the load.

- *Energy excess served*: An unforeseen upward wind realisation may occur in several scenarios, yielding a waste of wind energy, or energy excess served, when the committed thermal units are operating on their feasible minimum level.

We assume a fixed reserve to cover load deviations and forced outages of the thermal units. There is no provision for deviations of the wind power production since that source of uncertainty is implicit in the stochastic model. Note that, with this assumptions, in the intra-day perspective it is possible to have positive ENS values even when some reserve level is available, since the reserve is not considered as able to cover wind power deviations.

Each objective is represented by an utility function, and these are aggregated into a single additive utility function, that represents the overall utility of a feasible solution of the MOO problem. Note that for this model to be valid, it is assumed that the three criteria are mutually utility independent and additive independent. However, in real applications of this model, those conditions must be validated beforehand.

The proposed utility function for representing the satisfaction level for the preferences of a specific DM over each of the three criteria is given by equation (5.1). The function was proposed by Matos and Bessa [8] for setting the preferred operating reserve in power systems operations. Considering x_i a level between the ranges x_i^{max} and x_i^{min} defined by the DM for the criterion i, the utility in that criterion for each feasible value x_i is given by:

$$u_i(x_i) = (e^{\alpha . f(x_i)} - 1)/(e^{\alpha} - 1) \tag{5.1}$$

where $f(x_i) = (x^{max} - x_i)/(x^{max} - x^{min})$. The function $f(x_i)$ provides a scaling normalisation of x_i in order to obtain utility values belonging to the interval [0, 1].

The function provides enough flexibility since it allows to model different attitudes by changing parameter α. Negative values of α means risk aversion, represented by an utility function with a concave shape, as shown in Figure 5.1. Considering that the DM wants to minimise that criterion, he/she will be able to valorise a decrease on criteria i when its level is high since he/she is more interested in reducing the risk of having high values. In this way, the DM is willing to easily accept small values for that criterion and his/her level of satisfaction decreases at a low rate for lower values of the outcome. This attitude corresponds to the risk aversion attitude described in chapter 4.2.1.

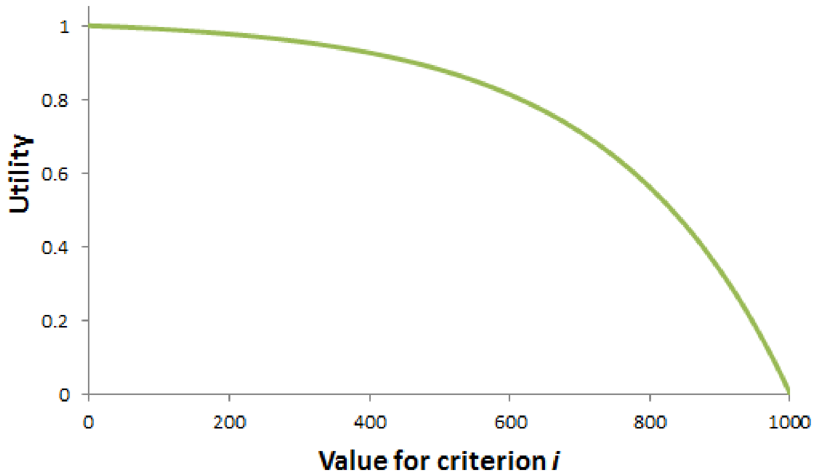


FIGURE 5.1: Utility function shape for a negative α

On the other hand, another DM profile can be represented by a positive α. That leads to an utility function with a convex shape, as represented in Figure 5.2. A DM with this profile is more interested in having lower levels for that criterion, accepting the risk of occurrence of high values, where his/her utility verifies a low rate decrease. This attitude corresponds to the risk proneness attitude described in chapter 4.2.1.

The more negative/positive the parameter α is, the more averse/prone is the DM attitude towards criterion i. An α value close to zero will represent an utility function with a shape approximated to a linear function. In Annex A we present an example on how to estimate the parameter α of an individual utility function with the shape proposed by equation 5.1 for the WTUCP. The proposed methodology is based on lotteries and aims at reaching indifference judgments in the DM perspective using the certainty equivalent concept.

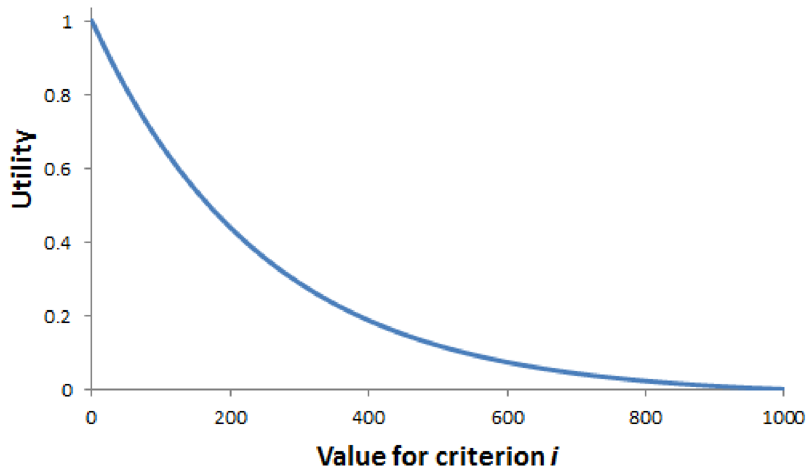


FIGURE 5.2: Utility function shape for a positive α

Since the commitment to be obtained in the day-ahead stage is for the whole day, daily values are attributed to the x_i variable on each criterion i in equations (5.1). In this way, the final solution of the MOO model corresponds to the most preferred solution, following the expected utility theory, when considering the valorisation given to the daily values of the different criteria.

Instead of simply minimising the operating costs, as shown in the objective function proposed in Chapter 3, the objective function of the proposed approach is presented in (5.2).

$$\max \sum_{s \in \mathcal{S}} prob_s.(k^{cost} u_s^{cost} + k^{ens} u_s^{ens} + k^{exs} u_s^{exs}) \tag{5.2}$$

In order to estimate the scaling constants k^{cost}, k^{ens} and k^{exs}, some interactive questions have to take place between the analyst and the DM. Note that this scaling constants are not weights directly defined by the DM that measure the relative importance between criteria. They are only components that allow to harmonise the utility values for the set of criteria in a single overall utility value, which allows to evaluate a solution according to the DM preferences over all criteria simultaneously. Therefore, the value of the scaling constants depend on the ranges defined by the DM, for the individual utility functions.

5.2 A MILP formulation for the non-linear additive utility function

Mathematical programs with non-linear functions are not easily handled by MIP solvers, whose performance has been growing up in the last years for linear problems. Therefore, in order to take advantage of the high performance of these MIP solvers, whenever possible the non-linear functions should be replaced by linear ones.

In this section we describe the linearisation methodology followed in this work to approximate each individual utility function with a linear one. The final purpose is to build a stochastic MILP model where each individual utility function is linearised through a pre-defined number of segments.

We always develop a lower approximation of each "true" utility function independently of being characterized by a concave or convex shape. This approximated decision allows us to develop an iterative methodology to define the number of segments to use in a piece-wise linear function that approximates the non-linear utility functions, as discussed in this chapter.

5.2.1 General Linearisation Formulation

This section aims at demonstrating how to compute a possible criterion level x_i and the correspondent utility u_i of a solution found using a disaggregated convex combination model [71] that approximates the non-linear function by a piece-wise linear function of K segments.

Let the domain of each individual non-linear utility function, let us say $f_i(x_i)$, be $W_i \leq x_i \leq B_i$, the range $[W_i, B_i]$ being previously defined when approaching the worst (W_i) and best (Bi) levels for criterion i. We will consider a partition of this domain by a certain fixed number of consecutive K segments. The segments have a domain $[a_{ik}, a_{i,k+1}]$ where $k = 0, ..., K-1$, a_{ik} is the abscissa on the left edge of segment k and $a_{i,k+1}$ the abscissa on the right edge of segment k, for criterion i. Let us also consider $b_{ik} = f(a_{ik})$ for $k = 0, ..., K$ as the ordinate of a_{ik}.

For each segment k, associate two non-negative real variables w^L_{iks} and w^R_{iks}. We also use the set of binary variables $z_{iks} \in \{0, 1\}$ to model the constraints that set that only one segment is selected. As we can see in constraints (5.3) a single segment k in the criterion i is selected. Only in the case of $z_{iks} = 1$ we allow that either w^L_{iks} or w^R_{iks} have a non-zero value (5.4). Then, $a_{ik}w^L_{iks} + a_{i,k+1}w^R_{iks}$ allows to represent the abscissa of a point that corresponds to a convex combination between the points in the interval $[a_{ik}, a_{i,k+1}]$. In other words, it allows to model a point that belongs to the fixed segment k, as shown in equation (5.5). In the same way, $b_{ik}w^L_{iks} + b_{i,k+1}w^R_{iks}$ allows to obtain the corresponding ordinate (5.6).

Since we are modeling the values of the operating costs, ENS or EXS, that are indexed to the scenarios, the linearisation must be done for all scenarios.

$$\sum_{k=0}^{K-1} z_{iks} = 1, \qquad \forall i \in \mathcal{I}, \forall s \in \mathcal{S} \tag{5.3}$$

$$w^L_{iks} + w^R_{iks} = z_{iks}, \qquad \forall i \in \mathcal{I}, k = 0 \dots K-1, \forall s \in \mathcal{S} \tag{5.4}$$

$$x_{is} = \sum_{k \in (K-1)} (a_{ik}w^L_{iks} + a_{i,(k+1)}w^R_{iks}), \quad \forall i \in \mathcal{I}, \forall s \in \mathcal{S} \tag{5.5}$$

$$u_{is} = \sum_{k \in (K-1)} (b_{ik}w^L_{iks} + b_{i,(k+1)}w^R_{iks}), \quad \forall i \in \mathcal{I}, \forall s \in \mathcal{S} \tag{5.6}$$

5.2.2 Setting the breakpoints (a_{ik},b_{ik})

In this section we describe how the input parameters a_{ik} and b_{ik}, that respectively define the abscissa and ordinate of the extreme points of each fixed segment, are calculated. They are necessary for the constraints (5.5) and (5.6) from the previous section. We aim at finding a lower approximation of the concave or convex non-linear utility functions.

Let us denote $f_i(x_i)$ according to equation (5.7), with x_i as a feasible level for the criterion i and $y(x_i) = (B_i - x_i)/(B_i - W_i)$.

$$f_i(x_i) = \frac{(e^{\alpha \cdot y(x_i)} - 1)}{(e^{\alpha} - 1)}, \forall i \in \mathcal{I} \tag{5.7}$$

Concave shape

The coordinates of the breakpoints of individual utility functions with a concave shape (negative α) are obtained by dividing the domain in K partitions to find the abscissas, according to equation (5.8), and then find the correspondent ordinates (5.9).

$$a_{ik} = L_i + \frac{k(U_i - L_i)}{K - 1}, \quad k = 0 \dots K, \tag{5.8}$$

$$b_{ik} = f_i(a_{ik}), \qquad k = 0 \dots K. \tag{5.9}$$

Each pair of points $([a_{ik}, b_{ik}])$,$([a_{i,(k+1)}, b_{i,(k+1)}])$, where $k = 0, ..., K-1$, defines a convex combination. The set of points constitute a piece-wise linear function that provides a lower approximation of the real concave utility function.

Convex shape

For convex shapes (positive α) of the individual utility functions the breakpoints cannot be assigned in the same way as in the concave shapes, otherwise they will set an upper approximation and not a lower approximation, necessary for the validation of the methodology described in section 5.2.3.

We start to define a set of breakpoints in the same way as for the concave shape case. We will call the coordinates as a^0_{ik} for the abscissa and b^0_{ik} for the ordinate, as shown in equations (5.10) and (5.11).

$$a_{ik}^0 = L_i + \frac{k(U_i - L_i)}{K}, \quad k = 0 \dots K, \tag{5.10}$$

$$b_{ik}^0 = f_i(a_{ik}^0), \quad k = 0 \dots K. \tag{5.11}$$

Then we find the slope of the tangent to the real utility function in the point with abscissa a_{ik}^0, as shown in equation (5.12).

$$m_k(a_{ik}^0) = \frac{\partial f_i(a_{ik}^0)}{\partial x}, \quad k = 1 \dots K - 1 \tag{5.12}$$

Now we can compute the model inputs a_{ik} with $k = 1, ..., K - 1$ as the intersection between the tangent lines to the real function in a_{ik}^0 and in $a_{i,k+1}^0$ where $k = 0, ..., K - 1$. Knowing that $a_{i0} = L_i$ and $a_{iK} = U_i$ we find all the necessary coordinates of the breakpoints within a lower approximation. By finding the ordinate of the a_{ik} values in the tangent lines expressions we find the model inputs b_{ik}. In Figure 5.3 an example of a piece-wise linearisation of a convex function with lower approximation is shown.

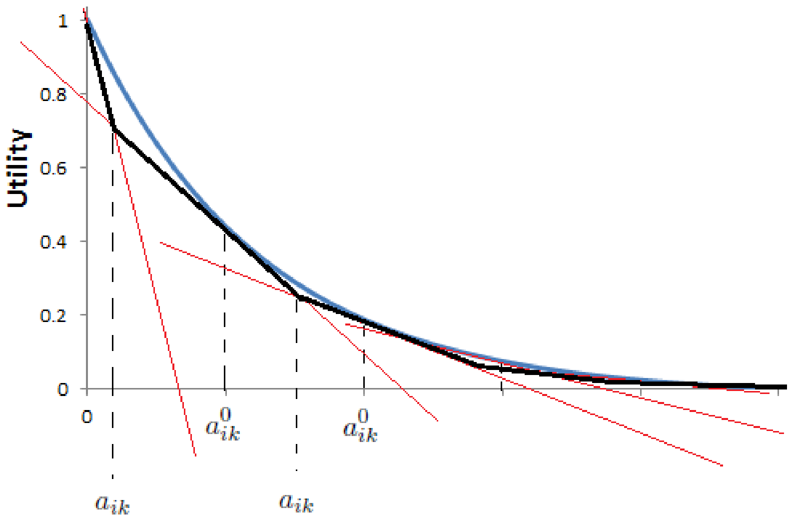


FIGURE 5.3: Piece-wise linearisation of a convex function with lower approximation

As we can see, a^0_{ik} are used to set the tangent lines (red lines) to the real function (blue curve) and the final segments (black lines) are defined as the intersection between tangent lines to the real function in consecutive a^0_{ik} values.

5.2.3 Methodology to fix the number of segments

In this section we describe an algorithm that uses successive linear approximations to approximate the non-linear utility functions of the WTUCP by increasing the number of segments among consecutive iterations. Since we deal with a lower approximation, we know that the total error between the piece-wise linear function and the real non-linear function decreases with the increasing number of segments.

According to algorithm 1, we start by setting variable K (number of segments to fix) to one. $U(x_i)$ denotes the (approximated) expected utility of each solution x_i found and returned by the solver in iteration i. e represents the relative error between $U(x_i)$ and the real expected utility $Real(x_i)$ for solution x_i when using the non-linear utility functions. In each iteration we increment the number of segments by one and solve the proposed WTUCP model with K segments for each of the utility functions. Then we compute the value of the relative error e. The algorithm stops when e is smaller than a pre-defined tolerance ϵ, defined by the user. The final number of K is considered to be adequate to be used in the model.

Algorithm 1 Iterative algorithm to define the number of segments

1: $K = 1$
2: $e = 0$;
3: **repeat**
4: $\quad K = K + 1$;
5: $\quad$ solve the WTUCP;
6: $\quad e = \frac{(Real(x_i) - U(x_i))}{Real(x_i)}$;
7: **until** $e < \epsilon$

The objective function is a sum of the individual utility functions. Since we deal with lower approximations for all the individual utility functions in all the scenarios, each approximated solution x_i returned by the solver with the piece-wise linear functions is a lower bound of the problem. In this way, it is necessarily equal of inferior to the real expected utility value of that solution x_i, that represents an upper bound of the problem. If the objective value of a solution x_i equals the objective value for that solution using the real utility functions (ϵ approximated to zero) in any iteration i, it means that the lower bound equals the upper bound and the optimal solution of the problem was found [72].

Applying the proposed algorithm it becomes possible to find a number of segments that provides a user-controlled margin of error between the solutions found by approximating the real utility functions and the optimal solutions. In this way, a number of segments that provides reasonable computational times and good solutions can be found and applied in simulated test cases.

5.3 Case study

5.3.1 Simulated cases

In order to provide clear case study for testing our approach, we use a power system and simulate the impact of using different profiles of the decision maker concerning the risk inherent to the wind uncertainty, when operating in the power system with large wind penetration. The main assumptions for the case study are described below.

The characteristics of the thermal units are based on the case studies presented in [28, 73] and were extracted from [10]. We include the modifications performed by the authors in this work. We use a set of 10 thermal units, 3 of which are peak (fast-start) units. These units have higher operating costs but provide additional flexibility, since they can be started up or shut down very fast, contrary to the conventional thermal plants. The input parameters concerning thermal units are shown in Table 5.1. In the "Initial" "State" column, a positive signal means the unit has been on and a negative signal means the unit has been off during the previous period. The value means the number of consecutive periods the units have been on/off including that period. Power limits and ramp rates are expressed in MW, startup costs are expressed in euros (€), the data concerning time periods is expressed in hours (h) and coefficients a_u, b_u and c_u are expressed in €$/h$, €$/MWh$ and €$/MW^2h$, respectively.

TABLE 5.1: Thermal generators data-set

Unit	a_u	b_u	c_u	P_u^{min}	P_u^{max}	r_u^{up}	r_u^{down}	In. State	T_u^{on}	T_u^{off}	t_u^{cold}	a_u^{hot}	a_u^{cold}
1	1000	16	0.00048	150	455	200	200	8	8	8	5	4500	9000
2	970	17	0.00031	150	455	200	200	8	8	8	5	5000	10000
3	700	30	0.002	20	130	100	100	-5	5	5	4	550	1100
4	680	31	0.0021	20	130	100	100	-5	5	5	4	560	1120
5	450	32	0.004	25	162	100	100	-6	6	6	4	900	1800
6	370	40	0.0071	20	80	80	80	-3	3	3	2	170	340
7	480	42	0.00079	25	85	85	85	-3	3	3	2	260	520
8	660	60	0.0041	10	55	55	55	-1	1	1	0	30	60
9	665	65	0.0022	10	55	55	55	-1	1	1	0	30	60
10	670	70	0.0017	10	55	55	55	-1	1	1	0	30	60

The reserve requirements concern the operating (spinning) requirements alone, since non-spinning or replacement reserve are not considered. Reserve requirements are assumed to be 10% of the system load demand, being always available to cover load deviations or forced outages of thermal units. The required operating reserves must be provided by thermal units.

The hourly load demands, wind power scenarios and the real hourly wind power outcomes were collected from the studies made by Botterud *et al.* in [10, 22, 23] . The authors used day-ahead deterministic point forecasts and realized wind power output for 15 hypothetical locations in the state of Illinois in 2006, obtained from the National Renewable Energy Laboratory's report called "Eastern Wind Integration and Transmission Study [74]". They used the wind power data forecasts developed for the period between October and December of 2006 to train the quantile regression and generate 10 wind power scenarios, per day. Figure 5.4 shows an example of the point forecast, the generated scenarios and the real wind power for day 87. More details about the scenario generation can be found in [10].

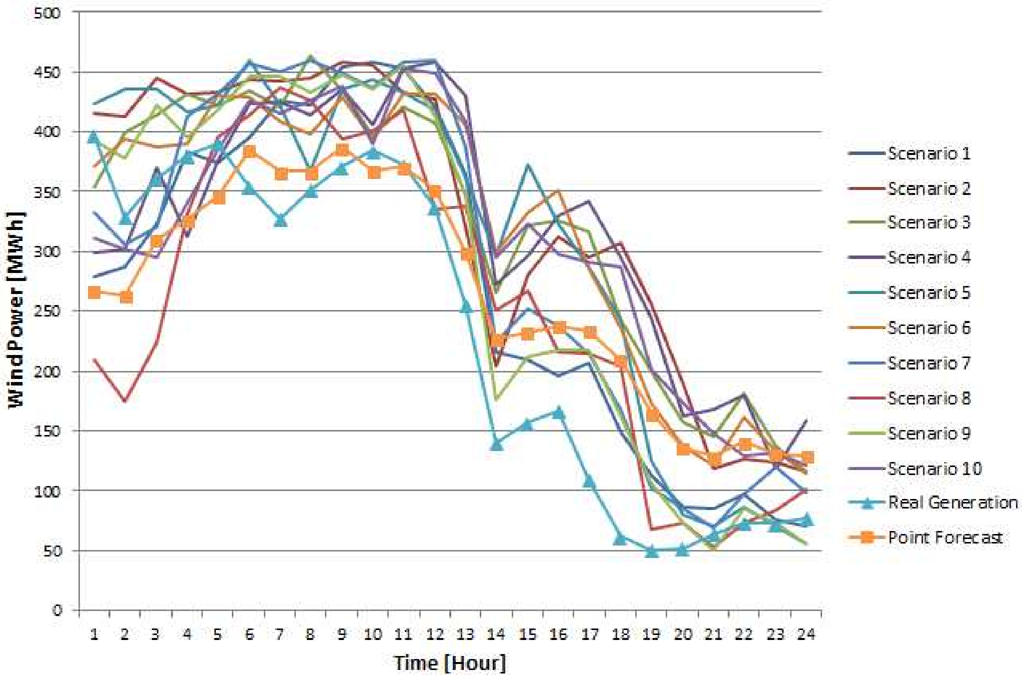


Figure 5.4: Wind power forecast (deterministic point forecast and 10 stochastic scenarios) and realized wind generation for day 87

In this work, simulations were run for the first 30 operating days of the referred study, in a one-month simulation period with data from October, 2006, Illinois. The model is run for each of those operating days, based on the set of 10 wind power generated scenarios from the point wind forecast for that day, each scenario with probability equal to 10 %. After finding the daily schedule (unit commitment) by maximising the expected utility, an economic dispatch model is run (by fixing the values of the variables representing the status of the units and re-solving the model), optimising the production level for the committed units considering now only one scenario: the real wind power verified on that day. This last procedure simulates the operation of the GENCO in the intra-day perspective, where the status of the units cannot be changed, being defined from the previous day. For simplicity we consider, in our test instance, a unique large wind power plant, operating with 500 MW capacity. The load demand values are scaled down to match the generation capacity in the test power system. The overall load demand can be served without using wind power, since thermal units provide enough capacity. In this way, the level of penetration of wind power to serve load demand can vary within a long range of possible values.

To present a clear demonstration on the impacts of variations in the decision risk attitudes, we simulate 3 different decision maker profiles and evaluate the impact on the 3 objectives considered: operating costs, load curtailment and waste of wind energy.

We used the same ranges in which the daily values for each objective can vary, as shown in Table 5.2, for all simulations. However, it should be kept in mind that different politics can be used by different generation companies to define those ranges. Table 5.2 shows the ranges for each objective. Some preliminary simulations showed that the daily operating costs can vary between 250000 €and 450000 €for the considered data-set. In terms of load curtailment, to achieve the maximum satisfaction level (utility = 1) then the decision maker satisfies all the load demand. He/she admits to curtail, at most, 1076,78 MWh per day, in which case the utility for load curtailment equals zero. Concerning the waste of wind energy, DM's have no wind curtailment as the best outcome, and the curtailment of 50 % of the wind farm capacity as the worst. Since the total installed capacity of wind power is assumed to be 500 MW, this percentage corresponds to 6000 MWh of maximum waste of energy allowed in a single day.

Table 5.2: Ranges considered for the measurement scales

	Lower	Upper
Cost (€)	250000	450000
ENS (MWh)	0	1076,78
EXS (MWh)	0	6000

The three DM profiles vary in the risk aversion/seeking attitudes regarding the three objectives. As shown in Table 5.3, we created a decision maker (DM1) who has a approximately linear utility curves for the cost and waste of wind energy, but is risk seeking (concave shape) concerning the possible outcomes of load curtailment. This DM would accept high values of load curtailment in order to reduce operating cost and waste of energy. The second decision maker, on the other hand, has the same attitude as DM1 for costs and waste of wind energy, but he/she is averse towards risk of having high load curtailment values (convex shape). The third decision maker (DM3) allows us to analyze the differences between DM2 and a more risk seeking attitude concerning the costs and waste of wind energy, by maintaining the load curtailment risk attitude.

Scaling constants were deduced according to the example shown in Annexx B, by considering the utility curves shape for the described profiles, and simulating exercises that take into account those profiles and risk attitudes previously described.

TABLE 5.3: Parameters for 3 simulated profiles

	DM1	DM2	DM3
α^{cost}	0	0	1
α^{ens}	2	-2	-2
α^{exs}	0	0	0
k^{cost}	0.6	0.4	0.2
k^{ens}	0.1	0.3	0.7
k^{exs}	0.3	0.3	0.1

In order to take advantage of the efficiency of MILP solvers, the individual utility functions were approximated by piece-wise linear functions, as described in section 5.2.1. Some preliminary simulations revealed that the model could be solved in reasonable time with piece-wise linear functions of up to 5 segments. However, it should be kept in mind that the solutions found in the simulated cases presented in this section are lower bounds of the problem and might be far from optimal considering a 5-segment approximation. Since time performances are not the main issue of the proposed methodology, numerical results of those preliminary simulations are not presented. The non-linear fuel cost functions were approximated by piece-wise linear functions with 4 segments, in a lower approximation, as described in section 3.2. The final MILP model was implemented in AMPL (A Modelling Language for Mathematical Programming) [75], and the CPLEX 12.1 as a MILP solver [76] was used to solve it. Default CPLEX parameters were set to solve the models.

5.3.2 Results

In this section, we provide detailed results for the overall simulations in order to show the impact of different risk DM profiles on a long-term simulation period (30 days).

We present daily values verified after the economic dispatch performed at RT stages, in the intra-day perspective, for each of the 30 operating days. Figures 5.5 and 5.6 show the daily operating costs (fuel and start-up costs of thermal units) and the daily load curtailment, respectively. Figure 5.5 shows that DM1, which profile presents a risk seeking concerning load curtailment, incurred in lower operating costs for all the simulation period when comparing to the other two DMs. This is not surprising, given that the utility assigned to the daily energy not served values vary at a low rate for high values of ENS, and he/she is willing to accept more risky schedules if it means to achieve a compensating decrease in the operating costs, which utility varies at a linear rate in all range.

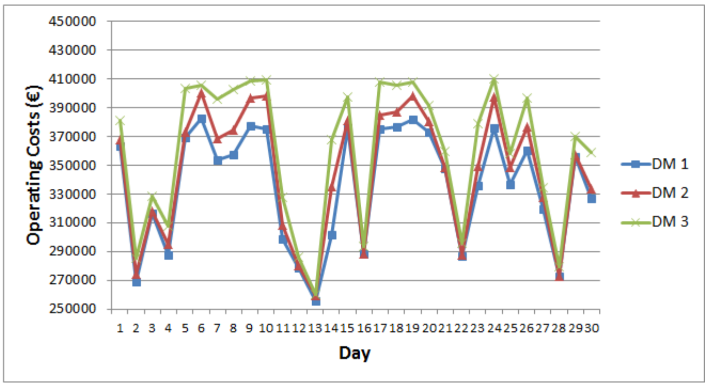


FIGURE 5.5: Daily operating costs for 30-day simulation period

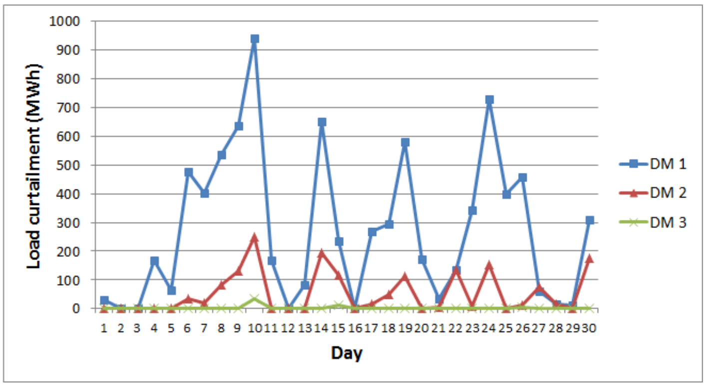


FIGURE 5.6: Daily energy not served for 30-day simulation period

DM2 presents a risk aversion towards ENS values, so his/her utility decreases at a high rate when ENS values become high. On this way, as the results showed Figures 5.5 and 5.6 state, this DM is more interested on having more committed units during the day, increasing the operating costs, in order to avoid high values of ENS. DM3, which maintains the same ENS risk aversion as DM2 but presents now a risk seeking attitude concerning costs (instead of linear), verify even lower ENS values and higher operating costs than DM2. The utility for operating costs values on this DM decrease at a low rate when costs are higher, so positive variations on avoiding load curtailments are now even more meaningful for him/her since his/her utility varies now at a low rate when costs become high. That is why DM3 is willing to pay even more than DM2 in order to avoid ENS, even thought DM2 and DM3 maintain the same attitude towards ENS.

Due to the assumption that the wind energy imply no costs, the waste of energy resulted zero for all 90 simulations, the reason why the figure for that objective is not presented. In every solution, all the available wind energy penetrated into the system to serve the load demand, with no wind power curtailments. The objective of minimising the waste of wind energy is not conflicting with the minimisation of costs, since the less of the former imply the less of the latter. The less waste of wind power, the more wind power being penetrated and the less thermal units are needed. On this way, the MOCO model includes two objectives (Operating costs and waste of wind energy) in conflict with a third objective (load curtailment).

The practical impact of the differences on the described DM risk profiles is easily stated by depicting the total number of hours of committed units, during the 30-day period, as shown in Figure 5.7. More risk seeking DM concerning costs and/or risk averse concerning ENS present schedules with a higher daily number of committed units. These DMs seek to be protected from the risk of lower wind power productions and aim at having more dispatchable thermal units available if needed. On this way, high values of ENS can be avoided. For a more detailed overview, Figure 5.8 shows the daily total number of hours of all committed units during the simulation period.

Figure 5.9 shows the utility verified in the end of each operating day. As we can see, the utility depends on the shape of the individual utility functions and scaling constants. For instance, DM1 gives less importance to ENS values than DM2, so the utility for ENS values is lower. Although he/she gives more importance to the operating costs than

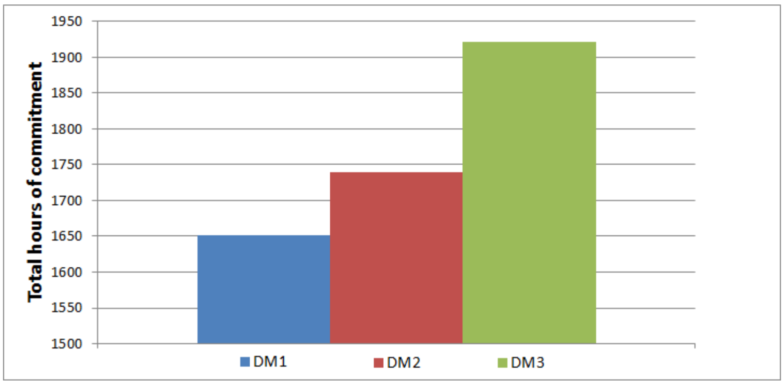


FIGURE 5.7: Total hours of commitment

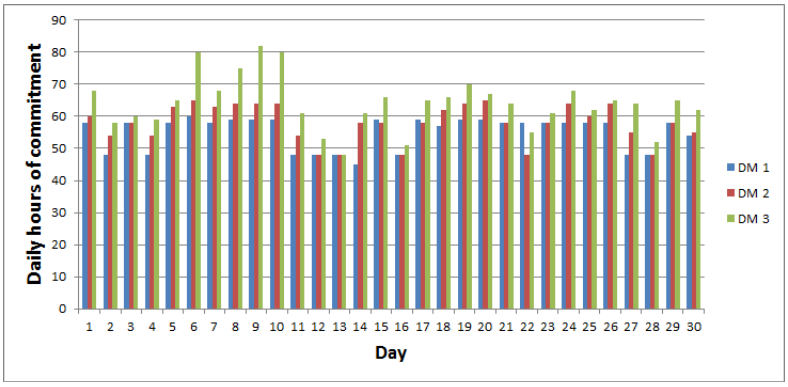


FIGURE 5.8: Daily hours of commitment for 30-day simulation period

DM2 (see scaling constants), the operating costs do not verify a big difference between DM1 and DM2. The daily utility values do not allow to compare the quality of solutions between DMs, since the utility is only used for the purpose of comparing and/or ranking alternatives under the same preference levels. These values mean the utility of the best solution found for each day/DM through the expected utility paradigm considering the estimated scenarios at the DA stage.

Figure 5.10 shows the computational times for the unit commitment (DA stage) and excludes the economic dispatch solving times. In practice, the UC time is the main interest for the DM since he/she aims at finding the schedule as soon as possible, at the DA stage. Results show that the computational times can vary between a long range, from 15.9 to 30047.2 seconds (8.35 hours), the reason why the results are presented in a logarithmic scale. Not surprisingly, DM1 notes higher computational times since MILP solvers require extra computational effort when maximising convex functions, although

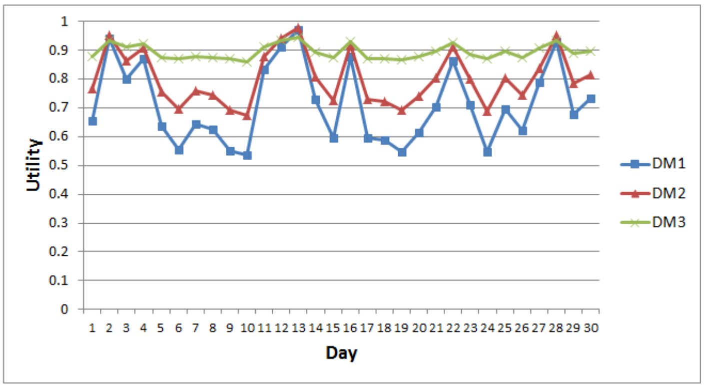


FIGURE 5.9: Daily utility values for 30-day simulation period

the functions are linearised. DM1 presents a convex (risk seeking) function concerning ENS in the objective function of the MOCO model, contrary to DM2 and DM3. These present similar computational times, stating that the model is able to provide good computational times when dealing with non-convex individual utility functions.

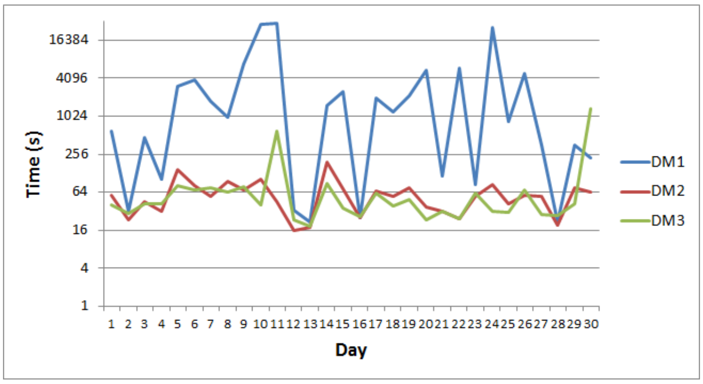


FIGURE 5.10: Computational times at the commitment stage

Results show that the proposed methodology is able to reflect different attitudes towards risk in the final solutions of the MOCO model. But, it is a fact that the solutions found at the DA stage for the WTUCP model are not guaranteed to be optimal in terms of optimisation, due to the several linearisations, and are not guaranteed to be non-dominated in the multi-criteria context. Nevertheless, results show that more economic schedules are found for DMs with an aversion attitude towards costs and/or seeking attitude towards ENS. On the other hand, high values for ENS are avoided by DMs that note a ENS aversion risk profile, and even lower ENS values are obtained if he/she is also risk seeking towards operating costs. Considering that the simulations were run for a small test instance with only 10 thermal units, the computational times obtained are prohibitive due to the several linearisations performed in the model. Specially if the objective function to maximise includes a convex set of points in the decision space, what might happen if the DM is risk prone towards one or more of the three objectives. In these cases, the computational times increase exponentially comparing with concave objective functions.

Chapter 6

Wind-thermal UCP with Pumped Storage Hydro

6.1 The role of hydro units with pumped storage in power systems operations

Although the benefits of wind power as a "clean energy" with lower environmental impacts and mainly in reducing operating costs, this renewable source of energy still presents many drawbacks that poses difficulty for managing power systems. The uncontrollable production level, the difficulty of forecasting the output power even for the coming periods and its intermittency that makes it difficult to maintain the stability of the power system are some of these disadvantages. Then, the increasing penetration of wind power in power systems requires additional resources to balance generation and demand, in order to guarantee the supply of electric energy, even when wind intensity is low. On this way, several alternative generation technologies able to deal with the wind variability have appeared.

The generation technologies include, for instance, conventional hydro units, pumped storage hydro (PSH) units, open cycle gas or combined cycle. In this work we focus on hydro units with energy storage capacity for several reasons discussed in this chapter.

Much of the nation's PSH plants were initiated during the mid to late 1970s and have been extensionally used. They can provide flexibility in the production of electric energy when using renewable sources. The storage devices integrated into the hydro units can help to compensate the fluctuation of wind energy. This is possible due to the pumping capacity of those units. Figure 6.1 shows an example of an isolated (not connected to a river) hydro unit with pumped storage system.

FIGURE 6.1: Hydro unit with pumped storage capacity [4]

The pumped storage system allows to store energy in the form of potential energy of water that can be pumped from a lower elevation to a higher elevation reservoir. A hydro unit with storage capacity can either be used to produce electric energy, when in generating mode, or to consume energy to pump water, when in pumping mode. As conventional hydro units, PSH units can have a single upper reservoir, as shown in Figure 6.1, which can be connected to a river or not, or two reservoirs, an upper reservoir and a lower reservoir. In the latter case, the turbines are located between the reservoirs.

The existence of reversible pump-turbines allows to change the water inflow direction. During periods of high demand, the unit can work as a generator. The stored water in the reservoir is released through turbines producing electric energy. On the other hand, during off-peak periods, energy from the power system, and namely from wind generation, can be consumed to pump water, which is stored in the reservoir. The stored water is then available to produce electric energy during peak load periods. The reversibility is possible due to the reversible pump-turbines, that are connected to the power grid. A diagram representing the structure and working principle of an isolated PSH unit with one reservoir is depicted in Figure 6.2.

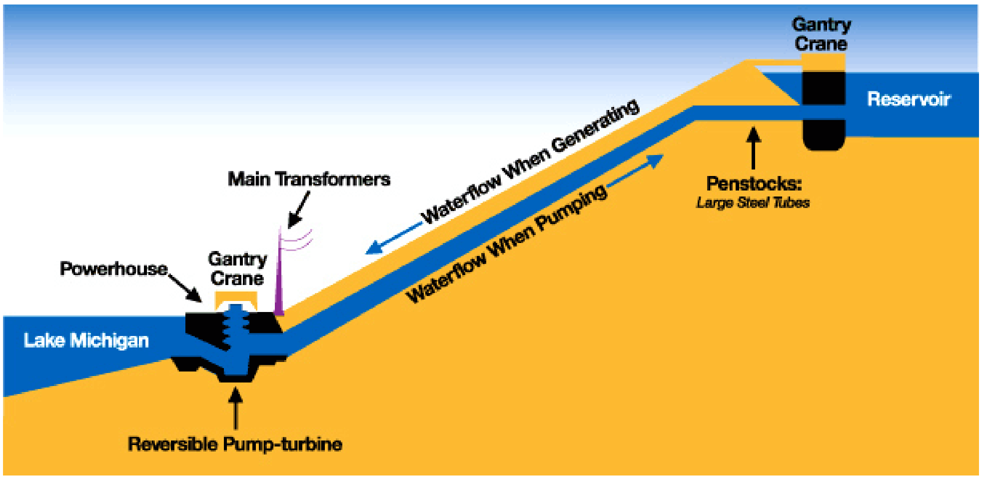


FIGURE 6.2: Diagram of a pumped storage system [5]

The additional flexibility provided by the system enlarges the penetration of renewable energy sources into the power system, since wind power surpluses can be used to pump and store water. Moreover, the excess of energy on wind energy production is generally higher during night periods, when the load demand is lower. For the same reason, in competitive environments it is possible to buy electric energy at low prices during the night. A study of the role of PSH units in electricity markets and suggestions for market designs are performed by Ela *et al.* in [77].

The pumping system allow generation to supply the load demand at its most efficient operation levels, and avoid the need for expensive peaking thermal plants (fast start-up plants) to be used during peak load periods. They can provide energy without the restrictions of conventional power plants. Their power is always available, even during dry periods, contrary to conventional hydro plants. Additionally, these power plants produce low-emission electricity when generating and, enlarging the penetration of wind energy, provide more "clean" energy to be used to serve the demand, instead of other contaminating technologies (such as fossil fueled thermal plants). Hydro plants with

PSH capacities can also increase the reserve capacity of the system when considering the water storage capacity.

However, there are some disadvantages related to the operation of PSH units. Firstly, the loss of energy during the pumping cycle, since the system can only pump about 75 % (in the form of water) of the energy consumed [78], known as the efficiency of the pumping cycle. Secondly, the need for electric energy available in the power grid in order to pump water during the required periods. Another disadvantage is the cost of storing water in the reservoir, since it is usually paid based on the energy stored per hour.

Nevertheless, the high costs of peaking thermal generators, which can provide flexibility due to its fast start-up/shutdown times, have been enough to justify the installation of pumping storage systems in hydro units operating in power systems with a large wind penetration. The storage capacity of the reservoir is a key problem, particularly in power systems with rigid limits imposed by security criteria. Brown, Peças Lopes and Matos [79] presented a model to optimise the storage capacity of hydro units in an isolated power system achieving good results. Results show that the integration of pumped storage capacities into hydro units can be an efficient way to allow a larger penetration of intermittent renewable sources. Iberdrola, the largest producer of wind energy with a worldwide wind capacity of 9302 MW in 2008, has been installing pumped-storage systems in Spain and Portugal, in order to accommodate the wind power variability. In the end of 2018 Iberdrola expects to provide nearly 1750 MW of installed wind capacity to the power system in those countries [78]. In this chapter we survey and discuss the formulations and approaches found in the literature when considering hydro units with pumped storage. In chapter 7 we make use of the multi-criteria utility-based approach to evaluate the impact of including PSH units in the UCP considering systems with a large wind penetration.

6.2 Wind-hydro-thermal UCP

The need of coordinating conventional and new technologies, such as the pumped storage systems, requires the development of more complex and sophisticated decision models. In this section, we discuss the integration of PSH plants in the UCP.

Considering hydro units, the problem becomes a scheduling and pre-dispatch problem with wind-hydro-thermal coordination, or wind-hydro-thermal unit commitment problem (WHTUCP). The challenge is to find out the optimal schedule for the set of periods over which thermal and hydro units must be committed/decommited, satisfying not only thermal constraints but also hydro constraints.

The power producer seeks to schedule the hourly production of each hydro plant. Decision variables concerning PSH commonly include water discharge/pumping rates and energy level of water in the reservoir(s). Additional binary variables to define the status of hydro units might be needed if these can either generate energy or use energy to pump water.

There are several assumptions that may be considered or not, and according to those assumptions the mathematical models can be written in different ways. Depending on if the generation company operates in a competitive environment or not, the objective function may vary from the maximisation of profits to minimisation of operating costs. In the case of competitive environments, it is usually considered that electric energy to pump water is always available at some price in the market. As a simplification of the problem, hydro operating costs are usually assumed to be zero and thus are not included in the objective function.

The constraints related to the PSH units also depend on the assumptions considered. The number of reservoirs (1 or 2), the possibility of water spillage or the consideration of water inflow from the river are some of the main issues. In Figure 6.3 we present a general representation of PSH units constraints used in mathematical models with PSH.

Technical constraints are related to physical restrictions of PSH power plants. Each reservoir capacity is bounded by upper and lower limits when storing water. Also the turbine generating cycle is bounded by the water discharge rates when in generating mode, or by

$$\begin{cases} \text{Technical constraints} \begin{cases} \text{Reservoir volume} \\ \text{Generation limits} \\ \text{Pumping limits} \\ \text{Spillage limits} \end{cases} \\ \text{System constraints} \begin{cases} \text{Water balance} \\ \text{Load balance} \end{cases} \end{cases}$$

FIGURE 6.3: Constraints related to the PSH units in the UCP

the pumping limits when pumping water to the upper reservoir. Hydro units connected to a river usually allow the possibility of spillage, to dump water without turning the generator, adding more flexibility in power system operations. Due to technical issues, water can be spilled up to a maximum pre-defined amount per period. The set of constraints related to the system operations include the water balance equations, ensuring the feasible balance of water inflows and outflows between consecutive periods, and the satisfaction of the load requirements, considering thermal, hydro and wind production of electric energy. The hydro units do not share the ramp restrictions and minimum ON/OFF time periods verified in thermal units, so their state can be re-scheduled in economic dispatch stages during the intra-day operation.

An important issue when modeling a problem with PSH units concerns the representation of the performance of hydro turbines. The power production of PSH units depends on several factors, such as the rate of water discharge, the water level in the reservoir and the design characteristics of the PSH, namely its turbine and generation efficiency factors. For a unit h, the generated power ph_h depends on the unit turbined outflow, q_h, on the net water volume, v_h, and on joint turbine and generator efficiency η_h^g :

$$ph_{ht} = 9.81\text{x}10^{-3}.q_h.v_h.\eta_h^g \tag{6.1}$$

The problem integrating hydro units becomes more complex, particularly when the influence of the water level in the reservoir, the so called head-effect, is taken into account. Due to its complexity, simplified approaches have been presented in the literature to represent the hydro production function, from piecewise linear [80] to quadratic concave

[81] functions. A reasonable representation is composed by a quadratic function of two variables in [82]. The power output ph_h of a hydro unit h can be represented by a sixth degree polynomial function of the water discharge rate q_h and storage volume v_h (see equation 6.2), where $c1_h$ .. $c6_h$ are coefficients computed beforehand.

$$ph_h = c1_h.q_h^2 + c2_h.v_h^2 + c3_h.q_h + c4_h.q_h + c5_h.v_h + c6_h \tag{6.2}$$

The function is a non-linear quadratic function of two variables (q_h and v_h), it is strictly concave (for given data-set), continuous and differentiable. Figure 6.4 shows the graphical representation of this function. Rahman, Viana and Pedroso presented in [6] an iterative piecewise linear approximation and hybridise MILP strategies with meta-heuristics based on "Local Branching" and "Particle Swarm Optimization" to solve the hydro-thermal UCP problem to the optimality considering this hydro production function.

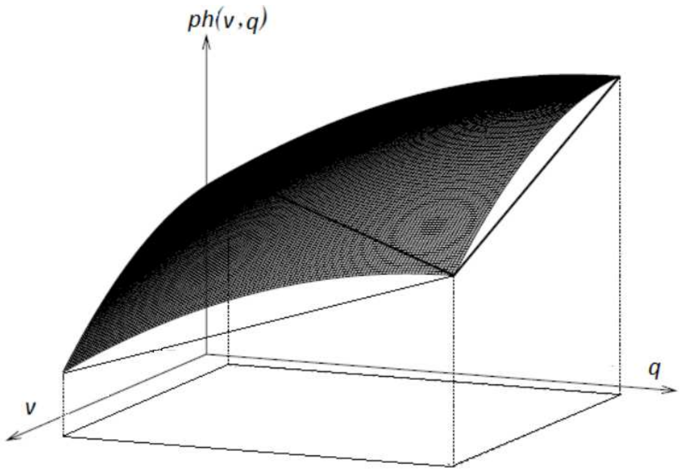


FIGURE 6.4: Graphical representation of the simplified hydro power production function in three dimension space [6]

The most common representation for hydro power production in MILP models is through a linear conversion of the water discharge rate (or volume of water), by using a coefficient that usually represents the efficiency of the turbine generating cycle [79, 83, 84].

6.3 Pumped Storage Hydro Modeling

The scheduling and pre-dispatch including PSH units in power systems has been a topic of research for a long time. In 1965, Kennedy and Mabuce analyzed in [85] the dispatch of PSH on an interconnected hydrothermal system, describing practical application techniques. Later on, Aoki *et al.* presented a new method for solving efficiently a large-scale optimal UCP including PSH units using Lagrangian relaxation [86].

More recently, Borghetti *et al.* [87] presented a MILP model to solve the UCP with both thermal and hydro units with pumped storage capacities, in a market-based environment. The authors considered hydro power plants with more multiple turbines, all of them being supplied by a single upper reservoir. The head-effect is taken into account by means of an enhanced linearisation technique. Ramp transition constraints and pumped-storage are other important technical issues included in the proposed MILP model. Interesting results were found for small instances, for a planning horizon of one week. However, solution accuracy and computational times verify a relevant decrease for bigger instances, as a consequence of the advanced linearisations introduced to the model.

Khatod, Pant and Sharma [84] presented a new approach for optimising a day-ahead scheduling considering wind and PSH units owned by an independent GENCO that aims at maximising profits in an electricity market. Hydro generation and pumping imply operating costs and a penalty is applied for unutilized wind energy, in order to avoid waste of this energy. In this approach, the amount of dispatched power during low price periods seeks to be as minimum as possible, while during high price periods wind and hydro energy is supplied at the maximum allowed level. The model appears to be simple and helpful for GENCOs using renewable sources and operating in electricity markets. However, due to the several simplifications and relaxations, the final solutions might be far from the optimal.

Hinojosa and Leyton [88] take advantage of evolutionary algorithms to solve the short-term hydro-thermal generation scheduling problem considering real non-linear functions for fuel costs and hydro power production. Hydro units are composed by on reservoir, without pumping capacities. The proposed methodology proved to be interesting for small and medium size instances.

A stochastic approach is introduced by Vespucci *et al.* [83] for the scheduling of a generation system including PSH units and wind power plants in a competitive environment. The proposed model assumes a hydro system with a set of interconnected hydro plants and considers water flows between hydro units and possibility of water spillage. The wind uncertainty is integrated by using a scenario tree to represent the wind hourly production. The system is mathematically represented by a directed multi-graph, where nodes represent reservoirs and arcs represent water flows. After testing in an Italien electricity producer, the authors found the stochastic model preferable to the equivalent deterministic model.

Duque *et al.* [89] and Gonzalez *et al.* [90] developed scenario-based stochastic approaches to optimise a joint operation between a wind power plant and a PSH farm in electricity markets. They concluded that hydro plants can be useful to minimise the imbalance costs caused by errors in the WPF.

As a conclusion on the literature review, stochastic approaches proved to be more adequate to solve scheduling problems with PSH units and large wind penetration. The wind variability can be balanced by the PSH units, that provide additional flexibility of operation. The objective function varies from the maximisation of profit (based on market energy prices) to the minimisation of costs. Hydro production is mainly considered as free of costs. The PSH units are mostly isolated (not connected to a river) and are provided with an upper reservoir. Evolutionary algorithms have proved to be able to find good solutions in reasonable times considering the real non-linear functions, but the final solution is not optimal. However, when exact methods are used to solve the problem, linearisations for fuel costs and/or hydro production are needed in order to achieve reasonable computational times.

Chapter 7

A Multiple Criteria Utility-based Approach for the WHTUCP

Notation

Constants

- η_h^p – efficiency of the pumping cycle of hydro unit h.
- η_h^g – efficiency of the generating cycle of hydro unit h.
- $d_h^{\mathrm{l}}, d_h^{\mathrm{u}}$ – lower and upper pumping power limits of hydro unit h [MW].
- $g_h^{\mathrm{l}}, g_h^{\mathrm{u}}$ – lower and upper generation limits of hydro unit h [MW].
- $cap_h^{\mathrm{l}}, cap_h^{\mathrm{u}}$ – lower and upper capacity limits of reservoir of hydro unit h [MWh].
- $vol_h^{\mathrm{initial}}, vol_h^{\mathrm{final}}$ – initial and final levels in the reservoir [MWh].

Variables

- Decision variables:

   - v_{hts} – energy stored in the reservoir of hydro unit h, in period t, for scenario s [MWh].
   - q_{hts} – water discharge rate of hydro unit h, in period t, for scenario s [MW].
   - pp_{hts} – pumping input power of hydro unit h, in period t, for scenario s [MW].
   - w_{hts} – water spillage of hydro unit h, in period t, for scenario s [MWh].

- Auxiliary variables:
   - z^p_{hts} – 1 if hydro unit h is in pumping mode, in period t, for scenario s, 0 otherwise].
   - z^g_{hts} – 1 if hydro unit h is in generating mode, in period t, for scenario s, 0 otherwise].

This chapter presents the assumptions and a formulation for the integration of PSH facility in the proposed WTUCP, in order to evaluate the influence of those units on dealing with wind power variability. The work hereby presented in an extension of the approach developed in chapters 3 and 5. We present the constraints related to the hydro component, as well as the necessary modifications introduced in the model. The objective is to investigate if the new WHTUCP model is able to reflect the DM risk profiles and find out the contribution of PSH facilities to improve the final solutions. In order to achieve that goal, we consider isolated PSH units that operate at no costs. Then, water flows from rivers or spillage of water are not considered. On this way, the operation of each PSH unit boils down exclusively to the consumption of energy to pump and store water or the usage of stored water to generate electricity used to serve the load demand.

7.1 Assumptions

Since we continue the proposed WTUCP model discussed before, the previous assumptions in the practical part presented before remain the same. Additionally, the following assumptions are made to formulate the integration of PSH into the model:

- The hydro system consists of a set of hydro units. Each hydro unit is provided with a turbine and a single upstream reservoir. Each hydro unit may either generate electric energy using stored water from the reservoir or consume energy to pump water into the reservoir;
- Head effect is not considered - Electric power output of hydro units does not depend on the water level in the reservoir. The discharge output power is defined by a linear conversion using a pre-defined coefficient (η_h^g) that represents the ratio of energy injected into the power system to the (equivalent) energy consumed from stored water.
- Water is always available to be pumped into the reservoir;
- The volume of water stored in the reservoir is represented by an equivalent energy level (MWh). The initial and final energy levels of the reservoir are known *a priori*;
- Only energy generated by wind turbines, in each period, can be used to pump water to the reservoir;
- Generation of electric power and water pumping by hydro units are considered at no costs;
- Hydro units cannot provide reserve;
- The possibility of water spillage is not allowed;

7.2 Mathematical formulation

In this section we present the mathematical formulation of the constraints related to the PSH units as an extension of the WTUCP model presented before. Since the hydro pumping and generation systems are assumed to operate at no costs, the objective function remain the same as described in chapter 5 (equation 5.2) for the wind-thermal model. Since hydro units do not share the same technical restrictions as thermal units (ramp constraints and minimum ON/OFF periods), their status can be changed and their production levels can be dispatched during intra-day operations. For this reason, all decision variables concerning hydro units are indexed by scenario.

- Reservoir volume of hydro units: The volume level of the reservoir of each hydro unit is limited by its minimum and maximum capacities and the initial and final energy levels are known *a priori*:

$$cap_h^{\mathrm{l}} \leq v_{hts} \leq cap_h^{\mathrm{u}}, \quad \forall h \in \mathcal{H}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{7.1}$$

$$v_{h1s} = vol_h^{\mathrm{initial}}, \qquad \forall h \in \mathcal{H}, \forall s \in \mathcal{S} \tag{7.2}$$

$$v_{hTs} = vol_h^{\mathrm{final}}, \qquad \forall h \in \mathcal{H}, \forall s \in \mathcal{S} \tag{7.3}$$

- Discharge capacity limits. They represent physical limitations on water discharge rates used for generation:

$$g_h^{\mathrm{l}} z_{hts}^g \leq q_{hts} \leq g_h^{\mathrm{u}} z_{hts}^g, \quad \forall h \in \mathcal{H}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{7.4}$$

- Pumping capacity limits. The pumping input power is also bounded due to technical limitations of the pumping system:

$$d_h^{\mathrm{l}} z_{hts}^p \leq pp_{hts} \leq d_h^{\mathrm{u}} z_{hts}^p, \quad \forall h \in \mathcal{H}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{7.5}$$

- Water balance equations (expressed in energy). The difference of energy stored in the reservoir (v_{hts}) between consecutive periods is given by the amount of water pumped into the reservoir (influenced by the pumping efficiency cycle η_h^p), minus the amount of water used for generation (q_{hts}).

$$v_{hts} - v_{h,t-1,s} = \eta_h^p . pp_{hts} - q_{hts}, \quad \forall h \in \mathcal{H}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{7.6}$$

- The available wind power FW_{wt} in each period may be used to serve the load demand (pw_{wts}), to pump water into the reservoir (pp_{hts}) or can be curtailed

(cw_{wts}):

$$\sum_{w \in \mathcal{W}} (pw_{wts} + cw_{wts}) + \sum_{h \in \mathcal{H}} pp_{hts} = \sum_{w \in \mathcal{W}} FW_{wt}, \quad \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{7.7}$$

- Load balance. The total amount of energy produced to serve the load demand includes now the energy generated by hydro units, influenced by the efficiency of the generation cycle η_h^g. Equations (7.8) replace equations (3.18) presented in section 3.2:

$$\sum_{u \in \mathcal{U}} p_{uts} + \sum_{w \in \mathcal{W}} pw_{wts} + \sum_{h \in \mathcal{H}} \eta_h^g . q_{hts} = D_t - ens_{ts}, \quad \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{7.8}$$

- Auxiliary constraints: Constraints impose that each hydro unit cannot be pumping and generating simultaneously during each time period.

$$z_{hts}^p + z_{hts}^g \leq 1, \quad \forall h \in \mathcal{H}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S} \tag{7.9}$$

7.3 Simulated cases and results

The characteristics of the hydro system were obtained from [89] and correspond to an actual Spanish real hydro-pump plant that covers the imbalances of a wind power producer. We considered a single PSH unit with an upstream reservoir, isolated and connected to the power grid. The characteristics used in the test simulations are presented in Figure 7.1. Note that the initial and final levels in the reservoir are both defined at 120 MWh, in order to avoid the inclusion of any inflow or outflow of energy and impose that all the water used for generation has to be pumped (before or after the generation) to the reservoir.

TABLE 7.1: PSH unit's characteristics

η_h^g (%)	88
η_h^p (%)	92
d_h^{l} (MW)	0
d_h^{u} (MW)	40.3
g_h^{l} (MW)	0
g_h^{u} (MW)	32.8
cap_h^{l} (MWh)	0
cap_h^{u} (MWh)	240
vol^{initial} (MWh)	120
vol^{final} (MWh)	120

The remaining data-set input parameters, concerning thermal units, load demand, wind information and DM profiles are the same as described in section 5.3.1.

The individual utility functions were approximated by piece-wise linear functions in a 5-segment approximation and the non-linear fuel cost functions were approximated by piece-wise linear functions with 4 segments, as done for the model to solve the WTUCP stated in chapter 5. The model was also implemented in AMPL (A Modelling Language for Mathematical Programming) [75], and the CPLEX 12.1 as a MILP solver [76] was used to solve it.

Figure 7.1 shows the amount of energy generated, per day, by the PSH unit. Since the water is pumped at a 92 % efficiency rate, and from that water only 88 % is converted in electric energy to serve the demand, we easily state that the generated hydro energy corresponds to 80,96 % of the wind energy consumed for it. It means a 19,04 % loss of energy when using the pumping system, which is usually the rate of real PSH units. Nevertheless, Figure 7.1 show a high penetration of hydro energy into the system. Considering the 40.3 MW capacity of PSH generating cycle and 24 periods, the maximum possible amount of daily hydro generation is 967.2 MWh. Simulations returned an average value of 131.6 MWh for DM1, 155.7 MWh for DM2 and 84.6 MWh for DM3.

Figures 7.2, 7.3, 7.4 and 7.5 show that the proposed methodology, with the inclusion of PSH units, is able to reflect the DM risk profiles in the commitment solutions, following

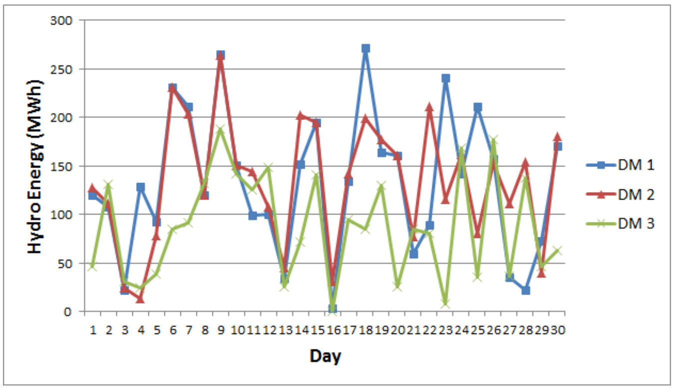


FIGURE 7.1: Daily hydro generation for 30-day simulation period

the same logic described in the results section of chapter 5. Analyzing the figures, we state that the results are consistent with the simulated profiles designed for the DMs, as in the previous model. In all simulations, once again the waste of energy resulted zero.

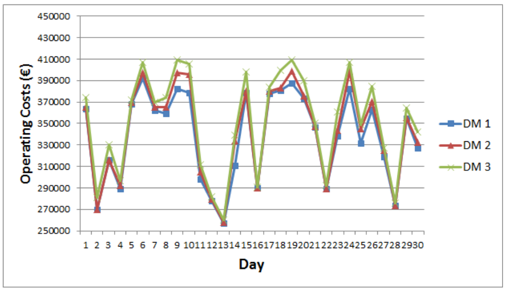


FIGURE 7.2: Daily operating costs with PSH units

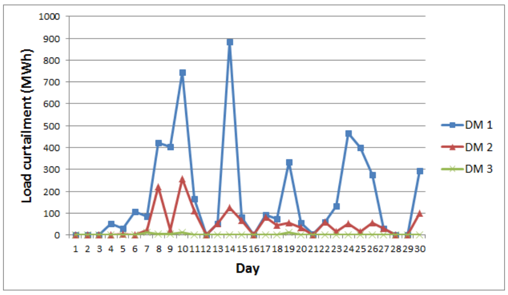


FIGURE 7.3: Daily ENS with PSH units

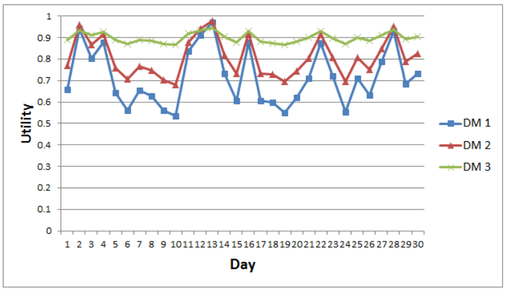


FIGURE 7.4: Daily utility values with PSH units

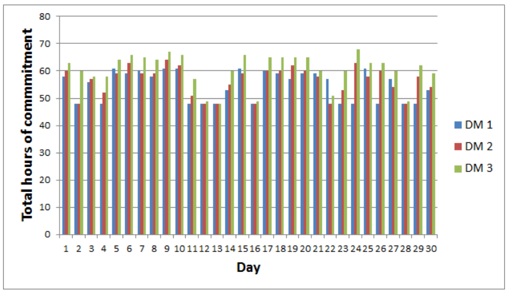


FIGURE 7.5: Daily hours of commitment with PSH units

We will analyze the impact for DM1, since that profile demonstrated, as expected, higher load curtailment values. As we can see in Figures 7.6 and Fig 7.7, the inclusion the PSH unit have impact in the best solution found for each day. By comparing the results for operating costs and load curtailment for the 30-day simulation, even thought being a small test instance, the PSH unit provides a relevant decrease in load curtailment values. In day 24, it decreases from 729.2 to 467.2 MWh of energy not served. The results for DM1 still demonstrates its ENS seeking attitude, by allowing the possibility of high ENS values, as happens in days 10 and 14. The operating costs are slightly higher in the WHTUCP model, stating the change of the best solutions found and returned by the solver.

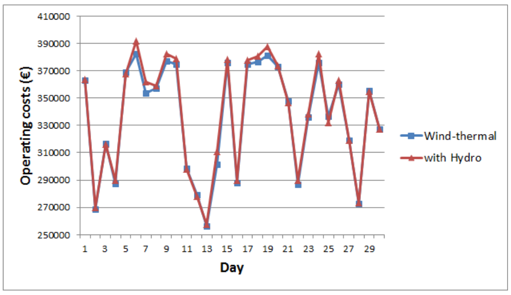


FIGURE 7.6: DM1 - Daily costs with and without PSH unit

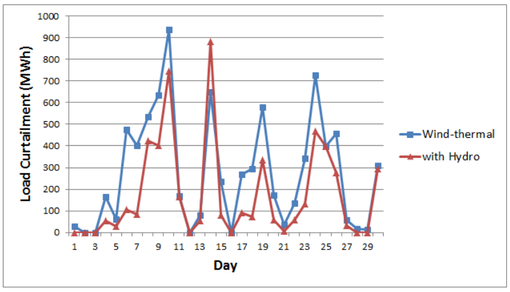


FIGURE 7.7: DM1 - Daily ENS with and without PSH unit

In order to evaluate if the inclusion of the PSH unit introduces a positive contribution, we compare the utility in the end of each operating days. Figure 7.8 shows that the utility, that corresponds to the satisfaction level after the economic dispatch stage, is slightly higher with the inclusion of the PSH unit. If the preferences of the DM are properly assessed, he/she would always prefer the solution obtained by solving the model including the hydro unit rather than the solution from the previous model.

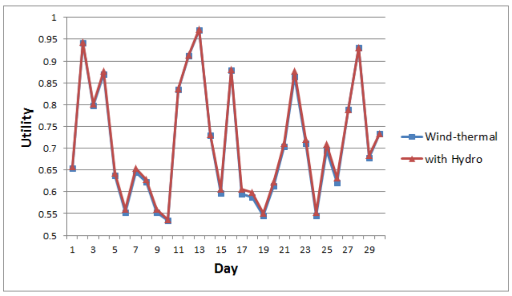


FIGURE 7.8: DM1 - Daily utility with and without PSH unit

Results for DM2 and DM3 demonstrated to have the same trend as the results for DM1.

In terms of computational times, we obtain the same conclusions deducted for the WTUCP model. Figure 7.9 show that the computational times can vary between a long range, from 19.6 to 37632.9 seconds (10.45 hours), for the same reasons. We can state that computational times are significantly higher for the model with the PSH unit, due to the 480 binary variables added into the problem.

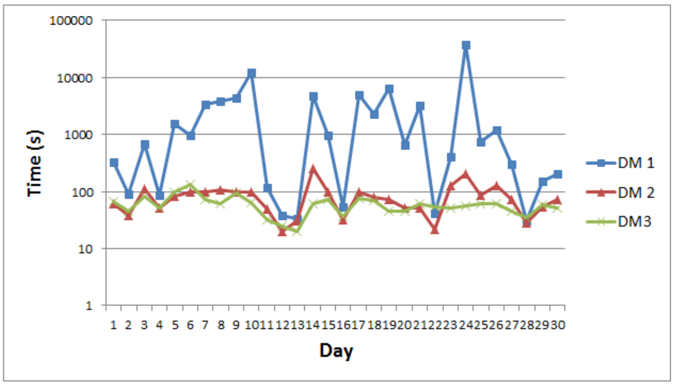


FIGURE 7.9: Computational times at the commitment stage

Chapter 8

Conclusions and Future Work

The accommodation of wind power in GENCO and ISO operations brought new challenges, both for short-term and long-term scheduling plans. By not considering the variability of the wind speed, less efficient, unreliable and more expensive schedules are obtained by deterministic models. For improving on these criteria, stochastic approaches are better than deterministic ones, when studying the WTUCP. Within stochastic approaches, the most common formulation found so far considers multiple scenarios and minimises an objective function that takes into consideration the expected objective value of total costs, load/reserve curtailments and waste of energy. Such approach proves to be simpler and computationally more efficient than others. A single schedule is obtained with minimum up/down and start-up constraints being forced for all scenarios, while ramps, load balance or generation limits can vary between scenarios.

The main drawback of the scenario-based stochastic formulations is that as all the constraints are valid for all scenarios, and very unlikely scenarios may introduce a significant impact in the objective value. Simply due to their possibility of occurrence they may require to commit extra thermal units in order to satisfy all the constraints for that unlikely scenario, increasing the operating costs. Other disadvantage is related to the possibility of occurrence of non-desired values for some indicators that the DM is not willing to pay. Considering, for example, the objective of minimising the sum of operational costs, demand not served and wind curtailment. Although a very unlikely scenario will contribute with small values to the objective expected value of the final solution, if this scenario occurs it can represent, for example, a significant value for the demand not served, which DM is not willing to pay. These drawbacks could be overcome by obtaining one schedule per scenario and the DM could choose among all possibilities according to his/her preferences. However, for real problems this approach seems to be computationally prohibitive. The number of solutions could be impractically large and the CPU would require a long time to make all the necessary computations.

Rescheduling more often in an intra-day manner produces more reliable and economic solutions for ISOs and GENCOs, respectively. This occurs particularly when peaking units are available because their state can be changed to tackle the uncertainty of wind forecasts, which are being updated in real-time operations.

Most of the works with accommodation of uncertainty of renewable sources with risk analysis consider the DM as risk averse and use the reserve requirements to build confidence in the schedules obtained. This type of models are usually rigid and conservative and non-adaptable to different attitude profiles. In this context, multi-criteria approaches with integration of the DM profile should be developed to properly reflect his/her attitude towards the risk of load/reserve curtailment in conflict with the total costs and waste of wind energy.

The main contribution of this work is the proposal of an alternative approach for the wind-thermal unit commitment problem. The risk attitude towards costs, the possibility of load curtailment and waste of energy are integrated and may be adjusted according to the decision maker preferences. Since the risk averse/proneness for each criterion may vary over time, we propose an individual utility function that can be adapted by setting a single parameter, which can be estimated through lotteries based on indifference judgments.

Despite the strong assumptions of utility independence and additive independence between criteria, which must be verified in order to validate the model, the methodology is able to model different attitudes of the decision maker in order to obtain a rational decision that corresponds to the most preferable feasible solution from the decision maker point of view, in terms of the expected utility over the set of possible estimated scenarios.

The non-linear individual utility functions are modeled through a piecewise linear disaggregated formulation that is valid either for concave or convex shapes. A process that iteratively reduces the error piecewise linear functions and the actual non-linear functions allows finding out an adequate number of segments to fix in the model before solving. The final stochastic MILP model, which is a MOCO model with articulation of preferences *a priori*, can be tackled by general-purpose solvers in order. Nevertheless, the solution is not guaranteed to be optimal (the most preferred) due to the several linearisations performed.

Some simulations were done by defining decision maker profiles ranging from a decision maker risk averse concerning ENS, to a decision maker that is willing to accept the risk of load curtailment if it means to avoid the waste of wind energy and, consequently, a reduction of costs. Results show that the MOCO model is able to reflect those profiles in the final solution.

Results showed that including pumped storage units can be an effective means of allowing larger penetration of intermittent wind generation. By including the pumped storage system, the solutions demonstrated to be improved when comparing to the wind-thermal model. PSH units can help to deal with the wind power variability by using wind energy to pump and store water that can be used for generation during periods of lower wind production and/or higher load demand. They proved to have a relevant participation in the energy production due to their flexibility, despite the energy losses implied on it.

The models presented in this thesis could be useful for assisting investment decisions about the inclusion of a new pumped storage hydro unit. Therefore, the developed formulation can be helpful to the GENCOs or ISOs in determining the daily scheduling of their wind/pumped storage, maximising their satisfaction level.

The proposed MOCO model revealed to be complex and may require a high computational effort top be solved, even thought the linearisations performed for all non-liner functions at a low number of segments and the small instances tested. The computational times revealed to be strongly dependent on the shape of the objective function, being higher if this function has a convex set of feasible solutions since we deal with a maximisation problem. For the small instances tested, the model provided good computational times for non-convex individual utility functions. Future research work can be developed in order to find more efficient ways to solve the model, in less computational times. Such work can include a different representation of the individual preferences of the DM, avoiding non-linear functions, or find more efficient way to linearise the proposed formula. Depending on the results, alternative optimisation techniques using iterative algorithms can be developed allowing to optimise the problem considering real cost functions and real utility functions.

The results that are presented in this thesis, concerning the development of a stochastic multi-objective model for the wind-thermal unit commitment problem with pumped storage hydro units, make us believe that this is a promising technique and that it would worth to invest on applying the utility theory to other problems, particularly if we consider the large extension of problems that include multi-criteria decisions under uncertainty.

Focusing on the WHTUCP, additional simulation tests can be done to test the influence of the scaling constants in the commitment decisions and consequent objective values. Wind production costs may be considered turning the objectives of minimising waste of wind energy and operating costs to be conflicting objectives.

An alternative approach considering different assumptions can be developed for competitive environments, where energy is always available to be consumed or generated, based on hourly prices. The extension of the model to represent interconnected hydro units in a cascade system is other topic of research.

Appendix A

Interaction for Estimating the Parameter α for the Utility Function

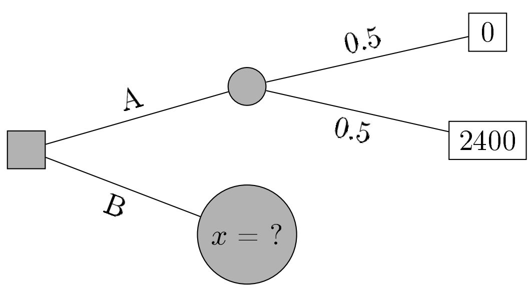
In this annex we explain through an example a methodology to estimate the parameter α of the individual utility function proposed in section 5.1 for the three criteria considered in the MOO model. The explanation makes use of a practical example with possible real values for the energy not served. For more details on this kind of procedures we refer to [45, 68, 69].

Firstly, the DM is proposed to give the best and worst outcomes for the criteria whose utility function we aim to estimate. Those limits have to be the same when assessing the scaling constants, as illustrated in Annex B. Considering one criterion, the lower limit can be set as a value that is at least as good as the best possible outcome, and the upper limit at least as bad as the worst outcome [45]. This means that if a DM sets the worst possible outcome for the ENS amount as, e.g. 1000 MWh for the whole day, when constructing the utility function and assessing the scaling constants it is legitimate to use an upper limit bigger than 1000 MWh for the ENS, but only if this limit is also used in the scaling constants assessment.

Let us consider that a DM found the best and worst possible outcomes for the ENS to be 0 and 2400 MWh, respectively. This could mean that the DM could admit as the best outcome not to curtail any load demand during the operating day, and as the worst outcome to curtail at most 10% of the load of a planning horizon with 24 periods of 1 hour each, and a load demand of 1000 MW per period.

Then, according to the proposed utility function, $u^{ens}(0) = 1$ and $u^{ens}(2400) = 0$. Now, to estimate the parameter α we will try to find the certainty equivalent for a given number l of lotteries. Each lottery gives us a different point (ENS, u^{ens}) in the utility function graph, besides the points (0, 1) and (2400, 0) already defined. For simplicity, those points are called utility points. The bigger l is, the more approximated to the preferences of the DM is the utility function, but also the more complex is the interaction and a bigger number of inconsistencies may be found. Since this is a simple example, we will perform only three lotteries. Let us start:

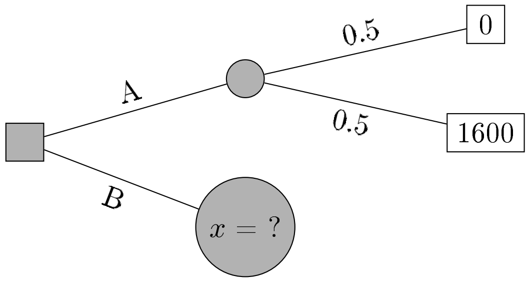
Analyst : *Imagine that you have the opportunity of playing lottery A below. What is the minimum amount, x, for which you would sell your opportunity to play the game ?*



DM : *I would accept a value of x = 1600 to avoid playing that lottery.*

This means that the DM is indifferent between having a ENS value of 1600 MWh and playing the referred lottery, suggesting the same utility or satisfaction level between the alternatives. So, $u^{ens}(1600) = 0.5u^{ens}(0) + 0.5u^{ens}(2400) = 0.5$. This value suggests from now a risk aversion concerning the ENS criterion since the certainty equivalent is higher than the expected value of the alternative A, which is 1200 MWh. However, this can be a consequence of the limits provided by the DM that may lead to this situation when are set too large. Let us continue.

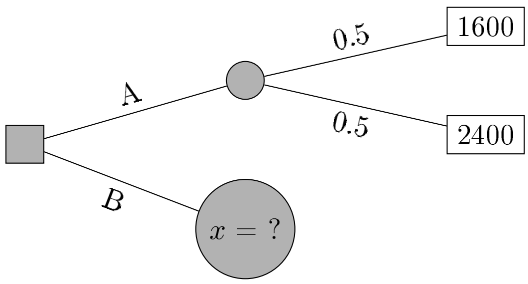
Analyst : *I understand. And which value would you accept for* x *to be indifferent between the alternatives A and B ?*



DM : *Well ... for that lottery I would be willing to accept* $x = 1000$*.*

With this answer we can compute that u^{ens} $(225) = 0.5\ u^{ens}(0) + 0.5\ u^{ens}(1600) = 0.75$. Finally:

Analyst : *I understand. And which value would you accept for* x *to be indifferent between the alternatives A and B ?*



DM : *With* $x = 2050$ *I would accept any of the alternatives.*

In this situation, u^{ens} $(2050) = 0.5\ u^{ens}(2400) + 0.5\ u^{ens}(1600) = 0.25$. Now we have 3 points that can be used to estimate α^{ens}. For that, we can compute the α^{ens} values for each point obtained, since all the other parameters (limits, ENS and utility values) of equation 5.1 are known. Table A.1 presents the set of points and α^{ens} values computed for each point.

TABLE A.1: Values of parameter α^{ens} for the deduced utility points

ENS (MWh)	u^{ens}	α^{ens}
1000	0.75	-1.49
1600	0.5	-1.44
2050	0.25	-1.46

With these values, the α^{ens} can be approximated as $\alpha^{ens} = (-1.49 - 1.44 - 1.46)/3 \approx -1.46$ [1]. In Figure A.1 is shown a graph with the points extracted from the interaction with the DM and an utility function with the estimated $\alpha^{ens} = -1.46$.

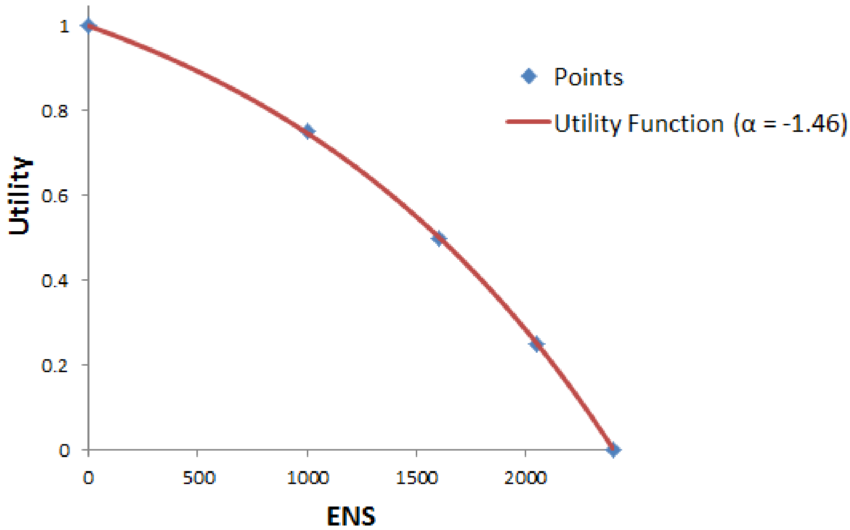


FIGURE A.1: Utility function approximation for a set of utility points

The proposed utility function assumes that the DM preferences over the costs, ENS and EXS values can be represented adjusting parameter α. However, the interaction between the analyst and the DM may result in a set of points that are not legitimate to be approximated by an utility function like the one proposed in section 5.1. In order to detect if the utility function really represents the DM preferences, consistency checks must be performed. These checks usually consist on asking for preferences between lotteries and check if the expected utility of the preferred ones are higher [45].

[1]Note that more appropriate methodologies may be used to estimate the value of α

Appendix B

Interaction for Estimating the Scaling Constants

In this Annex we exemplify how the scaling constants of an additive utility function described in chapter 4.2.2 can be obtained through an iterative process based in indifference judgments given by the DM. Once again, the basis of our example is the WTUCP. Remember that we consider that the mutually utility independence and the additive independence between criteria hold.

Usually the DM is not able to present two alternatives between which he/she assumes to be indifferent. However, a process can be followed to achieve indifference. Then, as mentioned in chapter 4.2.1, the overall utility of two equally preferred solutions on the DM perspective is the same, so that $U(x) = U(x')$ if and only if $x \sim x'$. If we have

$$U(x_1, x_2, ..., x_n) = k_1.u_1(x_1) + k_2.u_2(x_2) + ... + k_n.u_n(x_n) \tag{B.1}$$

and $U(x_i^-)$ is the worst possible outcome and $U(x_i^+)$ is the best possible outcome for the criterion i, then we know, according to the proposed utility function, that $U(x_i^-) = 0$ and $U(x_i^+) = 1$ for that criterion. It is possible to assess the k_i's using the ranges to achieve indifference judgments. It is necessary to have previously defined the individual utility functions for each criterion.

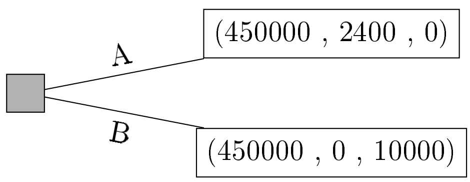
Let us consider that the ranges shown in Table B.1 were found using some method or that the DM has simply defined them.

TABLE B.1: Ranges considered for the measurement scales

	Best	Worst
Cost (€)	100000	450000
ENS (MWh)	0	2400
EXS (MWh)	0	10000

Since the scaling constants k_i are necessary to aggregate the independent utility values in a single utility value, the aim is to ask some meaningful questions to get some idea of the scaling constants values. We start presenting two alternatives. Either the DM prefers one of them or is indifferent.

Analyst : *Between alternatives A and B, which one would you prefer ?*



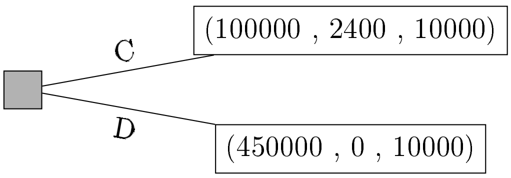
DM : *I would prefer alternative B.*

Since $U(A) = k^{exs}$ and $U(B) = k^{ens}$ we immediately state that $k^{ens} > k^{exs}$. If the DM says that he/she is indifferent, then we can assume $k^{ens} = k^{exs}$. Now we keep the non-preferred solution and decrease the quality of the preferred one, until an indifference is reached. In this way, we iteratively increase the value of ENS for alternative B, maintaining the same values for the other two criteria, and repeat the same procedure stated before until an indifference judgment between alternative A and an alternative, let us say, B', is reached. So, if the ENS value for B' is 550 MWh, and knowing that $U(B') = k^{ens}.u^{ens}(550)$ and $U(A) = k^{exs}$ we can compute equation B.2.

$$k^{exs} = k^{ens}.u^{ens}(550) \tag{B.2}$$

Repeating the process for the comparison between cost and ENS:

Analyst : *And what about the alternatives C and D, which one would you prefer ?*



DM : *I would prefer to have alternative C.*

We know that $U(C) = k^{cost}$ and $U(D) = k^{ens}$, then $k^{cost} > k^{ens}$. Decreasing the satisfaction level for solution C, an indifference can be obtained, for example, for a cost of 200000 €. In this way, we can compute equation B.3.

$$k^{ens} = k^{cost}.u^{cost}(200000) \tag{B.3}$$

Finally, we know that $k^{cost} + k^{ens} + k^{exs} = 1$, and in conjunction with equations (B.2) ad (B.3) we compute the weights. Let us suppose that the individual utility functions follow the function proposed in section 5.1 with $\alpha^{cost} = 0.5$ and $\alpha^{ens} = 2$. Then, we easily state that $u^{cost}(200000) \approx 0.66$ and $u^{ens}(550) \approx 0.57$.

Then,

$$\begin{cases} k^{exs} - 0.57k^{ens} \approx 0 \\ k^{ens} - 0.66k^{cost} \approx 0 \\ k^{cost} + k^{ens} + k^{exs} = 1 \end{cases} \equiv \begin{cases} k^{cost} \approx 0.49 \\ k^{ens} \approx 0.32 \\ k^{exs} \approx 0.19 \end{cases}$$

As we can see the scaling constants depend on the ranges considered, and are not weights that can be directly or intuitively given by the DM. As with the assessment of the individual utility functions, there is the need for consistency checks to build some confidence about the decision maker preferences.

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