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DEMAND RESPONSE AND RENEWABLE ENERGY INTEGRATION IN THE CHILEAN ELECTRICITY MARKET

TESIS PARA OPTAR AL GRADO DE MAGÍSTER EN ECONOMÍA APLICADA
MEMORIA PARA OPTAR AL TÍTULO DE INGENIERO CIVIL ELÉCTRICO

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En el mercado eléctrico chileno, las energías renovables tuvieron una participación de 43% durante el año 2017. En este contexto, se ha establecido el objetivo de lograr una participación del 60% de energías renovables para el año 2035. Estudios recientes sugieren que este objetivo podría alcanzarse; sin embargo, existen inquietudes sobre los impactos que podrían tener en la red estos niveles de energías renovables, lo que podría llevar a una incorporación ineficiente de estas tecnologías. Por otro lado, en el sistema eléctrico chileno actualmente la demanda eléctrica no está directamente expuesta al precio spot, por lo que no responde fácilmente a las condiciones del mercado. La literatura sobre Respuesta de la Demanda en el sistema eléctrico chileno es limitada y no existen estudios que analicen cómo la incorporación de la flexibilidad de la demanda podría impactar el uso eficiente de tecnologías de energías renovables en el mercado eléctrico chileno.

Esta tesis desarrolla un modelo determinista de Respuesta de la Demanda de tipo Unit Commitment (DR-UC), formulado como un problema no lineal entero mixto (MINLP) que utiliza una función de costos cuadrática de dos partes. Esto permite evaluar el impacto de la flexibilidad de la demanda tanto de tipo desplazable, como de tipo ajustable en un sistema con cinco tecnologías de generación (solar, eólica, hidráulica de embalse, hidráulica de pasada y plantas térmicas). A diferencia de la generalidad de la literatura que considera que sólo una fracción de la demanda es flexible, en este trabajo no se impone una restricción en términos del nivel de penetración de Respuesta de la Demanda. El problema se resolvió simulando la operación del sistema eléctrico chileno para distintos escenarios en el año 2035. Con esto, se logró evaluar los beneficios que proveería la flexibilidad de la demanda al mercado eléctrico chileno así como a la incorporación de energías renovables. Los beneficios de la Respuesta de la Demanda demostrados en este estudio son el límite inferior de los potenciales beneficios que le podría otorgar al sistema.

Los resultados sugieren que la incorporación de la flexibilidad de la demanda incrementaría la integración de energías renovables al año 2035. Esto se debe a la reducción de vertimiento renovable, del ciclaje del parque térmico y a la menor variabilidad del precio spot. Al incorporar flexibilidad de la demanda, la generación diésel se reduce hasta en un 42%, debido al desplazamiento de consumo desde las horas punta. Un resultado importante del estudio es mostrar que una Respuesta de la Demanda incrementaría las emisiones de CO_2, al permitir que las centrales a carbón operen a mayor capacidad.

Los códigos desarrollados para implementar el modelo y evaluar su impacto están publicados como software libre y están disponibles en el repositorio Git del proyecto, lo que es una las principales contribuciones del trabajo.

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In the Chilean electricity market, renewable energy sources had a participation rate of 43% of total electric generation. In this context, the target for renewable energy participation levels is 60% for 2035 during 2017. Recent studies suggest that this target is achievable. However, there are some concerns about the impact that renewable energy imposes on the grid, which could lead to the inefficient incorporation of these technologies. One reason for this potential inefficiency is that electricity demand is not directly exposed to the spot price, so it is not very responsive to market conditions. The current literature on demand-side flexibility in the Chilean electricity system is limited and there are no studies that analyse the effects of the introduction of demand flexibility on the efficient use of renewable energy technologies in the Chilean electricity market.

This thesis develops a deterministic Demand Response Unit Commitment (DR-UC) model. This model is formulated as a mixed-integer nonlinear program (MINLP) using a two-part quadratic disutility function. This formulation allows us to assess the impact of demand-side flexibility when demand can be shifted or adjusted in an electricity system using five different generation technologies (solar, wind, hydro reservoirs, run-of-the-river and thermal power plants). Unlike most of the literature, which considers that only a fraction of the total demand is flexible, I place no restriction regarding the amount of demand flexibility. I simulated the operation of the Chilean electricity system for different scenarios in the year 2035. I use the results of these simulations to assess the benefits provided by demand flexibility in the Chilean electricity market and the impact on renewable energy generation and on the operation of other technologies. The Demand Response benefits found in this study corresponds to a lower bound of its possible benefits to the system.

The results of this thesis suggest that demand-side flexibility integration increases the efficient use of renewable energy investment for the year 2035. This is due to the reduction of both renewable energy curtailment and cycling operation of low-cost thermal power plants, as well as lower spot price variability. When incorporating demand-side flexibility, diesel generation is reduced by up to 42% due to the shift in consumption from peak to non-peak hours. An important result of the study is to show that a Demand Response would increase CO_2 emissions because coal power plants operate at higher capacity.

The software code that implements the model and assesses its impact is offered as free software, and is one of the major contributions of this work. It is available in the Git repository of the project.

A quienes me han amado

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Chapter 1

Introduction

1.1 Motivation

With an installed capacity mainly driven by fossil fuels, there has been a big effort during the last years to plan and ensure a low carbon electricity grid in Chile. Recently, renewable energy (RE)[1] sources had a 43% of participation during 2017 (Ministerio de Energía (2018d)). In this context, the government has set a target for a 60% share of RE by 2035 and 70% by 2050 (Energía 2050 (2015)). In a recent study, PSR and Moray (2018) calculate that, with a cost-minimisation approach, the share of RE can actually achieve a 75% by 2030 with solar-wind penetration ranging between 38-47%. In another study, Matus et al. (2017) forecast a RE penetration of between 58-70% by 2030 and between 59-78% by 2035. They also argue that Non Conventional Renewable Energies (NCRE) [2] penetration could achieve levels between 28-42% and 31-54% in the years 2030 and 2035 respectively. It seems then that government goals might be achievable at least as a central planning problem by 2035. However, it is not clear whether there exist the correct price signals and mechanism in place in order to ensure the appropriate renewable energy investment and long-term resource adequacy, nor if the grid will be operated in an efficient way.

On the one hand some NCRE sources face an additional risk of not being able to fulfil their financial obligations in comparison to conventional base load technologies due to their variable and fluctuating nature. This risk is combined with a high hydrological variability context like it is in the case of Chile, having an impact directly on the results of tenders leading to outcomes with lower NCRE penetration than the optimal. This results in leading to inefficient outcomes (Marambio and Rudnick (2017)). There are also other undesired effects of an increasing penetration level of NCRE such as renewable energy curtailment caused by the technical restrictions of the rest of the electric system (Moreno et al. (2017), Matus et al. (2017)). Moreover, there are new challenges that an increase of NCRE penetration will impose on the grid such as the cycling operation of thermal generation units (CDEC-SING

[1] Here, for renewable energy (RE) we consider all types of hydro (small or big reservoirs and run-of-the-river), biomass, geothermal, solar, tidal and wind.

[2] Non Conventional Renewable Energies Sources defined by Chilean law include biomass, geothermal, small hydro plants (< 20 MW), solar, tidal and wind.

(2016), AG (2018)). All of these open the discussion on whether the correct market structures exist in place in order to ensure an efficient and reliable incorporation of these technologies.

The current literature on demand-side flexibility incorporation in the Chilean electricity market is very limited (see Section 4.4). In particular, to my knowledge, there are no studies done on how the incorporation of demand flexibility could impact the operation of the Chilean electricity system, and how it could improve renewable energy integration in the Chilean electricity market.

1.2 Aim

The aim of this study is to propose a model in order to incorporate demand-side flexibility in the Chilean electricity system. This study also aims to analyse its impact through an *unit commitment* optimisation problem for different renewable energy penetration scenarios in the year 2035.

1.3 Objectives

- Analyse the characteristics of the Chilean electricity system and market.
- Analyse the current and future challenges that an increasing level of renewable energy penetration imposes to the Chilean electricity system in the context of the opportunity for demand-side flexibility services.
- Propose a model for demand-side flexibility participation in the Chilean electricity system.
- Incorporate the demand-side flexibility model in an *unit-commitment* optimisation problem and simulate the optimal operation of the Chilean electricity system for different scenarios in the year 2035.
- Evaluate the impacts of this incorporation in valued renewable energy, renewable energy curtailment levels, spot prices, total costs and the cycling operation of thermal generation units.

1.4 Main Contributions

- This thesis develops a novel Demand Response Unit Commitment (DR-UC) model formulated as a mixed-integer nonlinear program by the use of a two part quadratic disutility function. Unlike the rest of the literature, we don't impose an upper bound of flexible-demand participation because in our model, demand-side flexibility services are quadratically valued.
- We confirm that demand response helps the integration and investment of renewable energy in the Chilean electricity system, which is aligned with previous findings found in the literature. However, we also find that for the particular case of Chile, in some

cases, a higher participation of demand-side flexibility, may drive higher CO_2 emission due to the replacement of diesel with coal generation.

1.5 Document Structure

The remainder of this work is organised as follows:

- **Chapter 2: The Chilean Electricity Market.** The following chapter briefs the current Chilean electricity market. It discusses the NCRE generators risk exposure in the tender system due to their variable nature as well as the market inefficiency of end-consumers not facing real-time spot-prices. This section also discusses how the Chilean grid operation is strained due to grid inflexibility.
- **Chapter 3: New Challenges for the Grid.** This chapter describes the operational challenges faced by the grid due to an increasing NCRE penetration.
- **Chapter 4: Literature Review on Demand Response.** In this chapter, a literature review of demand response mechanisms is presented.
- **Chapter 5: The Model.** This chapter shows and describes the proposed model for demand-side flexibility integration. It does also present the *unit commitment* optimization problem.
- **Chapter 6: Methodology.** This chapter describes the methodology used to analyse the impact of the presented model in the Chilean electricity system. The different case studies are presented in this chapter.
- **Chapter 7: Results and Discussion.** Results are shown and discussed in this section.
- **Chapter 8: Conclusions.** Finally, the main conclusions of the study are shown in this chapter.

Chapter 2

The Chilean Electricity Market

This chapter analyses the Chilean electricity grid and market. It starts with an overview of the grid characteristics, its current installed capacity and renewable energy potential. It continues with an explanation of how does the electricity market works in Chile and it discusses why do the grid operation is strained due to technical constraints. Then, it analyses the tender system and it identifies the risk that NCRE sources face due to their variable nature. The hydrological variability is also analysed as well as the wind-hydro correlation, both key phenomena in the spot-price variability. Then, it discusses the market inefficiency due to end-consumers not facing real-time spot-prices. Finally, it presents historical and current public policies on the integration of renewable energy.

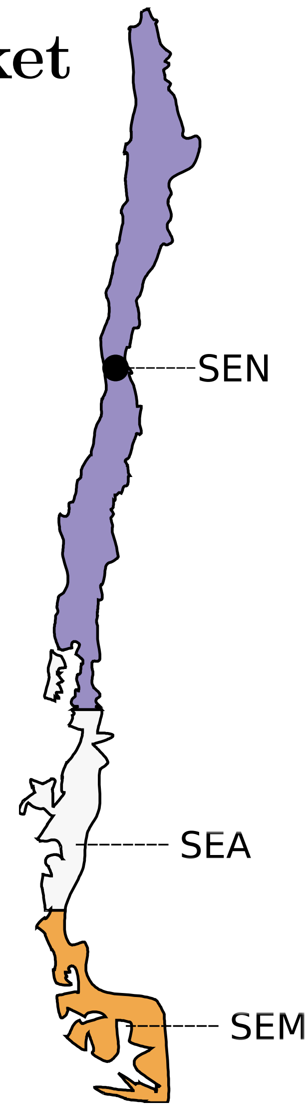

Figure 2.1: Map of the areas powered by the different interconnected systems in Chile. Source: Ministerio de Energía (2018c).

2.1 Grid and Potential for Renewables

2.1.1 The Grid

Chile is powered mainly by 3 interconnected systems: the *National Electric System* (SEN by its Spanish acronym), the *Aysen Electric System* (SEA) and *Magallanes Electric System* (SEM). They cover almost all the 4270 km. long continental territory as shown in Figure 2.1. Due to population concentration[1] and industrial activity, almost 99.3% of its installed capacity is located in the National Electric System, with technologies mainly driven by fossil fuels in the northern part of the SEN, and a mixture of hydraulic and fossil fuels in the southern part of the system. The portion of the actual energy generated per technology depends mainly on the season and in the

[1]Over 97% of Chilean population is located in the territory powered by the National Electric System (SEN).

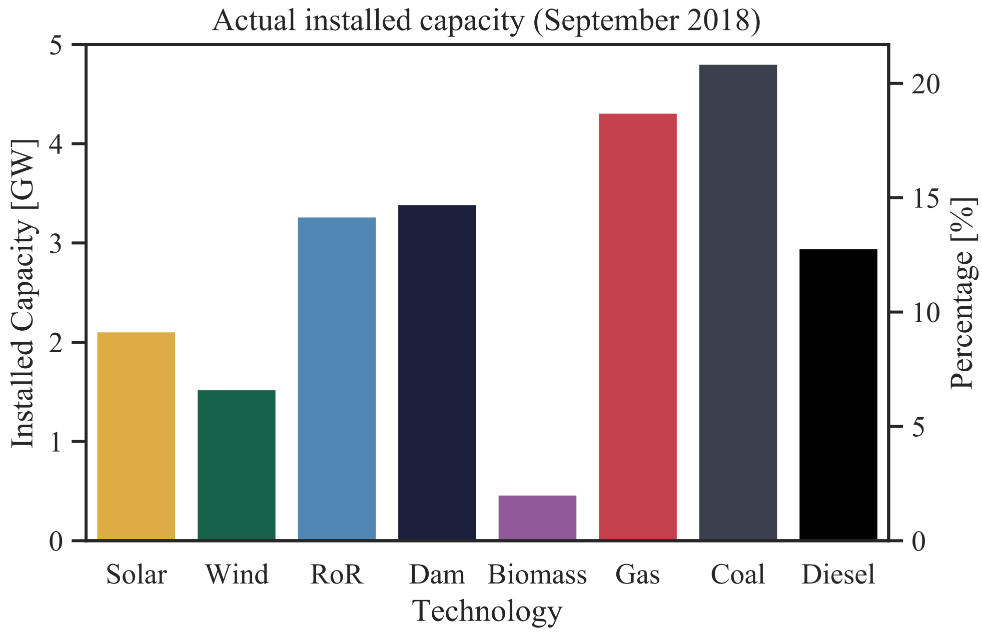

Figure 2.2: Installed capacity in the National Electric System by technology. Elaborated by the author using data from Ministerio de Energía (2018c).

hydrological situation. However, despite the enormous potential for renewable energy, in the SEN, almost 52% of its installed capacity is driven by fossil fuels. A detailed overview of the installed capacity in the SEN is shown in Figure 2.2.

2.1.2 Renewable Energy Potential

With a solar irradiance (GHI)[2] of above 5 $kWh/(m^2\text{d})$ in half of the Chilean territory[3] and 7 $kWh/(m^2\text{d})$ in the Atacama Desert (Haas et al. (2018)), the renewable energy potential in Chile is enormous [4]. In fact, in a study made by the Ministry of Energy and the German Agency for International Co-operation (GIZ), renewable energy potential was estimated at over 1.200 GW for solar photovoltaic (PV), 548 GW for concentrated solar power (CSP), 37.5 for wind power[5] and 12.5 GW for hydropower (GIZ and Ministerio de Energía (2014)) as shown in Figure 2.3, where renewable energy potential is shown for the northern part of the *SEN* (previously called *SING*) and the southern part of the *SEN* (previously called *SIC*)

[2]Global Horizontal Irradiance (GHI) is the total amount of shortwave radiation received from above by a surface horizontal to the ground.

[3]$kWh/(m^2\text{d})$ stands for kWh (energy) per m^2 (surface) per day.

[4]For example, Barcelona has a year average solar irradiance of 4.6 $kWh/(m^2\text{d})$, Paris of 3.3 $kWh/(m^2\text{d})$ and London of 2.61 $kWh/(m^2\text{d})$ (European Comission (2006)).

[5]The methodology used for this study considered wind-power capacity with an estimated capacity factor of at least 30% (See GIZ and Ministerio de Energía (2014) for a detailed description of the methodology.).

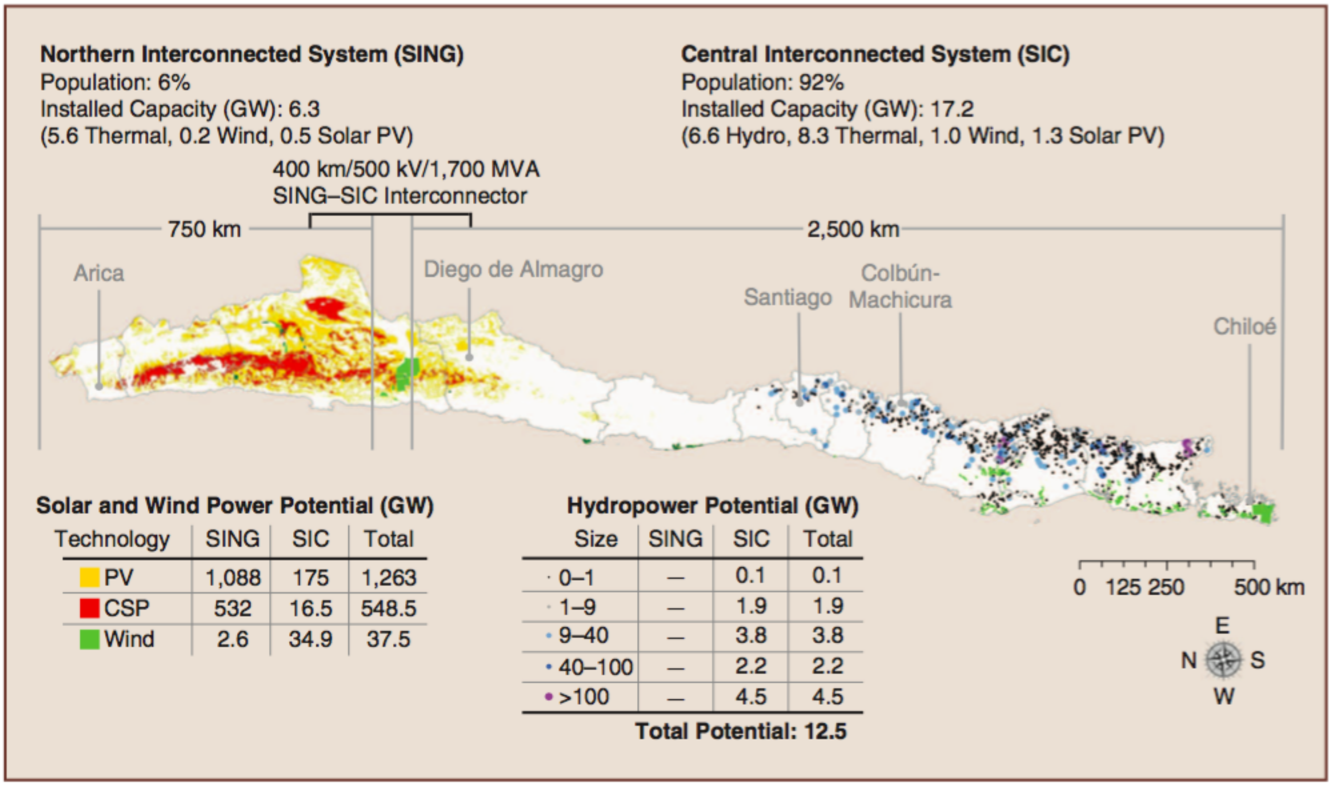

Figure 2.3: Renewable energy potential in the northern (SING) and southern (SIC) part of the SEN. Source: Moreno et al. (2017), GIZ and Ministerio de Energía (2014).

2.2 Market Characteristics

Currently, the Chilean Electricity Market consist of a cost-based market, where generators sell their electricity to regulated retailers and large industrial consumer through long-term fixed-price forward contracts. However, dispatch is mandatory and completely independent of any financial contract obligations a supplier might have[6]. The short run marginal cost dispatch regime is coordinated by the system operator (SO) [7] that computes offer curves using variable cost and technical characteristic of the individual generation units, the information of current and future reservoir levels and evolution of demand. In this structure, the system's marginal cost is the running cost of the most expensive unit required to meet system demand at a given time. As dispatch is mandatory, if a generator is not able to fulfil its financial contract obligations, it must buy the energy at the spot-market. Hence, in each hour a given generator is either a net supplier to the system or a net buyer. Net buyers pay net suppliers

[6]This design has been justified due to the high concentration of the generation market, which is dominated by 3 main firms, and the potential incentives of large hydro units to exercise market power through an strategic eater allocation (Arellano (2004)). Is important to note, however, that even if now it is not longer the case, and now there is less concentration in the Chilean electricity generation sector, the market design remains the same. More research needs to be done in order to analyse if this design is currently justified.

[7]In some bibliography it might be named as "Economic Load Dispatch Center" (CDEC by its Spanish acronym), or more recently as "National Electric Coordinator" (CEN), since the interconnection between the Northern and Central Interconnected Systems started already in 2017 (Coordinador Electrico Nacional (2018)).

the system's marginal cost.

To ensure wholesale competition, long-term forward contracts must be the result of the "contract market" in which generators and distributors that supply small (regulated) consumers participate in public, non-discriminatory and technology-neutral tenders (Rudnick and Mocarquer (2006)). In addition, each generation unit receives a monthly capacity payment based on its annual availability. The capacity payment equals the capital cost of the peaking technology (diesel turbine).

2.2.1 The Dispatch Model

The short-run marginal cost dispatch is coordinated by the SO in order to minimize the expected cost of supply and outage cost. Hence, the SO centrally dispatches power plants in strict merit order according to costs and technical characteristics of each generation unit, as well as the current state and projections of hydrological cycles and demand, until the amount of power demanded in each moment is covered. Here, the opportunity cost of reservoir water is calculated with a stochastic dual dynamic programming model at each instant and depends on the expectation of future rainfall, the current levels of the reservoirs, plans for future power plants, and on the expected future marginal cost of thermal plants (Fischer and Serra (2000)). This means that the SO trades off the benefit of using water today and displacing thermal generation, against the cost of not having water in the future and thus having to use thermal generation or ration costumers and pay the shortage cost (Galetovic and Muñoz (2009), Galetovic et al. (2015)). Hence, the opportunity cost of water equals the cost of the most expensive thermal unit dispatched.

2.2.2 Restricted Grid Operation

Technical characteristics of each generation unit considered in the SO dispatch includes upward and downward ramp rate limits[8], minimum operation levels[9], start-up and shut-down costs (cycling costs), as well as minimum operation time[10] and minimum downtimes[11] (Gonzalez et al. (2018)). As it is discussed in more detail in Chapter 3, these technical constraints imply that the dispatch can be inefficient if other sources of flexibility, namely demand side flexibility or storage, are not considered (as is currently the case).

Example 2.2.1. ***Minimum Operation Time***

In this example we will analyse the risk exposure of a wind power plant on having to buy energy into the spot market due to conventional power plant inflexibility. In this example we illustrate power plant inflexibility with a gas power plant restricted to

[8]Ramp rates are defined based on the speed at which output levels can be changed.
[9]Minimum operation levels are the minimum power a generator unit can provide.
[10]Minimum operation times are the minimum period that generation units should be in operation.
[11]Minimum downtimes are the minimum period that generation units should be out of operation.

its Minimum Operation Time, and alternatively, a diesel power plant more costly but flexible.

Let's consider a case with three types of plants: Type w plants (wind), type g plants (gas) and type d *plants (diesel). Let's consider that type w plants have zero operation cost and are not restricted to minimum operation time. Type g plants have lower operating cost than type* d *plants, but are restricted to a minimum operation time. Type* d *plants have no restriction on minimum operation time. Operating cost are then* $c_w = 0 < c_g < c_{\mathrm{d}}$, *while minimum operation times are* $\tau_w^{mot} = \tau_{\mathrm{d}}^{mot} = 0 < \tau_g^{mot}$. *We assume that demand justifies the installation of one of each types of plants, and that there are not ramp rates limits, minimum operation levels restrictions, nor cycling cost restricting the operation. Minimum downtimes are not considered either.*

Let's consider $\mathrm{d}(t)$ *a fixed net-load between $t = 0$ and $t = T$ (See Fig. 2.4), i.e.*

$$\mathrm{d}(t) = \left\{ \begin{array}{ll} Q, & t \leq T \\ 0, & t > T \end{array} \right\}$$

We consider that the financial obligation to supply $\mathrm{d}(t)$ *demand relies on type w plant. We also consider that the maximum net demand Q is lower than the maximum capacity of all three types of plants. On the other hand, it is expected that there will not be wind generation available before a certain time $t_w \in (0, T)$, but later, its availability will be enough to supply the maximum net demand Q. Hence, the wind availability $a_w(t)$ is (See Fig. 2.5):*

$$a_w(t) = \left\{ \begin{array}{ll} 0, & t \leq t_w \\ Q_w > Q, & t > t_w \end{array} \right\}$$

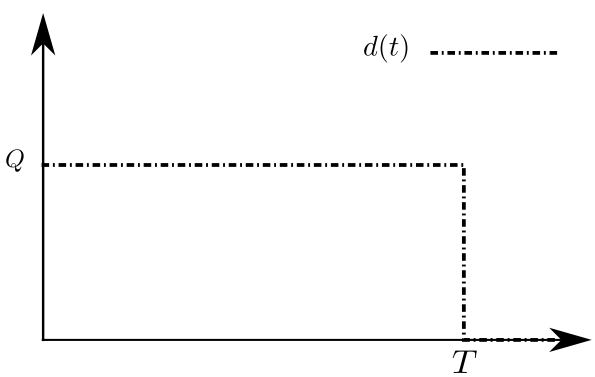

Figure 2.4: Example 2.2.1: Fixed net-load $\mathrm{d}(t)$.

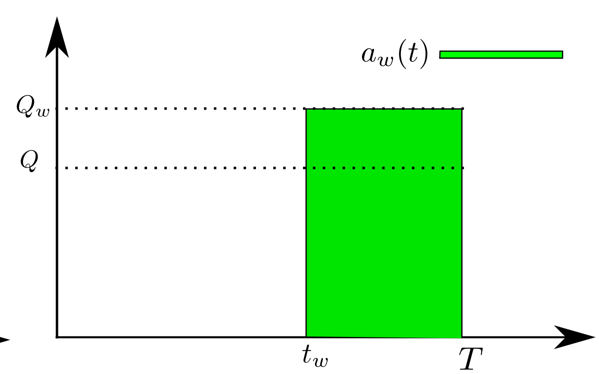

Figure 2.5: Example 2.2.1: Wind availability $a_w(t)$.

In this situation, the SO cannot rely only on type w plant, because its generation is zero before t_w. Furthermore, let's consider that the minimum operation time τ_g^{mot} is such that $\tau_g^{mot} > t_w$. Which means, that if type g plant is used, there will be at least wind power curtailment during $t \in (t_w, \tau_g^{mot})$, as it will not be possible to turn *off plant g before $t = \tau_g^{mot}$. Following a technical-restricted merit of order dispatch, as in the case of the Chilean electricity market, i.e. solving a minimisation cost problem restricted to each technology's minimum operation time, it will be optimal to use type g and type w plant only if the cost of supplying demand with gas power plant, and wind power after $t = \tau_g^{mot}$ is lower than the cost of supplying demand with a diesel power plant and then with wind power when wind is available, i.e.*

$$\begin{aligned} Q \cdot (c_g \cdot \tau_g^{mot} + c_w \cdot (T - \tau_g^{mot})) &\leq Q \cdot (c_\mathrm{d} \cdot t_w + c_w \cdot (T - t_w)) \\ &\Leftrightarrow \\ c_g &\leq c_\mathrm{d} \cdot \frac{t_w}{\tau_g^{mot}} \end{aligned} \tag{2.1}$$

In this case, the SO's dispatch and wind energy curtailment ($\kappa_w(t) = a_w(t) - q_w(t)$) will be as shown in Fig. 2.6. Otherwise ($c_g > c_\mathrm{d} \cdot \frac{t_w}{\tau_g^{mot}}$), it will be optimal to use type d *plant, and then type w plant to power demand. In this case, the SO's dispatch and wind energy curtailment will be as shown in Fig. 2.7*

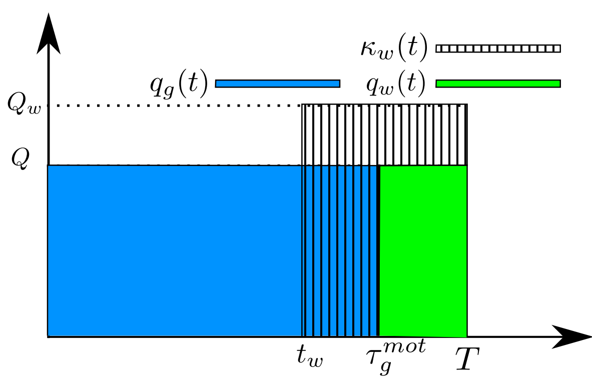

Figure 2.6: Example 2.2.1: System operation and curtailment using type g and type w plant.

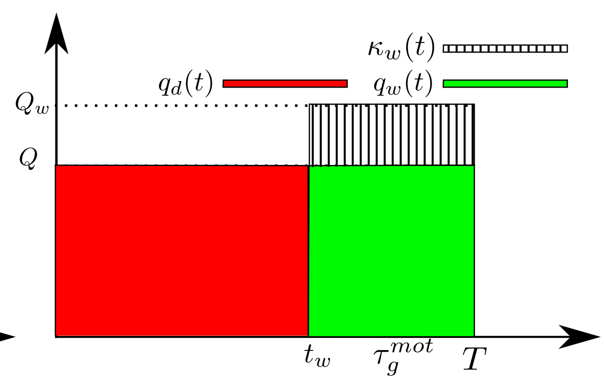

Figure 2.7: Example 2.2.1: System operation and curtailment using type d and type w plant.

In both cases, outcomes seem to be inefficient if other sources of flexibility exist and are not considered. For instance, if (2.1) is true, inefficiency consist in wind power having to buy energy in the spot market while being curtailed in $t \in (t_w, \tau_g^{mot})$. In fact, in this case even if type w plants have their renewable resource available, the grid operator will decide not to consider their contribution, and hence, type w plants would need to buy energy in the spot market (and pay c_g per unit of energy) in order to fulfil its financial contracts. Hence, type w plants risk exposure on participating in the spot market would not only rely on its ability to estimate its renewable resource availability, but will also rely on the rest of the grid's (in)flexibility, namely other type of plant's technical restrictions.

If (2.1) is not true, inefficiency consist in turning on a more expensive power plant. In this case, type w plant spot price exposure will be increased. Both cases are due to minimum operation time restrictions. For the first case, any demand reduction with a power-averaged cost of $c_R \leq c_g \cdot (\tau_g^{mot}/t_w)$ will increase market efficiency *avoiding wind curtailment between $t = t_w$ and $t = \tau_g^{mot}$(and gas emissions) between $t = 0$ and $t = t_w$, while for the second case, demand reduction cost should be even more cheap and satisfy $c_R \leq c_{\mathrm{d}} \leq c_g \cdot (\tau_g^{mot}/t_w)$.*

Even if this is a simple example to illustrate how minimum operation time restricts grid operation, this situation really occurs in dispatches following technical constraints (PSR and Moray (2018)) and are important to identify opportunities for demand response participation.

2.2.3 Free and Regulated End Consumers

The retail side of the Chilean electricity market is a natural monopoly formed by regulated distribution companies that acts as retailers selling electricity to regulated small and medium end-consumers ($<$ 5 MW) at a regulated nodal price (Palma et al. (2009)). Bigger end consumers ($>$ 5MW) are called "free end-consumers" and can freely negotiate their supply prices and conditions directly with generation or distribution companies. End-consumers with power between 500 kW and 5 MW can choose to face a fixed regulated price or to become "free end-consumers" and negotiate their supply energy price. Until 2009, the regulated nodal price were fixed every 6 months by the authority, based on the system expected spot prices for the next 48 months. Hence, retailed prices reflected the authority (rather than the market) expectation of the system marginal cost in the near future. However, since 2010, the regulated nodal price depends on the prices of the long-term forward contracts resulting from the tenders. This incorporates in regulated end-consumers prices the real cost expectations from actual market participants. (Moreno et al. (2010), Rudnick and Mocarquer (2006), Palma et al. (2009), Reus et al. (2018)).

Despite the fact that the price faced by end-consumers reflects the cost expectation of generators and distribution companies, real-time generation and prices are not driven by contract obligations. Moreover, end-consumers do not observe real-time spot prices and hence cannot react to them [12]. Fischer and Serra (2000) argue that early reformers regulated these prices to defend the interests of small consumers as they feared that residential and small commercial users would be unable to deal with wide variations in the price of electricity.

2.3 Long-Term Contracts vs. Real-Time Generation:

To ensure wholesale competition, long-term forward contracts must be the result of the "contract market" in which generators and distributors that supply small regulated costumers participate in public, non-discriminatory and technology-neutral tenders (Rudnick and Mocarquer (2006)). In addition, each generation unit receives a monthly capacity payment based on its annual availability. The law forces distribution companies to support their

[12]See Section 4.3.1 for a review on real-time prices alternatives.

entire demand through auctioned long-term contracts.

Both this long-term forward tenders and capacity payment are the actual mechanism to give revenue certainty for suppliers and ensure investment and resource adequacy as result (Street et al. (2009), Galetovic et al. (2015), Moreno et al. (2012)). In fact, systems with volatile real-time/spot market prices provide a very strong incentive for electricity retailers and large customers to purchase their electricity through fixed-price forward contract rather than face the risk of the extreme short-term prices. Also, capacity payments reduce the likelihood of long-term capacity-inadequacy problems because the promise of a capacity payment provides incentives for new generation units to enter the market (Galetovic et al. (2015)). However, on the supply side, the situation is not similar for all suppliers as their risk exposure will be dependent on their ability to generate and fulfil their contract obligations, which is variable and uncertain for some non-conventional renewable energies such as wind and solar. Because if a generator is not able to generate enough energy to fulfil its financial contracts, it must buy energy in the spot market. This means that its hourly power obligation coupled with its ability to generate will determine its short-term risk. In this sense, some NCRE generators face a higher spot price risk. This risk is increased with volatile marginal price, which is the case for electricity grids with high hydrological variability like Chile (Fischer and Galetovic (2003), Street et al. (2009)) AURES (2017)).

To tackle this and other issues, on January 2015, the Law 20.805 was introduced modifying the tender process and incorporating hourly blocks[13] in order to reduce the risk exposure of renewable energy generation such as wind and solar, improving their participation by giving them the possibility to bid during specific time blocks (Ministerio de Energía (2015), Marambio and Rudnick (2017), AURES (2017)). The results of the last tender in November 2017 [14] reached the lowest bid of USD 21.48/MWh, with an average price of USD 32.5/MWh, the lowest price ever awarded in Chile (Systep (2017b)). As discussed in Marambio and Rudnick (2017), the incorporation of hourly blocks reduce the risk of time-dependent generators (Sun only shines during the day, and wind power has more expected generation during the night). Despite this, their real-time variable nature still makes them face the spot-price risk, a risk that is not faced by base load (mainly big hydro and coal) power plants, which can constitute an opportunity for demand response participation to increase market efficiency.

Moreover, auctioned contracts are denominated in US dollars and can be indexed with several indexes as the United States' Consumer Price Index (US CPI) and fuel price index, which mitigate the fuel variability risk exposed by power plants. But they cannot be indexed to other hydrological related index (See AURES (2017) for more details about the bidding procedure and price indexing).

[13]For example, in the 2015 auction (Licitación de Suministro Eléctrico (2015/01), hourly blocks were a) between 00:00 and 07:59, and between 23:00 and 23:59; b) between 08:00 and 17:59; and c) between 18:00 and 22:59 (AURES (2017), Ministerio de Energía (2015)).

[14]National and International Public Tender to Supply Electrical Power and Capacity to cover the consumption of clients subject to price regulation (Supply Bid 2017/01).

2.4 Renewable Energy Policies

The first regulations to encourage the penetration of renewable energy in the Chilean electricity grid came on 2004, when a new law (Law 19.940, the "Short law I") allowed small power plants (< 9MW) to participate in the spot market at nodal price (see Section 2.2) and ensured them access to the distribution grid. This law also encouraged NCRE technologies by exempting them of transmission charges (total exemption for < 9MW, and partial exemption for installed capacities between 9 and 20 MW) (Palma et al. (2009), Ministerio de Economía (2004)). In 2005, the "Short Law II" (Law 20.018) encouraged investment in generation capacity through open and public energy supply tenders conducted by distribution companies, forcing them to have contracts for supplying their final consumers for at least the next 3 years. This law guaranteed that 5% of the energy contracted should come from NCRE sources.

Even if these laws created a base for the incorporation of NCRE sources into the grid, it has been argued that they were not enough to massively incentive NCRE investment (Sauma (2012)). This is why in 2008, a new law was approved in order to boost NCRE investment (Law 20.257). The law was called the "Non-Conventional Renewable Energy Law", and it not only defined what a Non-Conventional Renewable Energy source would be according to the Chilean regulation[15], but also required generators to demonstrate that a certain percentage of their total energy committed in their contracts was injected in the system by NCRE sources. The energy could be produced by their own plant, or by contracting from third parties (IEA (2016a), Ministerio de Economía (2008)). The objective was to achieve a 10% of NCRE generation by 2024[16]. Five years later, in 2013, this law was updated in order to target a share of 20% of NCRE by 2025 (Law 20.698, the Law "20/25") (Ministerio de Energía (2013)). In 2016, the Chilean government released the Energy 2050 Roadmap, which lays out a vision for the electricity and energy sector until 2050. The goal is to reach a share of renewable energies (RE) (both conventional and not conventional, hence, small and big hydro reservoirs) of 60% by 2035 and 70% by 2050 (Energía 2050 (2015)).

Recently, in October 2017, a new proposal for the regulation of ancillary services was published by the government (Ministerio de Energía (2017a)). According to this document, end-consumers could be considered as ancillary services providers through reduction or increment of consumption, either alone or aggregated. Even if this topic is still in discussion, the proposal highlights the aim of the government to do further changes and directly include end-consumers in the Chilean electricity market and in the challenge for renewable energy incorporation.

[15] According to this lad, NCRE sources include biomass, geothermal, small hydro plants (< 20 MW), solar, tidal and wind (Ministerio de Economía (2008)).

[16] This quota came into force at the start of 2010, and until 2014 will require 5% of electricity to come from non-conventional renewable energy sources. Starting from 2015, the obligation will be increased by 0.5% annually, reaching 10% in 2024.

2.5 Discussion

In this chapter we have analysed the Chilean electricity grid and market. The Chilean electricity market uses a merit order dispatch that does not depend on contract obligations.

Given that end-consumer face a fixed regulated price, they do not face neither NCRE variability risk, nor hydrological risk. Both risks are inefficiently allocated within generation and distribution companies, and are transferred to end-consumers by means of a risk-premium. Hence, if NCRE variability risk is considered by NCRE generators in the tender, it is expected that with more renewable energy penetration, the more premium is going to be transferred to end-consumers. This seems not to be efficient as price signals are probably unaligned with the real end-consumers' risk aversion profiles and valuation of energy. In fact, some end-consumers might be willing to react to real-time prices and reduce their overall electricity payment.

A similar discussion of risk allocation between generation firms, retailers and end consumers can be found in Reus et al. (2018), where the authors propose to introduce competition in the retail sector in Chile, which would incentivise retailers to offer a menu of different options for consumers with varying levels of risk, leading to an endogenous risk allocation between generation firms, retailers and consumers. Another proposed alternative is that end-consumers could participate directly in the market by responding to (real-time) spot-market price or signals. Strbac and Wolak (2017) argue that this situation could be better with a multi-settlement market: a day-ahead forward market and a real-time market, where loads can purchase energy in the day ahead market that they can subsequently sell in the real-time market (selling demand shifting/reduction).

This last alternative correspond to what is called *Demand Response*. In fact, *Demand Response* (DR) refers to the action of consumers time-shifting and/or reducing electricity consumption in response to a signal, usually in the form of a financial incentive[17]. As presented in this chapter, no type of Demand Response mechanisms currently exist in the Chilean electricity market. However, currently there exist the discussion about incorporating end-consumers as ancillary services providers, which highlights the possibilities of contributions of this work to this discussion.

[17]See Chapter 4 for a literature review on Demand Response.

Chapter 3

New Challenges for the Grid

The physical characteristic of electricity implies that consumption and generation must always be in an instantaneously balance. In this context, any operation of the grid must ensure this following the technical limitations of the supply side, the technical limitations the demand side, as well as from generation units. This task becomes more challenging as storage options are very costly and difficult to implement. On the other hand, due to the nature of some renewable energies (generation variability and uncertainty), their integration imposes new challenges for the grid operation, increasing the need for higher operational flexibility sources. A main source of flexibility in the generation side of the grid is the cycling operation of conventional power plants, which it is highly linked with their technical constraints. Also, as the merit of order dispatch follows power plants' technical restrictions, it is important to understand these restrictions.

This chapter starts with a description of the intermittent characteristic of some renewable energy sources. Then, it continues with an analysis of the new challenges that will be faced by the grid due to a higher penetration of these technologies. Finally, this chapter does an overview of the operational flexibility sources of the grid, mainly the conventional power plants' cycling operation.

3.1 Characteristics of Solar and Wind Generation

From the considered NCRE technologies[1], two of these sources, wind and solar, have the particular characteristic of being variable. Due to their dependence in climate conditions, they cannot be dispatched as conventional power plants can. In fact, their output is weather-dependant and therefore variable and less predictable (IEA (2016b)).

As described by Pérez-Arriaga and Batlle (2012), the intermittency characteristic of these technologies comprises two separate elements: *non-controllable variability* and *partial unpre-*

[1] As discussed in Section 2.4, Non-Conventional Renewable Energy (NCRE) sources defined in the Chilean electricity regulation are biomass, geothermal, small hydro plants ($<$ 20 MW), solar, tidal and wind.

dictability. These two characteristics are in fact the ones that impose the new challenges described in the next section.

3.2 Impacts of Renewable Generation into the Grid

Due to the variable characteristics of wind and solar explained above, their power output must be dispatched whenever their energy is available, forcing the electric system operator to coordinate the rest of conventional generation technologies in order to accommodate the existing demand and power contribution by solar and wind. This requires a higher level of system flexibility, since in such scenarios the system must respond by adjusting its dispatchable generation not only to a variable and to some degree uncertain demand profile; but also to a variable and unpredictable renewable generation.

In the following, some impacts that renewable generation impose on the grid are analysed. It is important to note that generally, these impacts depend on the specific context of each electricity system. Hence, the following list is based mostly on the current literature available for the Chilean electricity system.

- **Reduction of operational costs:** Due to the very low marginal cost (even zero) of renewable energies, overall operational costs are being reduced. In a recent study, PSR and Moray (2018) estimates that due to the increase of solar (from 7 to 11 GW) and wind (from 2 to 5 GW) energy penetration in the Chilean electricity system, total operation costs could be decrease by 18% between the years 2021 and 2030 even after considering the increase of flexibility costs. In another study, CDEC-SING (2016) estimates that for the year 2021, the increase of 30% in solar and wind penetration levels could reduce costs between 143 and 193 [MMUSD] annually.
- **Reduction of total emissions:** PSR and Moray (2018) estimates that despite the increment of total demand, between the years 2021 and 2030, total greenhouse emissions could be reduced up to 14%. The same study indicates that CO_2 emissions factors could be reduced by 40% in terms of $tonCO_2/MWh$ for the total electricity system.
- **The increase of cycling operation levels of conventional generation units:** As defined in Van den Bergh and Delarue (2015), the cycling operation is the change of the output of a power plant by starting up, shutting down, ramping up or ramping down.

  Here is important to note that depending on the literature, the cycling operation might refer to when (i) the generation unit cycles from its minimum operational level to its maximum power output due to load following (*ramping/load following cycle*), or to when (ii) the generation unit starts up, shuts down, and starts up again (*start-up/shutdown cycle*). In this thesis we will refer to this situations as *load following operation* and *start-up/shutdown cycling operation* respectively.

  The relationship between renewable energy penetration and cycling operation of conventional power plants is extensively discussed in the literature (Van den Bergh and Delarue (2015), Lew et al. (2012)). In particular, in higher solar power penetration

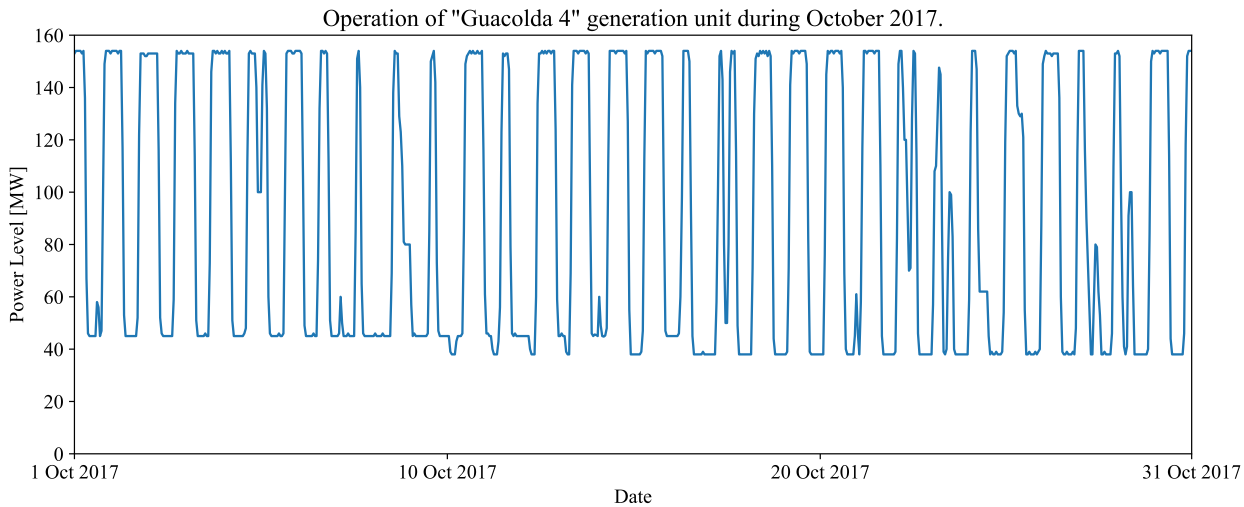

Figure 3.1: Operation of *Guacolda 4* coal generation unit during October 2017. Elaborated by the author using data given by *Systep*.

levels scenarios, conventional power plant's cycling operation levels are expected to increase (IEA (2016b)). However, their cycling operation level would depend on their variable cost and technical restrictions.

For instance, in the Chilean electricity system, on the one hand, it is expected that the start-up/shutdown cycling operation levels of gas power plants will be increased due to renewable energy penetration (Matus et al. (2017)). On the other hand, and due to minimum operation times and minimum operational levels constraints, as well as lower variable costs, it is expected that start-up/shutdown cycling operation levels of coal generation units will not be affected significantly (Ministerio de Energía (2018e), Bassi (2016)). In this case, coal generation units will be forced to operate at their minimum operational level during the day when solar power generation is higher, and then, increasing their operation level to their maximum during the night. In this case, coal generation units will be forced to increase their load following operation levels (PSR and Moray (2018), Ministerio de Energía (2018e) and Bassi (2016)). For instance, in recent years, the coal generation unit *Guacolda 4* has increased dramatically its load following operation level due to solar energy penetration (Systep (2017a)). Fig. 3.1 shows the actual operation of the *Guacolda 4* unit during October 2017, where it's possible to observe that operates at its maximum power level during the night, and at its minimum operational level during the day when solar generation is higher.

An important consequence of higher cycling levels are the so called *cycling costs* that involves load following (ramping) costs, start-up and shutdown costs. Matus et al. (2017) estimates that start up and shutdown costs could represent 6% of total costs in the Chilean electricity system by 2035, in an scenario where wind and solar penetration represents a 49%.

- **The increase of renewable energy curtailment levels:** In the case of the Chilean electricity system, due to the technical restrictions of conventional generation units, it is expected that the curtailment level of renewable energy will increase as the penetration level of these technologies increase. In fact, minimum operation levels restrictions of coal generation units could produce a wind energy curtailment level of 11% by 2030 and of 18% by 2035 (Matus et al. (2017)) .

3.3 Flexibility Sources

Power system flexibility describes the ability of a system to adapt to the patterns of electricity generation and consumption in order to maintain the balance between supply and demand in a reliable cost-effective manner (IEA (2014)). Power system flexibility can be provided not only by the generation side, but also from some resources as storage, demand-side response and grid infrastructure. Given that the main topic of this study is related to the flexibility that the demand side of the electricity system can provide, this section will only analyse the operational flexibility that can be provided by the generation side, leaving demand-side flexibility analysis for the next chapter.

As it was explained in Section 3.1, solar and wind energy sources are not controllable. Hence, an analysis of generation-side flexibility is then reduced to flexibility of conventional power units, which greatly depends on their technical restrictions and operational costs.

In the following, we describe some technical characteristics that restrict the operation of conventional generation units. A more detailed discussion can be found in Silva (2018), where the author analyses the technical flexibility of thermal power plants in the current Chilean electricity grid, or in Gonzalez et al. (2018) where the authors make a review of the operational flexibility and emissions of gas and coal generation units.

- **Maximum power levels**: It defines the upper limit of electric power that a power generator can provide in safety conditions.
- **Minimum operating levels**: They define a power limit below which some plants cannot operate. This has direct implications in the dispatch and pricing system. With respect to this, Fischer and Serra (2003) analyses the proprieties of a standard peak-load pricing scheme in the presence of minimum operating levels, proposing a reward structure that lead to the correct short and long term operation.
- **Minimum operation times**: They define the minimum period for which generation units should be in operation before it can be turned off again (Gonzalez et al. (2018), Lambert et al. (2017)). This restriction can lead to some situations in which renewable energy is curtailed because the conventional generation unit cannot be turned off due to its minimum operation time restriction.
- **Minimum downtimes**: They are the minimum period of time that generation units should be out of operation before they can be turned on again (Gonzalez et al. (2018)). This implies that sometimes some generation units are not being turned off because they are going to be needed in a period of time shorter than their minimum downtime, forcing them to work at their minimum operation levels even if some lower cost generation unit is available causing possible renewable energy curtailment.
- **Start-up and shut-down costs**: They are the costs involved in turning on or off a power plant. Together they constitute the power plants *start-up/shutdown cycling cost*. As explained in Pérez-Arriaga and Batlle (2012), start-up and shutdown costs exists

due to components fatigue, and creep-related wear and tear which results in increased capital, maintenance and repair expenditures.

- **Load following (ramping) costs:** They are the capital replacement costs and maintenance costs related to load following (Van den Bergh and Delarue (2015)).

Is important to note that the total cost of cycling is not always well understood, as it is discussed in Van den Bergh and Delarue (2015). In fact, system operators might underestimate total cycling cost and only take start-up and shutdown costs when making unit commitment decisions, as it is currently the case in Chile (neglecting load following/ramping costs). According to Van den Bergh and Delarue (2015), start-up and shutdown costs could be only 10-20% of total cycling cost.

As both load following operation and start-up/shutdown cycling operation are expected to increase due to a higher renewable energy penetration level, in this thesis both start-up/shutdown and load following costs will be considered, even if currently the Chilean electricity System Operator does not take load following cost into account when making unit commitment decisions.

Chapter 4

Literature Review on Demand Response

Demand Response (DR) refers to the action of consumers time-shifting and/or reducing electricity consumption in response to a signal, usually in the form of a financial incentive. Also, the term *Demand Response* is used to refer to the mechanisms that encourage this behaviour. For instance, the incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardised (U.S. Department of Energy (2006)). In the context of electricity markets with regulated end-consumers that face a fixed regulated price (as is the case of Chile), without any Demand Response mechanism there would be no incentive for end-consumers to reduce their consumption during high wholesale prices, neither during other events identified by the system operator. Hence, it is important to understand this technique in order to analyse how to incorporate changes in the market rules and hence encourage demand-side participation.

This chapter first does an overview of the different types of loads involved in electricity consumption. It then does a literature review on how demand reduction or rescheduling affects end consumers' utility. Then two generic categories of Demand Response mechanisms or market models are described. Finally, this chapter ends with a review of studies on DR in the context of the Chilean electricity market.

4.1 Types of Electric Demand

According to Liu et al. (2015), electricity demand can be classified in 4 different types: *fixed*, *elastic*, *adjustable* and *shiftable* demand. Understanding this classification will allow a better design of Demand Response mechanisms. This section focuses on the definition and flexibility description of each type of demand, but it does not discusses about the cost involved in each demand type's management[1].

[1] See Section 4.2 for costs involved.

a) **Fixed demand:** A fixed demand is a demand that is not flexible and follows a fixed consumption baseline. This type of demand is important as it helps to give certainty about the actual overall demand profile, but it is not useful for a Demand Response mechanism.

b) **Elastic demand:** Considering *elasticity* as in the economic sense of *price elasticity of demand*[2], an elastic demand is a type of demand that it is expected to be reduced if the price of electricity increases. Following the definition made by Liu et al. (2015), an *elastic demand* would *exhibit a monotonically non-increasing curve on the price quantity function*[3]. With this definition, managing elastic demand would require a deep understanding of the actual price elasticity of electricity, which could eventually not be fixed in time. In fact, starting from the assumption that load responsiveness to prices differs across time periods, Wang et al. (2010) uses the idea of *Price Elasticity Matrices* to summarise in one matrix all time-period price influence on electricity.

   More discussion on elastic demand can be found in Bie et al. (2015) and Feuerriegel and Neumann (2014). Bie et al. develop a scheduling method considering (elastic) Demand Response, while Feuerriegel and Neumann do a literature review on how consumer react to electricity price changes, arguing that the integration of Demand Response techniques is closely linked with the reaction of consumers to price changes.

c) **Adjustable demand:** Similar to fixed demand, a consumer with adjustable demand has a preferred consumption profile, [4] but is willing to make adjustments at a cost (Liu et al. (2015), Feuerriegel and Neumann (2014)). Adjustments can be either on reduction of electric demand or on demand increment in a given time, which could either lead to or not lead to possible overall energy consumption curtailment (reduction).

   Understanding the difference between real-time demand change and overall demand curtailment is crucial to model adjustable Demand Response correctly. If we denote $\mathbf{D} = (D_1, ..., D_T)$ as the vector of baseline demand or preferred consumption profile over time, and $\mathbf{Q} = (Q_1, ..., Q_T)$ as the vector of the actual consumption, we can calculate $\mathbf{R} = (R_1, ..., R_T) = \mathbf{D} - \mathbf{Q}$ as the vector of demand reduction or increment in every time $t \in \{1, .., T\}$. With this notation R_t would reflect real-time demand change ($R_t > 0$ would mean demand reduction in time t, while $R_t < 0$ would mean demand increment in time t), whereas $R = \sum_{t=1}^{T} R_t$ would denote overall demand curtailment or overall demand increment, which refers to the total energy consumed.

d) **Shiftable demand:** Shiftable or deferrable demand is a type of demand that requires a *total amount of energy* to be delivered within a given time range and is flexible with regard to the time of delivery within that range (Liu et al. (2015), Feuerriegel and Neumann (2014)). Typical shiftable loads include electric vehicles (EV), thermal loads [5], industrial

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[2] Price elasticity of demand is the variation in demand in response to a variation in price.

[3] In Liu et al. (2015), the valuation of energy consumption is considered as a concave function (non-increasing marginal value) of the consumption, that can be either quadratic or linear.

[4] Examples of preferred consumption profile can be charging an electric vehicle or heating a space at a fixed power rate in a defined time window.

[5] See Example 4.1.1.

laundry facilities and sewage treatment plants[6,7]. An example of demand modelled as shiftable demand can be found in Papadaskalopoulos and Strbac (2016), Paola et al. (2015) and De Paola et al. (2016), where the authors do not consider a disutility incurred by the end consumer as long as restrictions of total energy E_{tot} consumed and maximum power input are fulfilled. For instance, electric vehicles with variable charging rate are examples of adjustable demand modelling without considering user disutility (Papadaskalopoulos and Strbac (2016))[8]. A similar approach is presented in Liu et al. (2015), where the authors consider a minimum power input restriction and do not consider costs faced by end consumers given that the total energy delivered remain unchanged. In Navarro et al. (2012), a load shifting algorithm is proposed to assess the potential peak reduction from demand side management strategies. Other models adding a *non-interrupted* constraint can be found in Siano and Sarno (2016) and Papadaskalopoulos and Strbac (2016), where the authors consider non-interruptible loads that can be shifted in pre-defined periods at a fixed power rate without affecting the user comfort settings[9].

An advantage of shiftable demand is that it requires no explicit valuation of the electricity, nor elasticity, and opens a possibility for consumers to respond to market prices and adjust their consumption pattern to reduce their payments.

Example 4.1.1. ***Thermal loads as thermal storage***

Thermal loads such as heating, ventilation, and air conditioning, as well as lightning are examples of adjustable demand (Papadaskalopoulos et al. (2013)). This is because, within certain limits, thermal loads can be considered as (thermal) storage systems (Siano and Sarno (2016)) and can be easily used in Demand Response programs. However, understanding thermal load behaviour requires good modelling of the thermodynamics involved[a]. Also, as some thermal loads need to maintain certain temperature, works like in Strbac et al. (1996) and Strbac and Kirschen (1999) insist in the importance of taking into account the ***load recovery effect*** *that happens before or after a load reduction period (if we reduce thermal demand now, it will eventually increase later). To tackle this challenge, Strbac et al. (1996) introduced a square matrix that describes the load redistribution of demand-side bidders, allowing to model all possible load redistribution patterns. Other contributions can be found in Wang et al. (2010) (using the time-dependent price elasticity matrices introduced in Section a) and Trovato et al. (2016),*

[6] An analysis of sewage treatment plants and other deferrable loads to mitigate the variability and randomness of wind power generation can be found in Papavasiliou and Oren (2008).

[7] In other literature, demand of washing machines are called *passive load* as it can be shifted without disturbing the normal behaviour of the household occupants (Navarro et al. (2012)).

[8] In Papadaskalopoulos and Strbac (2016), the authors consider smart charging electric vehicles (EV) that requires a total energy E_{tot} to be consumed within a certain time window T, restricted to a energy balance modelling, a minimum and maximum instantaneous battery state of charge $E^{min} \leq E_t \leq E^{max}$ and a maximum charging rate of the battery P^{max}.

[9] In Siano and Sarno (2016), the authors introduce a more complex model considering earliest starting and lastest ending time of a load. In Papadaskalopoulos and Strbac (2016), the authors consider sequences of phases occurring in a fixed order with fixed duration and at a fixed power rate, where the flexibility involves the deferability of these cycles up to a maximum delay limit set by the users.

where the authors introduce a model that explicitly incorporates the control of Thermostatic Controlled Loads (TCL) dynamics (e.g. refrigerators) and their load recovery pattern.

Also, some works in the literature refer to the benefits and potential usage of electrical heating for Demand Response programs. In particular, Darby (2018) discusses how electrical heating can respond to network conditions by storing energy and offering rapid-response ancillary services to the grid.

[a]See Siano and Sarno (2016) for a model of Heating Ventilation and Air Conditioning (HVAC) appliances, Zhang et al. (2014) for a physical model used to simulate load shapes of different electro-thermal technologies, and Good et al. (2015) for a domestic multi-energy model comprised of physically based space heating, domestic hot water (DHW), cooking and electrical appliance models.

4.2 End-consumer's Cost Function

An important aspect of electricity demand is the understanding of how the changes in electricity consumption patterns affect or benefit end consumers[10]. It is expected that this would depend on the type of demand involved and the type of Demand Response (Albadi and El-Saadany (2007)). Demand responses can be separated in two general actions: first, consumers can reduce their electricity consumption in certain periods (adjustable demand) without changing consumption patterns during the rest of the periods. This option would involve a temporary loss of comfort. Secondly, end consumers may respond shifting demand from a particular period to another. As it was discussed in the previous section, some authors (Papadaskalopoulos and Strbac (2016), Paola et al. (2015), De Paola et al. (2016), Siano and Sarno (2016)) consider that there might not be loss of comfort if shiftable demand is rescheduled keeping constant the total energy consumed. However, we think that this assumption is not realistic, as there might always arise some rescheduling cost. This rescheduling cost can be as simple as the *levelized cost of the technology*[11].

[10]There exist, however, growing evidence that the assumption that *people are economic actors* is inadequate when dealing with the complexities of energy-use within the home (McKenna et al. (2011)). For instance, McKenna et al. (2011) do a literature review of existing residential Demand Response projects, supporting the idea that the principal challenge in Demand Response is no longer the technology itself but rather its acceptance and use by the consumer. A further critic of this assumption is done in McKenna et al. (2017), where the authors propose a new conceptual framework to analyse this issue. Another discussion exist on how the end consumer respond, despite price tariffs (hence, utility function). For example, Wilhite and Ling (1995) presents results of a three-year investigation of the relationship between billing information and household energy consumption in Oslo, Norway. They show that more informative bills resulted in energy savings of about 10%. We will not do further literature review on this topic, however, we encourage the reader to do so.

[11]We use the concept from *Levelized cost of renewable energy*, which is the net cost to install a renewable energy system divided by its expected life-time energy output. In the context of a shiftable demand, the *levelized cost of the technology* would be the net cost to install the shiftable-demand technology (e.g. control and communication hardware) divided by its expected life-time energy usage.

4.2.1 Costs

a) **Adjustment cost:**

Following the notation introduced previously, if $\mathbf{D} = (D_1, ..., D_T)$ is the vector of baseline demand, $\mathbf{Q} = (Q_1, ..., Q_T)$ is the vector of the actual consumption and $\mathbf{R} = (R_1, ..., R_T) = \mathbf{D} - \mathbf{Q}$ is the vector of demand reduction or increment in every time $t \in \{1, .., T\}$, a common assumption for demand adjustment is that the cost incurred for a demand reduction or increment R_t in time t can be modelled with a cost or disutility function $C(R_t)$ that is continuous and convex with $C(0) = 0$ (Chen et al. (2010)[12], Yang et al. (2013), Liu et al. (2015), Xu et al. (2016), Yu and Hong (2017)). The convexity of the cost function usually comes from the assumption that consumers utility function is concave (i.e. consumer's marginal utility decreases with their energy consumption (Xu et al. (2016))). In particular, for an end consumer n, Chen et al. (2010) and Yu and Hong (2017) consider a cost function of the type

$$C_n(R) = \alpha_n \cdot R^2 + \beta_n \cdot R \tag{4.1}$$

where Chen et al. assume $\alpha_n > 0$ and $\beta_n \geq 0$, while Yu and Hong consider $\alpha_n > 0$ and $\beta_n > 0$. Both parameters are considered consumer dependent parameters and reflect the attitude of a consumer with respect to the provision of demand reduction; a greater value of α or β implies that a consumer holds a more conservative attitude towards providing demand reduction, and vice versa. It is a general agreement in the literature, that this utility function can be used both for demand adjustments in a particular time t, and for overall demand curtailment.

b) **Rescheduling cost:** It is very difficult to estimate the cost that might arise time-shifting a shiftable demand. However, in the upper limit, we can consider that an electric demand is a shiftable type of demand due to an storage technology (e.g. battery, thermal storage). In this case, a useful measure is the *Levelized Cost of Storage* (LCOS) (Pawel (2014), Jülch (2016), Belderbos and Delarue (2016)), which refers to the discounted cost of electricity per unit of discharged electricity due to the use of a storage technology. A general expression for the LCOS is (Jülch (2016))

$$LCOS = \frac{CAPEX + \sum_{t=1}^{t=n} \frac{A_t}{(1+\mathrm{i})^t}}{\sum_{t=1}^{t=n} \frac{W_t^{out}}{(1+\mathrm{i})^t}}, \tag{4.2}$$

where the capital expenditure (CAPEX) is added to the annual cost A_t of the storage system at each point of time t over the lifetime n of the storage, discounted with the interest rate i. This sum is divided by the sum of the annual energy outputs W_t^{out}, which is also discounted. A_t is composed of the operation cost $OPEX_t$ and the reinvestments in storage system components $CAPEX_t^{re}$ at the time t. At the end of the storage lifetime a recovery value R is included (See Jülch (2016) for further information[13].). With this

[12] Chen et al. (2010) even assume an increasing and strictly convex cost function

[13] In fact in the annual cost A_t, Jülch also considered a cost of electricity supply, which is determined by the electricity price c_{el} , multiplied with the annual electricity input W_{in}. However, for better comparison, Jülch did not consider this term in her calculations, hence, we neither consider it here.

definitions, $A_t = OPEX_t + CAPEX_t^{re} - R_t$. Jülch analysed different technologies and estimated that, among others, for 2030 the LCOS for Li-ion batteries at 365 cycles per year (daily operation) will decrease to between 0.93 and 0.244 [USD/kWh][14].

In Nguyen et al. (2013), an explicit cost for time-shifting electricity demand is introduced. According to Nguyen et al., if a customer n shifts a demand quantity x_n from t_0 to $t_0 + T_n$, then its utility ΔU_n derived from the consumption of this particular quantity generally changes as follows:

$$\Delta U_n^{t_0} + T_n = \Delta U_n^{t_0} \cdot \exp^{-r_n \cdot T_n} \tag{4.3}$$

Equation 4.3 implies that as customer n delays consumption, its utility decays exponentially given a discount rate r. Additionally, if consumption is delayed forever ($T_n \to +\infty$), the utility will be reduced to zero (i.e. $\Delta U_n^{t_0} + T_n \to 0$). This is the case of curtailment without recovery.

4.2.2 Time-dependent Utility Function

The cost incurred due to some energy reduction or increment could not be equal in every period. Hence, some authors consider time-dependent utility functions, where consumers may have different valuation of electricity consumption for different times. Examples of works in the literature introducing time dependent utility functions are Chen et al. (2010) and Liu et al. (2015), however both authors end up using the same utility function for every time on the numerical example sections.

4.2.3 Increasing/Decreasing Demand

Another characteristic of a Demand Response utility function is to value differently when demand increases than when demand decreases from a given consumption baseline. In particular, Liu et al. (2015) introduces a (user and time-dependent) convex deviation cost function that values differently demand reduction ($r_t > 0$) than demand increment ($r_t < 0$). Considering an end consumer n and $\mathbf{r_k}^+ = (r_1^+, ..., r_T^+)$ and $\mathbf{r}^- = (r_1^-, ..., r_T^-)$ as the vectors of demand increment and demand reduction respectively [15], Liu et al. use a quadratic function of the type $C_{n,t}(r_{n,t}^+, r_{n,t}^-) = \alpha_{n,t}^+ \cdot {r_{n,t}^+}^2 + \beta_{n,t}^+ \cdot |r_{n,t}^+| + \alpha_{n,t}^- \cdot {r_{n,t}^-}^2 + \beta_{n,t}^- \cdot |r_{n,t}^-|$. This type of utility function values differently demand reduction than demand increment, and also different in every moment of time. However, in the numerical example section, Liu et al. end up using an unique $\beta = \beta^+ = \beta^-$ for every time t. For the quadratic term, Liu et al. only drop out the time-dependent characteristic using different values for α^+ and α^-.

[14] Note that the LCOS dimension is cost per unit of (levelized) energy

[15] Fomally, r_t^+ can be defined as $r_t^+ = \left\{ \begin{array}{ll} r_t, & r_t < 0 \\ 0, & r_t \geq 0 \end{array} \right\}$, while r_t^- can be defined as $r_t^- = \left\{ \begin{array}{ll} r_t, & r_t > 0 \\ 0, & r_t \leq 0 \end{array} \right\}$. See Liu et al. (2015) for more details.

It is clear that a negative value of α^- would increase end consumer's utility for a demand increment. In particular, Yang et al. (2013) consider an utility function such as if the actual load is greater than the user's normal demand, the cost function becomes negative, meaning that the users are satisfied.

4.3 Market Models: Demand Response Mechanisms

Following the classification made in Albadi and El-Saadany (2007) and Braithwait and Eakin (2002)[16], DR mechanisms can be separated in two main categories: *Priced Based Programs* (PBP) and *Incentive-Based Programs* (IBP). PBP are generally related to prices for electricity consumption, whereas IBP are more related to payments for load reduction. The idea of demand-side bidding can be found in both categories: the difference is that in PBP mechanisms, bids are for electricity consumption, whereas in IBP mechanisms, bids are for load reduction. In the following, a description and deeper literature review on each type of these categories is done. For a comparison of the acceptability of different tariff structures in the UK, see Darby and Pisica (2013).

4.3.1 Priced Based Programs (PBP)

Priced Based Programs are mechanisms based on dynamic pricing rates in which electricity tariffs are not flat, so the electricity rates fluctuate sometimes following the real time cost of electricity, or other times some particular strategy in order to induce required aggregated electricity consumption. The most common examples of this type of priced based programs are Time-of-Use (TOU) pricing and Real-Time Pricing (RTP). With TOU, the system operator or utility companies can encourage consumers to shift their demand to off-peak hours by setting different prices during the day (Yang et al. (2013)). On the other hand, in a RTP scenario, prices are often updated hourly, reflecting the marginal cost of electricity (Braithwait and Eakin (2002)). This means that during a period of high wholesale prices, end consumers face high retail prices which provide an incentive to reduce their electricity consumption.

Examples of these types of programs have been implemented in Spain and in the UK. For the one hand, in Spain, since March 2014, there exist a RTP-type pricing program called *Voluntary Price for the Small Consumer (PVPC)*[17], in which every day the regulator updates the electricity prices based on the daily and intra-day market prices (Conde and Moreira (2015), OMIE (2018)). On the other hand, in the UK, TOU pricing for small consumers were first introduced in 1965, leading to important results in tems of growing the off-peak consumption (Hamidi et al. (2009)). Currently, in the UK exist the *Economy 7* tariff, which gives 7h of continuous low elecricity tariff (mostly overnight) to consumers (Hamidi et al. (2009), Warren (2014)). Another TOU program in the UK is the *Economy 10* tariff that provides 10h of low electricity tariff; usually 2h in the morning, 3h in the afternoon and 5h

[16]In Braithwait and Eakin (2002) a similar classification is made, but using different names.

[17]PVPC by its acronym in Spanish: *Precio Voluntario para el Pequeño Consumidor*

overnight (Hamidi et al. (2009)). See Grünewald et al. (2015) for a review of the benefits of TOU tariffs in high wind scenarios in the UK.

A general challenge in this type of programs is to properly know each end consumer's value of electricity consumption over time, and hence, their response (Kirschen (2003)). However, using certain market mechanism, it is possible to incentive end consumer to reveal their private information through properly designed mechanisms (Xu et al. (2016)). In Yang et al. (2013), a game-theoretic approach to optimise Time-of-Use (TOU) pricing strategies is proposed to increase social welfare. In the model, the utility company sets the electricity prices, and end consumers respond to the price by adjusting the amount of electricity they use. In the second part of Chen et al. (2010) a RTP mechanism is introduced, in which end consumers can shift their demand accordingly and strategically. In another work, Papadaskalopoulos et al. (2011) present a TOU-type decentralised day-ahead market mechanism in which each market participant calculates its own optimal consumption level and bid for electricity demand given the market prices. In this model, bids made by end consumers are vectors of electricity demand for all hours of the market horizon (e.g. following day) and the central planner updates the prices based on the bids of the market participants. This involves an iterative process to achieve optimality. However, it has been criticised that this iterative process proposed may not converge (Liu et al. (2015)). Other works involve price-responsive appliances that can schedule their own power consumption on the basis of an electricity price signal received from a central entity (De Paola et al. (2016), Paola et al. (2015)). Following these works, Paola et al. (2018) reduce the computational complexity of the coordination of the large population of appliances by clustering the devices.

The concept of *demand aggregators* is also introduced. For example, in Yu and Hong (2016), a one leader, N-followers Stackelberg game is introduced, in which end consumers are aggregated by a single virtual retailer or demand aggregator that offer real-time *virtual retail prices*. In the paper, demand aggregators observe RTPs from a central entity and manage end consumers' response by offering them *virtual retail prices* based on the identified best-response strategies of the end-consumers.

4.3.2 Incentive-Based Programs (IBP)

On the other hand, incentive-based programs rely on contractual arrangements designed by policy-makers to elicit demand reductions from consumers when it is needed (U.S. Department of Energy (2006), Yu and Hong (2017)). The design of this types of programs requires to understand end consumers' competences and preferences. In Martinez and Rudnick (2013), *discrete preferences models* are used to properly design incentive programs and schemes to manage demand. Following the notation introduced by Albadi and El-Saadany (2007) and Braithwait and Eakin (2002), IBPs can be classified in *interruptible/curtailable* programs and *market based IBP* programs.

- **Interruptible/curtailable programs:** In this more traditional or classical Demand Response mechanism, the system operator, utilities or demand aggregators remotely manage the loads and end users receive payments for their participation in the programs, and eventually for their performance (Braithwait and Eakin (2002)).

- **Market-based programs:** In market-based programs, payments are offered for end users' performance depending on their amount of load reduction or reschedule. A typical example of market-based programs is *demand bidding* that allows end consumers or their aggregator to bid load reductions into day-ahead or hour-ahead wholesale energy markets. The load reductions are then scheduled and dispatched in a manner similar to the scheduling and dispatch of generators. (Braithwait and Eakin (2002), Albadi and El-Saadany (2007)). In Xu et al. (2016) a uniform-price market mechanism is introduced, where every end consumer submits a single bid for demand reduction. The required amount of load adjustment is covered by several end consumers offering demand reduction. In this work, each agent acts strategically and the monetary reward incentives consumers to reveal their private information. In order to achieve a Nash equilibrium, it is needed the total capacity limit (for demand reduction) to be much larger than the total amount of load to be adjusted. In a similar approach, Chen et al. (2010) propose in the first part of the paper a supply function bidding scheme for allocating load reduction among different end consumers. In this paper, every end consumer submits a parameterised "energy reduction supply" function to a central entity which finally decides a market clearing price based on the bids of end consumers. The authors argue that in a competitive market where consumers are price taking, the system achieves an efficient equilibrium that maximises social welfare. Also, some works as in Yu and Hong (2017) propose the use of *demand aggregators*, where a three hierarchical level market is proposed: a grid operator (GO), multiple demand aggregators and corresponding end consumers. In this paper, the GO first posts an incentive for aggregated demand reduction to aggregators, who then participate in a sub-program, offering incentives to enrolled end consumers to achieve the desired demand reduction following a Stackelberg game approach. This model is very similar than the one presented in Yu and Hong (2016) (PBP mechanism), however, instead of offering prices for electricity consumption, here, the prices are for load reduction.

Example 4.3.1. ***The PJM's Demand Response program:***

As analysed by Walawalkar et al. (2008), the Pennsylvania-New Jersey-Maryland Interconnection (PJM) has implemented an (Economic)[a] *Demand Response Program, in which the operator pays the Locational Marginal Price (LMP) for unit of energy reduction to customers if the LMP in a given zone is above a trigger point (set by PJM at 75 USD/MWh during 2006). PJM offers this DR program in both its day-ahead and real-time markets. Hence, market participants can decide whether to bid a demand reduction into the market, and then decide what kind of DR supply curve to bid into the market.*

[a] *Economic* is the name for the Demand Response program

4.4 Demand Response and the Chilean Electricity Market

Currently, the available literature about the incorporation of demand-side flexibility in the Chilean electricity market is very limited[18]. The first studies that used these concepts for the Chilean context were Martinez and Rudnick (2012) and Morales et al. (2015). On one hand, Martinez and Rudnick (2012) review strategies, challenges and opportunities of incorporating Demand Response programs in emerging countries, with an emphasis on designs for Latin America (particularly on Brazil, Colombia and Chile). On the other hand, Morales et al. (2015) discuss the possible participation of the mining industry in this type of mechanisms. More recently, Flores (2015) and Inzunza et al. (2016) incorporated demand-side flexibility in electricity planning studies for Chile. In both works, a fixed fraction of total demand is considered as a shiftable demand that needs to keep constant the overall energy consumption in a 24 hours period. A cost function as in Liu et al. (2015) (but only linear, however) is introduced, valuing differently reduction and increment of energy. In the numerical examples, Flores (2015) considers[19] $\beta^- = 2$ USD/MWh and $\beta^+ = 1$ USD/MWh. Inzunza et al. (2016) considers $\beta^- = \beta^+ = 0$. With respect to the fraction of flexible demand, Flores (2015) considers a fixed percentage of shiftable demand (5%). Inzunza et al. (2016) assess the impact of 0, 200 and 400 MW of shiftable demand in portfolio risk and total operational costs.

In particular, none of these studies do a sensibility analysis of the flexibility cost. And to our knowledge, there are no studies that analyses the impact of the incorporation of demand-side flexibility on renewable energy curtailment, the cycling level of conventional power plants, or the total green house gases emissions in the Chilean electricity market

[18] This section discusses the available academic literature available on DR in the Chilean electricity market. For current policies on renewable energy integration see Section 2.4, where the current government's proposal for ancillary services regulation is described (See Section 2.5 for a discussion).

[19] Here, we follow the notation introduced in Liu et al. (2015) and further used in section 4.2

Chapter 5

The Model

In order to assess the benefits that the incorporation of demand flexibility could provide to Chilean electricity market, we propose a model where the electricity demand is considered to be both adjustable and flexible, and hence, it becomes an active actor of the system. We consider the case in which the demand incurs a cost for providing flexibility to the system. Then we analyse the impacts and benefits of this incorporation for the rest of the electricity system.

This chapter describes the incorporation of demand flexibility within a deterministic Demand Response Unit Commitment model (DR-UC), formulated as a mixed-integer nonlinear program (MINLP). The DR-UC model determines the optimal Demand Response and optimal scheduling of a given set of power plants to meet a nationwide electricity demand. It considers a one-bus system with 5 generation technologies (Water reservoir, run-of-the-river, wind, solar and thermal), different power plants' technical restrictions and renewable energy availability. We also model a general type of flexible demand that comprises both adjustable and shiftable type of demand[1]. In order to do this, the model uses a two-part disutility function that allows to assess both the amount of real-time load adjustments and the amount of one-day overall energy demand curtailment[2].

5.1 Overview

Let's consider a time horizon T indexed by [3] $t \in \mathcal{T}$, a vector of aggregated baseline electricity demand $\mathbf{D} = (D_1, ..., D_T) \in \mathbb{R}_+$ and a set $\mathcal{G}$ of generators. Let's also consider the 5 following disjoints subsets of generation technologies: the subset $\mathcal{G}_T$ of thermal power plants; the subset $\mathcal{G}_D$ of hydro reservoirs (dams); the subset $\mathcal{G}_{RoR}$ of run-of-the-river plants; the subset $\mathcal{G}_S$ of solar power plants and the subset $\mathcal{G}_W$ of wind power plants. Here $\mathcal{G} = \mathcal{G}_T \cup \mathcal{G}_D \cup \mathcal{G}_{RoR} \cup \mathcal{G}_S \cup \mathcal{G}_W$.

[1] See section 4.1.

[2] As explained in Section 4.1.c, if $\mathbf{D}$ is the vector of baseline demand, $\mathbf{Q}$ is the vector of actual consumption, and $\mathbf{R} = \mathbf{D} - \mathbf{Q}$ is the vector of demand reduction or increment, then, R_t would denote a real time demand adjustment, whereas $R = \sum_{t=1}^{T}(R_t)$ would denote overall e demand curtailment, which refers to the total energy consumed

[3] Here, every $t \in \mathcal{T}$ can represent an entire hour, half an hour or a day.

A full description of the nomenclature used in this model can be found in the *Nomenclature* section at the end of this document, before the Bibliography section.

5.2 Responsive Demand

In the following, we consider a novel two-part quadratic disutility function that values both the amount of real-time load adjustments and the amount of overall demand curtailment.

Given the vector of aggregated baseline electricity demand $\mathbf{D}$ previously introduced, if $\mathbf{Q} = (Q_1, ..., Q_T)$ is the vector of final consumption, we define the Demand Response vector $\mathbf{R} = (R_1, ..., R_T) = (\mathbf{D} - \mathbf{Q}) \in \mathbb{R}$. Hence, for every $t \in \mathcal{T}$, R_t denotes a real-time demand reduction or increment in time t ($R_t > 0$ indicates a demand reduction of R_t units during time t when $Q_t < D_t$, while $R_t < 0$ indicates a demand increment in $|R_t|$ units in time t when $Q_t > D_t$). Also, let's consider a set $\mathcal{D}$ of days within the $\mathcal{T}$ time horizon and the set $\mathcal{T}_\mathrm{d} \subseteq \mathcal{T}$ of time units (e.g. hours) within a day $\mathrm{d} \in \mathcal{D}$, so $\mathcal{T} = \bigcup_{\mathrm{d} \in \mathcal{D}} \mathcal{T}_\mathrm{d}$. With this definitions, the proposed Demand Response disutility function $C_{DR}(\mathbf{R})$ is modelled as the following:

$$C_{DR}(\mathbf{R}) = \underbrace{\sum_{t \in \mathcal{T}} \Big(\alpha_a \cdot R_t^2 + \beta_a \cdot |R_t| \Big)}_{Adj.} + \underbrace{\sum_{\mathrm{d} \in \mathcal{D}} \left\{ \alpha_c \cdot \left(\sum_{t \in \mathcal{T}_\mathrm{d}} R_t \right)^2 + \beta_c \cdot \left(\sum_{t \in \mathcal{T}_\mathrm{d}} R_t \right) \right\}}_{Curt.} \tag{5.1}$$

The proposed function in eq. (5.1) is composed mainly by two parts. On the one hand, the first term (*Adj.*) corresponds to a quadratic *adjustment cost*, that depends on the real-time demand adjustment R_t. As in Liu et al. (2015) and Flores (2015), the absolute value term values both demand increment and demand reduction. However, for simplicity we assume that the incurred cost is the same for demand increment and for demand reduction. On the other hand, the second term (*Curt.*) corresponds to a quadratic *curtailment cost*, that depends on the overall energy reduced within a specific day. Be aware that rather than incorporating a restriction on the total amount of energy to be consumed within a day, we allow the total energy consumed to be reduced at a quadratic cost that depends on α_c and β_c. We assume that the total aggregated demand $\mathbf{D}$ provides flexibility at the cost introduced in eq. (5.1). Hence, we do not consider a cost of lost load[4]. Also, the disutility function's parameters α_a, β_a, α_c and β_c are supposed to be representative of the aggregated flexible demand, and not representative of a particular end consumer.

The proposed two-parts disutility function is a versatile formulation that allows to model simultaneously adjustable and shiftable demand. In the following, we describe three different

[4]In fact, in the current literature is common to find that only a fraction θ of demand is considered to be flexible at a given cost. For example, Flores (2015) considers a fraction $\theta = 0.05$ (5%) of the total demand to be shiftable at a linear cost. However, later he needs to introduce a cost of lost load that values the adjustment cost of the rest of the demand (the inflexible 95% of the demand). We think that with a quadratic term in the cost function, we can provide a more general, compact and realistic expression of the cost involved in demand management.

case studies that can be assessed using eq. (5.1): a) only shiftable demand, b) only adjustable demand and c) mixture of technologies.

a) **Only shiftable demand:** Using

$$\alpha_c = \beta_c = +\infty, \quad \alpha_a, \beta_a \geq 0,$$

the total amount of energy curtailed within a day becomes infinitely expensive, which is analogue to a restriction of the type ($s.t. \sum_{t \in \mathcal{T}_{\mathrm{d}}} R_t = 0, \quad \forall \mathrm{d} \in \mathcal{D}$ as in Inzunza et al. (2016), Flores (2015), Papadaskalopoulos and Strbac (2016), Paola et al. (2015), De Paola et al. (2016) and Siano and Sarno (2016)). Here, demand can be shifted within the same day at a shiftable cost $\sum_{t \in \mathcal{T}} (\alpha_a \cdot R_t^2 + \beta_a \cdot |R_t|)$, but the total energy must remain constant.

b) **Only adjustable demand:** Using

$$\alpha_c = \beta_c = 0, \quad \alpha_a, \beta_a \geq 0$$

the only cost involved in the demand management becomes the adjustment cost. Hence, only real-time adjustment is valued, regardless of the total amount of energy consumed within the day. This is the case of demand curtailment cost used in Walawalkar et al. (2008), Chen et al. (2010), Yang et al. (2013), Liu et al. (2015), Xu et al. (2016) and Yu and Hong (2017).

c) **Mixture of technologies:** Finally, using

$$\alpha_c, \beta_c > 0, \quad \alpha_a, \beta_a \geq 0,$$

a mixture of both cases is considered, which is a more realistic assumption as in a nation-wide electricity system every type of demand is expected to be found.

5.3 Generators' Costs

In this section we introduce the costs involved in electricity generation. In particular, and as it was discussed in Chapter 3, we consider three aspects of the total *generators' operational costs*: a) *generation costs*, b) *start-up and shut-down costs (on/off costs)* and c) *load following (ramping) costs*. In the following we describe this three components for a given generation unit $g \in \mathcal{G}$ with a variable cost c_g^v, start-up cost c_g^{on}, shut-down cost c_g^{off}, ramping cost c_g^{ramp} and maximum power level P_g^{max}. We consider the decision variables, $P_{g,t} \in \mathbb{R}_+$, $ON_{g,t} \in \{0,1\}$ and $OFF_{g,t} \in \{0,1\}$. $P_{g,t}$ is the amount of power at which the generation unit g is operating in time t. The binary variables $ON_{g,t} \in \{0,1\}$ and $OFF_{g,t} \in \{0,1\}$ indicate if the generation unit g is turned on or off in time t ($ON_{g,t} = 1$ means that the generation unit is turned on in time t, while $OFF_{g,t} = 1$ means that the generation unit is turned off in time t; otherwise these variables are equal to 0. See eq. (5.14) for the formal definitions of these state variables.)

a) **Generation cost $C_{g,t}^{gen}$:**

$$C_{g,t}^{gen} = c_g^v \cdot P_{g,t} \tag{5.2}$$

b) **Start-up and shut-down cost (on/off cost)** $C_{g,t}^{on/off}$**:**

$$C_{g,t}^{on/off} = c_g^{on} \cdot ON_{g,t} + c_g^{off} \cdot OFF_{g,t} \tag{5.3}$$

c) **Load following (ramping) cost** $C_{g,t}^{ramp}$**:** Given operational levels $P_{g,t}$ and start-up and shut-down state variables $ON_{g,t} \in \{0,1\}$ and $OFF_{g,t} \in \{0,1\}$, the load following or ramping cost is defined in the following equations[5]:

$$C_{g,t}^{ramp} \geq c_g^{ramp} \cdot (P_{g,t} - P_{g,t-1} - ON_{g,t} \cdot P_g^{max}) \tag{5.4}$$

$$C_{g,t}^{ramp} \geq c_g^{ramp} \cdot (P_{g,t-1} - P_{g,t} - OFF_{g,t} \cdot P_g^{max}) \tag{5.5}$$

The parameter P^{max} in eqs. (5.4) and (5.4) forces the load following cost to be zero if a generation unit is started up or shut down, because in these situations, the ramping cost is already incorporated in the start-up or shut-down cost (Van den Bergh and Delarue (2015)).

With the previous definitions, given the operational variables $P_{g,t}$, $ON_{g,t}$ and $OFF_{g,t}$, the total operational cost $C_{g,t}^{total}$ of generator $g \in \mathcal{G}$ at time $t \in \mathcal{T}$ becomes:

$$C_{g,t}^{total}(P_{g,t}, ON_{g,t}, OFF_{g,t}) = C_{g,t}^{gen} + C_{g,t}^{on/off} + C_{g,t}^{ramp} \tag{5.6}$$

where $C_{g,t}^{gen}$, $C_{g,t}^{on/off}$ and $C_{g,t}^{ramp}$ are as in eqs. (5.2), (5.3) and (5.4)-(5.5) respectively.

5.4 Objective Function

The objective function seeks to minimze the sum of generators' operational costs and Demand Response costs for the total time horizon.

$$\min_{\{P_{g,t}, u_{g,t}, R_t\}_{t\in\mathcal{T}, g\in\mathcal{G}}} \quad C_{DR}(\mathbf{R}) + \sum_{t\in\mathcal{T}} \sum_{g\in\mathcal{G}} C_{g,t}^{total}(P_{g,t}, ON_{g,t}, OFF_{g,t}) \tag{5.7}$$

Where C_{DR} is as in eq. (5.1) and $C_{g,t}$ as in eq. (5.6). Here, the decision variables are:

- $P_{g,t} \in \mathbb{R}_+$: Operational level of each generation unit $g \in \mathcal{G}$ at every time $t \in \mathcal{T}$.
- $u_{g,t} \in \{0,1\}$: Binary state variable of each generation unit $g \in \mathcal{G}$ at every time $t \in \mathcal{T}$. This variable is equal to 1 ($u_{g,t} = 1$) if the generation unit $g \in \mathcal{G}$ is on at time $t \in \mathcal{T}$. Otherwise, is equal to 0.
- $R_t \in \mathbb{R}$: Aggregated demand reduction or demand increment at time $t \in \mathcal{T}$.

[5]In fact, a more strict definition could be $C_{g,t}^{ramp} = c_g^{ramp} \cdot \max\{(P_{g,t} - P_{g,t-1} - ON_{g,t} \cdot P_g^{max}), (P_{g,t-1} - P_{g,t} - OFF_{g,t} \cdot P_g^{max})\}$, however as the objective function minimises $C_{g,t}^{ramp}$, eqs. (5.4)-(5.5) are enough to correctly define $C_{g,t}^{ramp}$.

5.5 Model Constraints

The solution must meet several technical constraints. For those constraints related to generation units, we follow the constraints for a unit commitment optimisation problem presented in Llaitul (2017).

5.5.1 General Constraints

- **Power balance**: At any time, the total power generated must be equal to the actual aggregated electricity consumption Q_t, which is equal to the aggregated baseline demand D_t minus the aggregated demand reduction or increment R_t.

$$\sum_{g \in \mathcal{G}} P_{g,t} = (D_t - R_t), \quad \forall t \in \mathcal{T} \tag{5.8}$$

- **Demand Response constraints**: We assume that the responsive demand cannot reduce its consumption at a lower level than its original baseline. Hence:

$$R_t \leq D_t, \quad \forall t \in \mathcal{T} \tag{5.9}$$

  Also, we assume that the responsive demand cannot increase its consumption in a higher level than its original baseline:

$$R_t \geq -D_t, \quad \forall t \in \mathcal{T} \tag{5.10}$$

- **Online units state variable:** As it was already anticipated in the previous section, the state variable $u_{g,t}$ must be binary in order to denote the state of the unit.

$$u_{g,t} \in \{0, 1\}, \quad \forall t \in \mathcal{T}, \forall g \in \mathcal{G} \tag{5.11}$$

  If the generation unit g is on in time t, then $u_{g,t} = 1$, otherwise, $u_{g,t} = 0$.

- **Start-up and shut-down state variables:** Given the binary state variables $u_{g,t}$, we define the binary variables $ON_{g,t}$ and $OFF_{g,t}$ to identify if a generation unit $g \in \mathcal{G}$ has been turned on or off in time $t \in \mathcal{T}$.

$$ON_{g,t} \in \{0, 1\}, \quad \forall t \in \mathcal{T}, \forall g \in \mathcal{G} \tag{5.12}$$

$$OFF_{g,t} \in \{0, 1\}, \quad \forall t \in \mathcal{T}, \forall g \in \mathcal{G} \tag{5.13}$$

$$u_{g,t} = u_{g,t-1} + ON_{g,t} - OFF_{g,t}, \quad \forall t \in \mathcal{T}, \forall g \in \mathcal{G} \tag{5.14}$$

5.5.2 Thermal Generators

We consider that, apart from the maximum operational level P_g^{max}, every thermal generator $g \in \mathcal{G}_T$ has a minimum operation time τ_g^{on}, minimum downtime τ_g^{off}, maximum up ramp rate ρ_g^{up} and maximum down ramp rate ρ_g^{down}. Hence, the operation constraints particular for thermal generators are modelled as the following:

- **Minimum and maximum power levels:**

$$P_g^{min} \cdot u_{g,t} \leq P_{g,t}, \quad \forall t \in \mathcal{T}, \forall g \in \mathcal{G}_T \tag{5.15}$$

$$P_{g,t} \leq P_g^{max} \cdot u_{g,t}, \quad \forall t \in \mathcal{T}, \forall g \in \mathcal{G}_T \tag{5.16}$$

These constraints impose the power level to be equal to 0 if the generation unit is off ($u_{g,t} = 0$)

- **Minimum operation times:**

$$\sum_{\tau=1}^{t} ON_{g,\tau} \leq u_{g,t}, \quad t \leq \tau_g^{on} \in \mathcal{T}, \quad \forall g \in \mathcal{G}_T \tag{5.17}$$

$$\sum_{\tau=t-\tau_g^{on}}^{t} ON_{g,\tau} \leq u_{g,t}, \quad t > \tau_g^{on} \in \mathcal{T}, \quad \forall g \in \mathcal{G}_T \tag{5.18}$$

- **Minimum downtimes:**

$$\sum_{\tau=1}^{t} OFF_{g,\tau} \leq 1 - u_{g,t}, \quad t \leq \tau_g^{off} \in \mathcal{T}, \quad \forall g \in \mathcal{G}_T \tag{5.19}$$

$$\sum_{\tau=t-\tau_g^{off}}^{t} OFF_{g,\tau} \leq 1 - u_{g,t}, \quad t > \tau_g^{off} \in \mathcal{T}, \quad \forall g \in \mathcal{G}_T \tag{5.20}$$

- **Ramp rate limits:**

$$P_{g,t} - P_{g,(t-1)} \leq \rho_g^{up}, \quad t > 1 \in \mathcal{T}, \quad \forall g \in \mathcal{G}_T \tag{5.21}$$

$$P_{g,t-1} - P_{g,t} \leq \rho_g^{\text{down}}, \quad t > 1 \in \mathcal{T}, \quad \forall g \in \mathcal{G}_T \tag{5.22}$$

Here we assume that ramp rate limits are always higher than the minimum power level ($\rho_g^{up}, \rho_g^{\text{down}} \geq P_g^{min}, \quad \forall g \in \mathcal{G}_T$) otherwise, thermal power plants could never be turned on or off.

5.5.3 Hydro Reservoirs

We consider that, apart from their maximum power capacity P_g^{max}, every hydro reservoir $g \in \mathcal{G}_D$ has an efficiency factor η_g, a minimum volume level V_g^{min} and an initial volume level for time $t = 0$, $V_{g,0} \geq V_g^{min}$. Also, for every hydro reservoir $g \in \mathcal{G}_D$ we consider a known vector of water inflow $\mathbf{Q}_g^{in} = (Q_{g,1}^{\text{in}}, ..., Q_{g,T}^{\text{in}})$. We consider that hydro reservoirs do not have minimum operational levels, neither ramp rate limits. We model the following restrictions in order to optimise the use of the water inflow and stored energy. The restrictions are the following:

- **Positive operational level:**

$$0 \leq P_{g,t}, \quad \forall t \in \mathcal{T}, \quad \forall g \in \mathcal{G}_D \tag{5.23}$$

- **Maximum power level:**

$$P_{g,t} \leq P_g^{max}, \quad \forall t \in \mathcal{T}, \quad \forall g \in \mathcal{G}_D \tag{5.24}$$

- **Water inflow and stored water:** Given a efficiency factor η_g, if the water reservoir uses an outflow Q^{out} in its turbines, it generates then a power equal to $P_{g,t} = \eta_g \cdot Q^{out}$. Hence, we can write the outflow in terms of the power level ($Q^{out} = \frac{P_{g,t}}{\eta_g}$), and the equation of state becomes.

$$V_{g,t} = V_{g,(t-1)} + Q^{\text{in}}_{g,t} - \frac{P_{g,t}}{\eta_g}, \quad \forall t \in \mathcal{T}, \quad \forall g \in \mathcal{G}_D \tag{5.25}$$

- **Minimum stored energy:** We impose that the reservoir's stored water cannot be lower than its minimum volume level.

$$V_{g,t} \geq V_g^{min}, \quad \forall t \in \mathcal{T}, \quad \forall g \in \mathcal{G}_D \tag{5.26}$$

- **Final stored energy:** Finally, we impose that at the end of the time horizon, the stored energy must be at least equal to the initial stored energy level.

$$V_{g,T} \geq V_{g,0}, \quad \forall g \in \mathcal{G}_D \tag{5.27}$$

Note that there there is no valuation of stored water for any time after $t = T$. Given restriction (5.27), all hydro resources from $\mathbf{Q}_g^{in}$ are completely available for its usage during the time horizon. This is because this model is for short term operation optimisation, and hence it is needed to be inserted in a long-term planning problem in order to calculate the future value of stored water (See Section 6.5 for Limitations).

The units here are $[hm^3]$ (hectometre) for $V_{g,t}$ and $[hm^3/h]$ (hectometre per hour) for $Q_{g,t}$.

5.5.4 Run-of-the-river

We consider that run-of-the-river generation units do not have storage capacity. Given a known vector of water inflow $\mathbf{Q}_g^{in} = (Q^{\text{in}}_{g,1}, ..., Q^{\text{in}}_{g,T})$ and a efficiency factor η_g, the restrictions are:

- **Positive power level:**

$$0 \leq P_{g,t}, \quad \forall t \in \mathcal{T}, \quad \forall g \in \mathcal{G}_{RoR} \tag{5.28}$$

- **Maximum power level:**

$$P_{g,t} \leq P_g^{max}, \quad \forall t \in \mathcal{T}, \quad \forall g \in \mathcal{G}_{RoR} \tag{5.29}$$

- **Inflow restriction:**

$$P_{g,t} \leq \eta_g \cdot Q^{\text{in}}_{g,t}, \quad \forall t \in \mathcal{T}, \quad \forall g \in \mathcal{G}_{RoR} \tag{5.30}$$

5.5.5 Solar and Wind Generators

For a solar or wind generator $g \in \mathcal{G}_S \cup \mathcal{G}_W$, we consider an installed capacity P_g^{inst} and known normalised availability vector $\mathbf{P}_g^{avail} = (P_{g,1}^{avail}, ..., P_{g,T}^{avail})$.

- **Positive power level:**

$$P_{g,t} \geq 0, \quad \forall t \in \mathcal{T}, \quad \forall g \in \mathcal{G}_S \cup \mathcal{G}_W \tag{5.31}$$

- **Maximum power level:**

$$P_{g,t} \leq P_{g,t}^{avail} \cdot P_g^{\text{inst}}, \quad \forall t \in \mathcal{T}, \quad \forall g \in \mathcal{G}_S \cup \mathcal{G}_W \tag{5.32}$$

Chapter 6

Methodology

In order to assess the impact of the incorporation of demand flexibility in the Chilean electricity market, this study simulates the operation of the Chilean electricity system using the 3 different versions of the model presented in the previous chapter[1] for 2 different scenarios in the year 2035 and for 2 different hydrologic situations (a humid and a dry year). In order to do this, this study considers part of the results of the *Long Term Energy Planning (PELP)*[2] study (Matus et al. (2017), Ministerio de Energía (2018e)) and historical data from the *Energy Center of the Mathematical and Physical Sciences Faculty at Universidad de Chile*. Also, some assumptions and simplifications were taken into account. This chapter first explains where and how the input data was taken, and it describes the assumptions and simplifications used. Then, this chapter describes the case studies used for the simulations, as well as an illustrative example of the model. This chapter ends with the limitations of this work.

6.1 Input Data

To build its test cases, this study consider part of the results of the *Long term energy planning (PELP)* study (Matus et al. (2017), Ministerio de Energía (2018e)), specifically the electricity demand and installed capacity results. The PELP study was carried out by the Chilean Ministry of Energy and optimised the long-term investment of different electricity technologies for a 30-years horizon of the Chilean electricity system considering 5 different energy scenarios and 4 different hydrological situations. The results of the PELP study are publicly available in the study's website[3] and they consist of demand profile projections, optimal installed capacities, as well as simulations of one-year hourly operations of the national system. An important feature of the PELP study is that the installed capacities results are available at a single power plant resolution. Also, demand projections are available at an hourly resolution. The available information at the PELP study's website include all the

[1]Only shiftable demand, only adjustable demand and a mixture of technologies.

[2]PELP by its acronym in Spanish: *Planificación Energética de Largo Plazo*

[3]See http://pelp.minenergia.cl

Scenario	**A**	**B**	**C**	**D**	**E**
Social opposition for projects.	high	low	high	medium	medium
Energy demand.	low	high	medium	low	high
Battery storage development.	high	low	medium	medium	high
Environmental externalities costs.	as today	higher	as today	as today	higher
Renewable technology costs.	low	low	medium	high	low
Fossil fuels costs.	medium	high	low	low	high

Table 6.1: Scenarios considered in the PELP study. Source: Matus et al. (2017)

relevant technical characteristics of the power plants considered. Hence, the PELP study and its results, become ideal to build case studies in order to evaluate the impact of the incorporation of demand side flexibility.

With regard to the resource availability for hydro (water inflow), wind (wind velocity) and solar (solar irradiation) power plants, the present study takes data from *Energy Center of the Mathematical and Physical Sciences Faculty at Universidad de Chile* [4] considering statistical data to build 2 different hydrologic conditions: a humid and a dry year. Also in this study we follow the methodology used in Llaitul (2017), where the author reduces the problem dimension by grouping run-of-the-river plants in 8 different *hydrological zones*. A similar technique is used with solar and wind power plants, grouping them in 4 different solar and wind zones respectively. The following is an explanation of this methods:

6.1.1 Energy Scenarios

Four different criteria were taken into account to build different scenarios in the PELP study. These criteria were: social opposition for projects, energy demand projection, battery storage development, environmental externalities cost, renewable technology costs and fossil fuel cost. Depending on their level (high, medium, low), the PELP study built 5 different scenarios, as shown in Table 6.1[5].

From the 5 different scenarios used in the PELP study, this study considers *scenario D* and *scenario E*. This is because these scenarios are opposite in terms of renewable energy integration. In fact, while scenario D considers a high cost for renewable technologies and low cost for fossil fuels, scenario E considers the opposite. The same for the environmental externalities cost. This allows us to assess the value of demand flexibility integration in two opposite scenarios in terms of renewable energy integration in Chile. Table 6.2 shows values of fossil fuel costs and demand projections considered for scenarios D and E[6]. Load duration curves describing demand electricity demand projections are shown in Fig. 6.1.

[4]For more information about the Energy Center, visit http://centroenergia.cl/en/quienes-somos/

[5]We encourage the reader to see a detailed explanation of the PELP study's energy scenarios in the available literature (Matus et al. (2017), Ministerio de Energía (2018e)).

[6]In Table 6.2, the USD value is fixed at the year 2016.

Scenario		D	E
Fossil fuel costs			
Coal	[USD/ton]	67.1	96.6
Gas	[USD/MMBtu]	8	11.7
Diesel	[USD/m^3]	587.2	961.3
Demand			
Total energy per year	[TWh]	118.2	145.4
Maximum power	[GW]	16.9	20.8

Table 6.2: Fossil fuel costs and demand projections for scenarios D and E in 2035. Source: Ministerio de Energía (2017b)

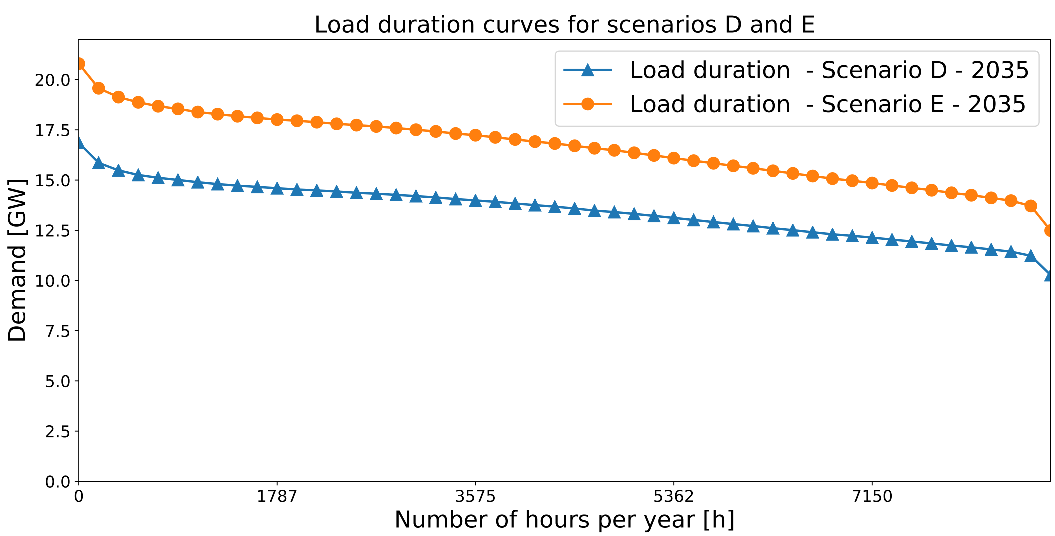


Figure 6.1: Load duration curves for scenarios D and E in 2035. Elaborated by the author using data from Matus et al. (2017) and Ministerio de Energía (2018e).

6.1.2 Installed Capacities:

Installed capacities were also taken from the results of scenarios D and E. This was done in order to build the test cases of the current study. For simplicity, and in order to adapt the input data to the model, we just considered solar, wind, run-of-the-river, hydro reservoirs, gas, diesel and coal power plants[7]. We consider that this simplification is consistent with the importance of these technologies in comparison with the rest. In fact, the installed capacity of these technologies were 97 and 95 percent of the total for scenarios D and E respectively. Furthermore, in the operation simulations of the PELP study, these technologies provided more than the 96 percent of the total energy in average for both scenarios. For a complete list of the considered generation units, see Appendix B.

Be aware that currently exist the expectation for some thermal generation units to close their operation in the near future, and hence, some of them are not expected to exist in the year 2035. This work considers the installed capacities from the PELP study and does not considers those expectations.

Minimum power levels P^{min}, maximum power levels P^{max}, minimum operation times τ^{on}, minimum downtimes τ^{off} and CO_2 emissions factors for each thermal generation unit were taken from the results of the PELP study. Ramp rate limits ρ^{up} and ρ^{down} were obtained directly from the Ministry of Energy (Ministerio de Energía (2018a) and Ministerio de Energía (2018b)). Variable costs c^v were calculated as in eq. (6.1) using the heat rate h_g, the price of the fossil fuel ρ_{ff} in the given scenario and the non-fuel variable cost c_g^{nfvc} for each thermal generation unit $g \in \mathcal{G}_T$. These parameters were taken from Comisión Nacional de Energía (2015), Ministerio de Energía (2017b) and Comisión Nacional de Energía (2018)[8].

$$c_g^v = h_g \cdot \rho_{ff} + c_g^{nfvc}, \quad \forall g \in \mathcal{G}_T \tag{6.1}$$

Table 6.3 shows a summary of installed capacities and installed capacity weighted average variable cost[9] per technology for scenarios D and E. Figure 6.2 shows a bar plot of the installed capacities considered. Finally, values for load following costs c^{ramp} were taken from Van den Bergh and Delarue (2015). Table 6.4 shows the load following costs and emissions factors considered in this work.

6.1.3 Hydrological Profiles and Zones

- **Hydrological profiles:** This study takes data from the *Energy Center* of the *Faculty of Physical and Mathematical Sciences at Universidad de Chile* considering historical data to build hourly water inflow profiles for 2 different hydrological year types: a

[7] In other words, we left out concentrated solar power, biomass and cogeneration technologies.

[8] The available information in the literature for these parameters was mixed using different units. Hence, these parameters were first standardised in order to always use the same units depending on the fossil fuel and be consistent with the available information of prices ([USD/ton] and [ton/MWh] for coal, [USD/m^3] and [m^3/MWh] for diesel and [USD/MMBtu] and [MMBtu/MWh] for natural gas).

[9] Given P_g^{max} and c_g^v , the installed capacity weighed average variable cost for technology X is then $\bar{c}_X^v = (\sum_{g \in \mathcal{G}_X} c_g^v \cdot P_g^{max})/(\sum_{g \in \mathcal{G}_X} P_g^{max})$

Scenario	**D**			**E**		
	Inst.Cap.		**Var. Cost**	**Inst.Cap.**		**Var. Cost**
	[GW]	[%]	[USD/MWh]	[GW]	[%]	[USD/MWh]
Solar	6.3	22.3	0	13.6	33.2	0
Wind	4.2	14.6	0	7.9	19.3	0
Run-of-the-river	4.3	15.3	0	4.3	10.6	0
Hydro reservoir	2.8	10	0	2.8	6.9	0
Gas	3.3	11.6	71.1	3.3	8.1	101.2
Coal	5	17.7	27.1	5	12.3	37.8
Diesel	2.4	8.5	182.7	4	9.7	313.2
Total Renewable	17.7	62.1	0	28.7	70	
Total Thermal	10.8	37.9	75.7	12.3	30	143.6

Table 6.3: Installed capacities and weighted average variable costs for scenarios D and E in 2035. Elaborated by the author using data from Matus et al. (2017), Ministerio de Energía (2017b), Comisión Nacional de Energía (2015) and Comisión Nacional de Energía (2018).

	c^{ramp} [USD/MW]	emission factor [tonCO_2/MWh]
Gas OCGT	0.896	0.56
Gas CCGT	0.56	0.46
Coal	2.016	1.27
Diesel	0.56	0.88

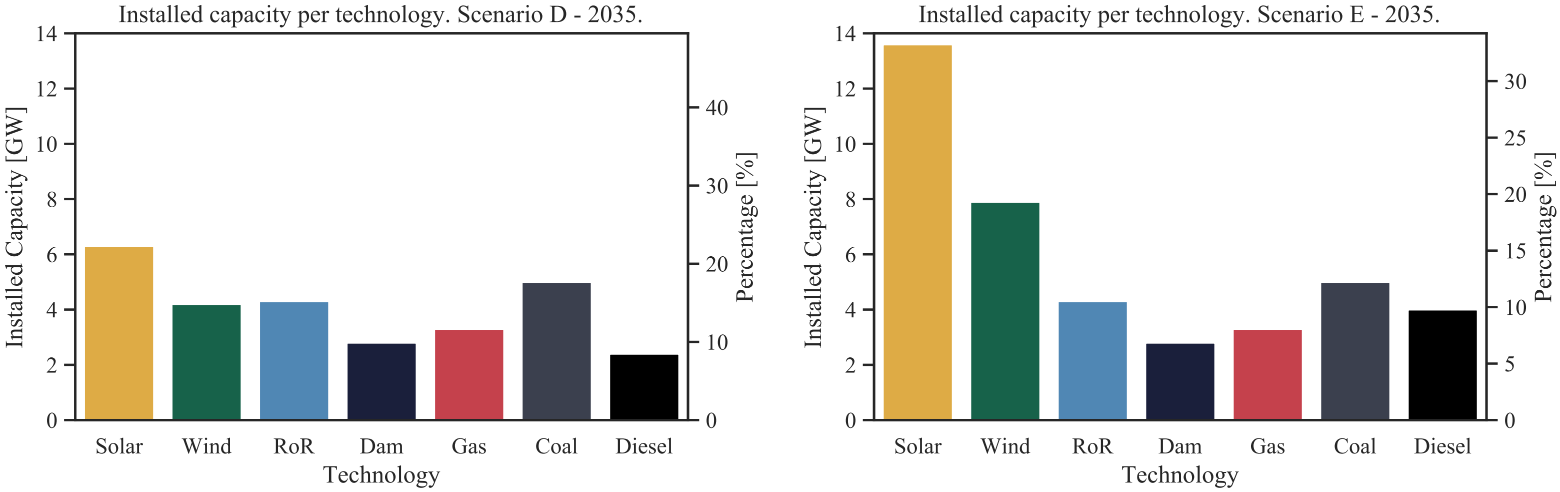
Table 6.4: Load following costs and emissions factors considered.
Source: Van den Bergh and Delarue (2015) and Ministerio de Energía (2017b)

dry year and a *humid year*. For the dry year we consider historical data available from the year 2007. For the humid year we consider data from the year 1973. These years were considered as their data represents 2% and 98% of exceedance probability respectively[10]. The historical data obtained from the *Energy Center* consist of weekly average values for each year. In this study we use smoothed data in an hourly resolution as in Llaitul (2017) in order to avoid discontinuity.

- **Hydrological zones:** In this study we follow the methodology used in Llaitul (2017), where the author reduces the problem dimension by grouping run-of-the-river plants in 8 different *hydrological zones*, in which every run-of-the-river plant in the same hydrological zone would have the same representative hourly water inflow. With this technique, all run-of-the-river plants can be grouped in 8 different representative run-of-the-river plants.

Let's consider 8 new disjoints sets $\{\hat{\mathcal{G}}^n_{RoR}\}_{n\in\{1,\ldots,8\}}$ of grouped run-of-the-river plants, such that $\mathcal{G}_{RoR} = \bigcup_{n\in\{1,..,8\}} \hat{\mathcal{G}}^n_{RoR}$. Hence, every run-of-the-river generator $g \in \mathcal{G}_{RoR}$ would

[10]In statistics, exceedance probability refers to the chances that a particular measure will be surpassed in value by another, randomly selected measures. In the Chilean electricity market is calculated as the percentage of hydrological years that are more humid than the actual one. I.e. an excedeence probability above 50% represent years comparatively dry; and excedeence probability under 50% represent hydrological years comparatively humid.



(a) Scenario D, year 2035.

(b) Scenario E, year 2035.

Figure 6.2: Installed capacities for scenario D and E in the year 2035

belongs to one of the 8 zone sets $\hat{\mathcal{G}}^n_{RoR}, n \in \{1,..,8\}$. We assume that every run-of-the-river generation unit in the same zone n has the same water inflow vector $\hat{\mathbf{Q}}^{in}_n$:

$$\mathbf{Q}^{in}_g = \hat{\mathbf{Q}}^{in}_n, \quad \forall g \in \hat{\mathcal{G}}^n_{RoR}, \quad \forall n \in \{1,...,8\} \tag{6.2}$$

Given assumption (6.2), for every zone $n \in \{1,...,8\}$ we define an equivalent efficiency factor $\hat{\eta}_n$ and an equivalent maximum power output $\hat{P}^{max}_n$ for each zone $n \in \{1,...,8\}$ as in eq. (6.3) and eq. (6.4) respectively.

$$\hat{\eta}_n = \sum_{\in \hat{\mathcal{G}}^n_{RoR}} \eta_g, \quad \forall n \in \{1,...,8\} \tag{6.3}$$

$$\hat{P}^{max}_n = \sum_{\in \hat{\mathcal{G}}^n_{RoR}} P^{max}_g, \quad \forall n \in \{1,...,8\} \tag{6.4}$$

Water inflow vectors for the chosen hydrological profiles and zones are shown in Fig. 6.3 and Fig. 6.4 for a typical humid and a typical dry year respectively.

6.1.4 Solar and Wind Profiles and Zones

With regard to the the solar and wind profiles we follow a similar methodology as for the run-of-the-river power plants, also presented in Llaitul (2017), where all solar and wind power plants are grouped in 4 different zones: SING, SIC_NORTH, SIC_CENTER, SIC_SOUTH. Here, we also consider 4 representative solar profiles and 4 representative wind profiles.

Let's consider the solar and wind zones set $\mathcal{Z}$ = {SING, SIC_NORTH, SIC_CENTER, SIC_SOUTH}, 4 new solar power plants disjoints sets $\{\hat{\mathcal{G}}^z_S\}_{z \in \mathcal{Z}}$ and 4 new wind power plants disjoints sets $\{\hat{\mathcal{G}}^z_W\}_{z \in \mathcal{Z}}$, such that $\mathcal{G}_S = \bigcup_{z \in \mathcal{Z}} \hat{\mathcal{G}}^z_S$ and $\mathcal{G}_W = \bigcup_{z \in \mathcal{Z}} \hat{\mathcal{G}}^z_S$. Hence, every solar (wind)

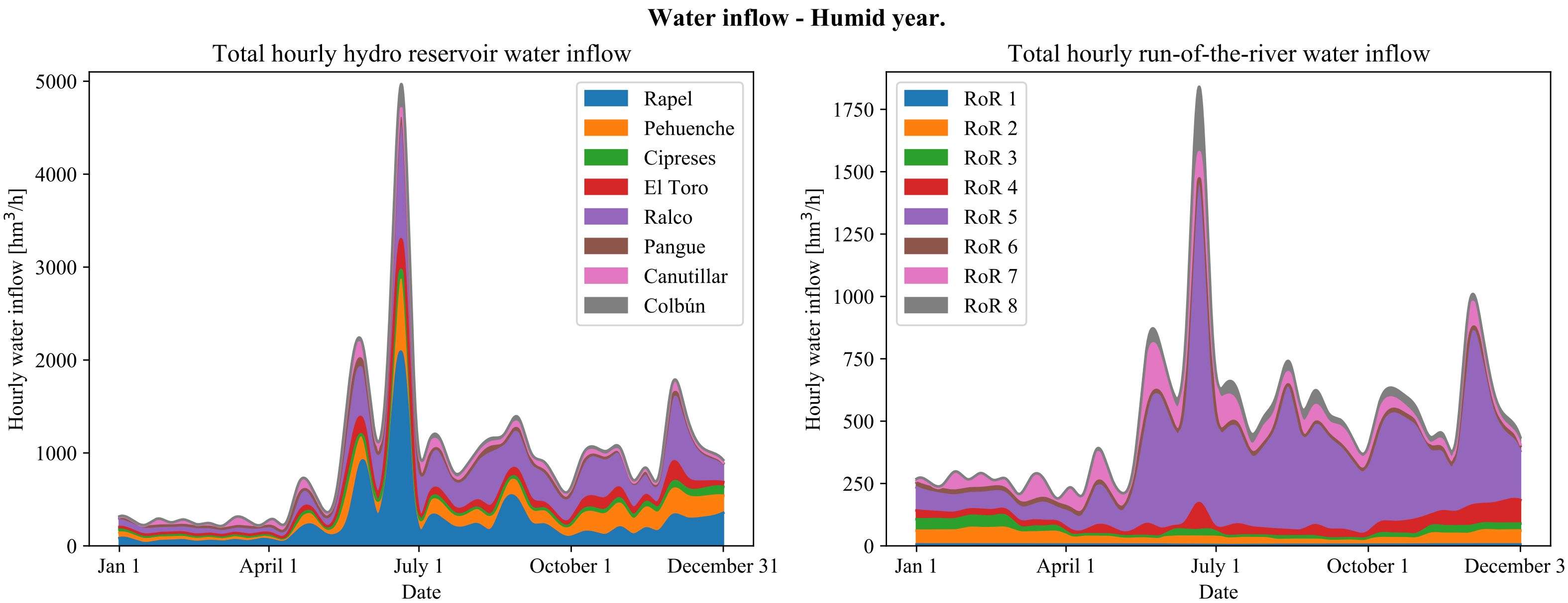


Figure 6.3: Total hourly water inflow profiles during a typical *humid* year.

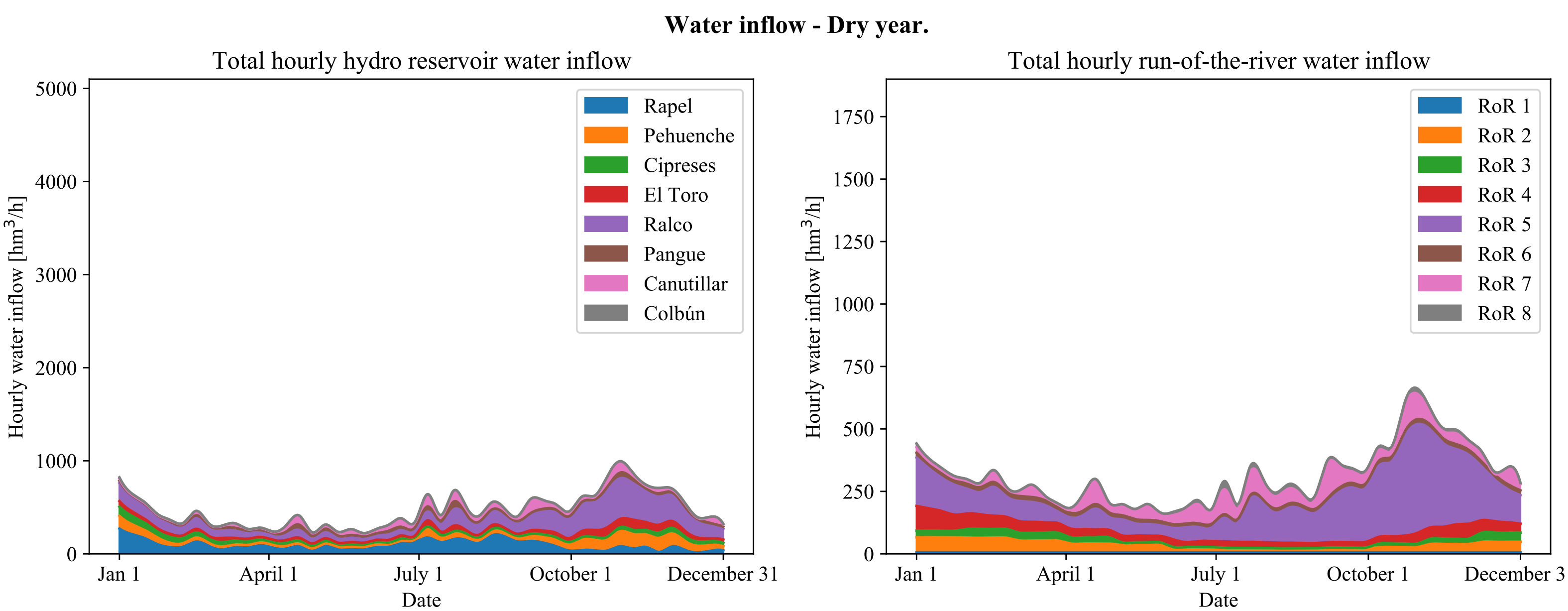


Figure 6.4: Total hourly water inflow profiles during a typical *dry* year.

power plant $g \in \mathcal{G}_S$ ($g \in \mathcal{G}_W$) would belong to one of the 4 zone sets $\hat{\mathcal{G}}^z_S, z \in \mathcal{Z}$ ($\hat{\mathcal{G}}^z_W, z \in \mathcal{Z}$). We assume that every solar (wind) generation unit in the same zone z has a normalised power availability vector $\hat{\mathbf{P}}^{avail}_{S,z}$ ($\hat{\mathbf{P}}^{avail}_{W,z}$), i.e.

$$\mathbf{P}^{avail}_g = \hat{\mathbf{P}}^{avail}_{S,z}, \quad \forall g \in \hat{\mathcal{G}}^z_S, \quad \forall z \in \mathcal{Z} \tag{6.5}$$

$$\mathbf{P}^{avail}_g = \hat{\mathbf{P}}^{avail}_{W,z}, \quad \forall g \in \hat{\mathcal{G}}^z_W, \quad \forall z \in \mathcal{Z} \tag{6.6}$$

Given assumptions (6.5) and (6.6), for every zone $z \in \mathcal{Z}$, we define an equivalent installed capacity $\hat{P}^{inst}_{S,z}$ for solar technologies and an equivalent installed capacity $\hat{P}^{inst}_{W,z}$ for wind technologies for every zone $z \in \mathcal{Z}$ as in Eq. (6.7) and Eq. (6.8) respectively.

$$\hat{P}^{inst}_{S,z} = \sum_{g \in \hat{G}^z_S} P^{inst}_g, \quad \forall z \in \mathcal{Z} \tag{6.7}$$

$$\hat{P}^{inst}_{W,z} = \sum_{g \in \hat{G}^z_W} P^{inst}_g, \quad \forall z \in \mathcal{Z} \tag{6.8}$$

6.2 Assumptions and Simplifications

In the following we explain the assumptions and simplification as well as the model simplifications.

- **Typical weeks:** In order to reduce the problem size, each year was represented by a reduced number of typical weeks. This allows consideration of hourly and seasonal variations in demand and renewable (hydro, solar and wind) profiles, while limiting the solution time (Flores-Quiroz et al. (2016)). In this study, the year was represented by 4 typical weeks, each of them representing a group (season) of 3 months. For simplicity, in this study the first season groups January, February and March; the second season groups April, May and June; the third season groups July, August and September; and the forth season groups October, November and December.

  The four typical weeks (672 hours) were characterised by (i) an hourly system demand vector $\mathbf{D} \in \mathbb{R}^{672}_{\geq 0}$, (ii) hydro reservoir water inflow vectors $\mathbf{Q}^{in}_g \in \mathbb{R}^{672}_{\geq 0}$ for every hydro reservoir $g \in \mathcal{G}_D$, (iii) run-of-the-river water inflow vectors $\hat{\mathbf{Q}}^{in}_n \in \mathbb{R}^{672}_{\geq 0}$ for every run-of-the-river zone $n \in \{1, ..., 8\}$, (iv) solar power availability vectors $\hat{\mathbf{P}}^{avail}_{S,z} \in \mathbb{R}^{672}_{\geq 0}$ for every zone $z \in \mathcal{Z}$ and (v) wind power availability vectors $\hat{\mathbf{P}}^{avail}_{W,z} \in \mathbb{R}^{672}_{\geq 0}$ for every zone $z \in \mathcal{Z}$.

  Each of these representative[11] inflow and availability vectors were extracted in a different way:

[11] Here we abuse of the adjective 'representative' (also used in the previous section) in order to refer to the subset of elements from which each yearly inflow and availability vector will be represented.

- **Hydro reservoir and run-of-the-river:** The hydro reservoir and run-of-the-river representative water inflow vectors are intended to represent the the entire year. In order to do this, and as water inflow change smoothly throughout the year, the vectors representing 4 representative weeks (672 hours) correspond to a subset of the hole year (8760 hours). Mathematically this was done by the use of a time step $\tau = [\frac{8670}{672}] = 52$ so each representative water inflow vector takes values from the original vector every τ hours. If $\mathbf{Q}_{g,\,t}^{in,4weeks}$ is the 4-weeks representative water inflow vector for hydro reservoir $g \in \mathcal{G}_D$, and $\hat{\mathbf{Q}}_{n,\,t}^{in,4weeks}$ is the 4-weeks water inflow vector of run-of-the-river zone $n \in \{1, ..., 8\}$, then:

$$\mathbf{Q}_{g,\,t}^{in,4weeks} = \mathbf{Q}_{g,\,(\tau \cdot t)}, \quad t \in \mathcal{T}^{4weeks}, \quad g \in \mathcal{G}_D \tag{6.9}$$

and

$$\hat{\mathbf{Q}}_{n,\,t}^{in,4weeks} = \hat{\mathbf{Q}}_{n,\,(\tau \cdot t)}, \quad t \in \mathcal{T}^{4weeks}, \quad n \in \{1, ..., 8\} \tag{6.10}$$

- **Solar and Wind:** For the solar and wind availability vectors, a representative week was extracted within each season. In order to do this, and to choose a representative week in terms of variability, for each season we took the week with the variability closest to the average variability of the season. The same was done for the demand vector.

Finally, as 4 weeks represents a fraction of a normal year, in order to evaluate total costs and other variables, each of them was multiplied by 13.04 to reflect the yearly operating cost[12].

- **Minimum operating time restriction:** Not all thermal power plants have minimum operating time restrictions. In order to reduce the problem complexity, we impose the minimum operating time restriction only for generation units with $\tau_g^{on} > 1$. Hence, Eqs. (5.17)-(5.18) were replaced by (6.11)-(6.12).

$$\sum_{\tau=1}^{t} ON_{g,\tau} \leq u_{g,t}, \quad t \leq \tau_g^{on} \in \mathcal{T}, \quad \forall g \in \{g \in \mathcal{G}_T | \tau_g^{on} > 1\} \tag{6.11}$$

$$\sum_{\tau=t-\tau_g^{on}}^{t} ON_{g,\tau} \leq u_{g,t}, \quad t > \tau_g^{on} \in \mathcal{T}, \quad \forall g \in \{g \in \mathcal{G}_T | \tau_g^{on} > 1\} \tag{6.12}$$

- **Minimum downtime restriction:** Likewise, Eqs. (5.19)-(5.20) were replaced by Eqs. (6.13)-(6.14)

$$\sum_{\tau=1}^{t} OFF_{g,\tau} \leq 1 - u_{g,t}, \quad t \leq \tau_g^{off} \in \mathcal{T}, \quad \forall g \in \{g \in \mathcal{G}_T | \tau_g^{off} > 1\} \tag{6.13}$$

$$\sum_{\tau=t-\tau_g^{off}}^{t} OFF_{g,\tau} \leq 1 - u_{g,t}, \quad t > \tau_g^{off} \in \mathcal{T}, \quad \forall g \in \{g \in \mathcal{G}_T | \tau_g^{off} > 1\} \tag{6.14}$$

[12] As a year have 52.14 weeks, hence, any results from 4 representative weeks must be multiplied by a factor of $52.14/4 = 13.04$

- **Ramp rate restrictions:** Not all thermal generation units are bounded by their ramp rate restrictions. In fact, if a generation unit $g \in \mathcal{G}$ has a up ramp rate restriction such that $\rho_g^{up} > P_g^{max}$, there is no use to impose a ramp-up rate restriction. The same for ramp-down rate restrictions and units with $\rho_g^{down} > P_g^{max}$. Hence, in order to reduce the problem complexity, Eqs. (5.21)-(5.22) were replaced by Eqs. (6.15)-(6.16)

$$P_{g,t} - P_{g,(t-1)} \leq \rho_g^{up}, \quad t > 1 \in \mathcal{T}, \quad \forall g \in \{g \in \mathcal{G}_T | \rho_g^{up} < P_g^{max}\} \tag{6.15}$$

$$P_{g,t-1} - P_{g,t} \leq \rho_g^{\text{down}}, \quad t > 1 \in \mathcal{T}, \quad \forall g \in \{g \in \mathcal{G}_T | \rho_g^{\text{down}} < P_g^{max}\} \tag{6.16}$$

- **Dimension reduction:** In the presented model, demand flexibility is defined by 4 values: α_a, β_a, α_c and β_c. In order to reduce the problem complexity, the quadratic factor Δ was introduced imposing:

$$\alpha_a = \Delta\beta_a \tag{6.17}$$

$$\alpha_c = \Delta\beta_c \tag{6.18}$$

With this, Demand Response parameters are reduced to 3: Δ, β_a and β_c.

6.3 Case Studies

For each combination of scenarios and hydrologic situations for the year 2035 (scenario D in a dry year, scenario D in a humid year, scenario E in a dry year, scenario E in a humid year), this study considers 4 case studies: *business as usual (BAU)*, *only shiftable demand (BAT)*, *only adjustable demand (CUR)* and *mixture of technologies (MIX)*. In the following, we explain, extending the description introduced in Section 5.2:

a) **Business as usual (BAU):** The first case study corresponds to the case without any demand flexibility. In order to do this, we consider

$$\Delta > 0, \quad \beta_a, \beta_c = +\infty \tag{6.19}$$

b) **Only shiftable demand (BAT):** We consider a case in which only shiftable demand flexibility is considered in the electric system. Imposing

$$\beta_c^{BAT} = \infty, \qquad \beta_a^{BAT} \leq 0, \tag{6.20}$$

demand can be shifted within the same day at a cost per real-time adjustment, but the total energy must remain constant (see Section 5.2). This is analogue to a case where demand flexibility is provided by storage technologies (hence, the abbreviation *BAT*, referring to batteries).

For the base case, the chosen value for $\beta_{a,B}^{BAT}$ was 50 [USD/MWh] which is half[13] the average value of optimistic expected levelized costs of storage (LCOS) value for storage

[13] Jülch (2016) calculates the LCOS per unit of energy delivered in an entire cycle. As modelled in Eq. (5.1), β_a counts both demand increment (charging) and demand reduction (discharging). Hence, β_a shold take half the LCOS.

technologies used at 365 cycles per year (daily operation)[14] according to Jülch (2016). Also, in order to do a sensibility analysis, 4 other values were chosen, two values lower than 50, and two values higher than 50. Th values for $\beta_{a,B}^{BAT}$ for the BAT case study are:

$$\beta_a^{BAT} \in \{12.5, \quad 25, \quad \beta_{a,B}^{BAT} = \mathbf{50}, \quad 100, \quad 150\} \quad [USD/MWh] \tag{6.21}$$

c) **Only adjustable demand (CUR):** We also consider a case in which only adjustable demand is considered and there are no storage technologies. By imposing

$$\beta_c^{CUR} = 0, \qquad \beta_a^{CUR} > 0, \tag{6.22}$$

only real-time adjustments are considered, regardless on the total amount of energy consumed within the day. This is analogue to a case where demand can only be curtailed at a given cost (hence, the abbreviation CUR).

For the base case, the chosen value for $\beta_{a,B}^{CUR}$ was 125 [USD/MWh] which is equal to the average local marginal price (LMP) of the BAU case (withour DR)[15]

$$\beta_a^{CUR} \in \{50, \quad 100, \quad \beta_{a,B}^{CUR} = \mathbf{125}, \quad 150, \quad 200, \quad 300\} \quad [USD/MWh] \tag{6.23}$$

d) **Mixture of technologies (MIX):** We consider a last case with a mixture of adjustable and shiftable demand. Here, values for β_a^{MIX} (adjustable term) were taken from the CUR case ($\beta_a^{MIX} \in \{50, 100, 125, 150, 200, 300\}$), while values for β_c^{MIX} (curtailment term) were taken from the BAT case ($\beta_c^{MIX} \in \{12.5, 25, 50, 100, 150\}$). Correspondingly, the base case is with $\beta_{a,B}^{MIX} = 50$ and $\beta_{c,B}^{MIX} = 125$.

Finally, the chosen values for Δ were taken from Walawalkar et al. (2008). Taking historical bids for demand reduction in the DR program in the Pennsylvania-New Jersey-Maryland Interconnection (PJM), Walawalkar et al. calculates three different demand reduction supply curves (see Example 4.3.1 for more information). From these curves, the Δ value was calculated using the definition in Eq. (6.18). In order to do a sensibility analysis on the quadratic term of the cost function, the following two values for Δ were chosen (Walawalkar et al.):

$$\Delta \in \{0.0013, 0.002\} \tag{6.24}$$

6.4 Example: MOLs, MOTs and DR curtailment

To give a simple and illustrative example of the model presented in Chapter 5 and the assumptions and study cases presented in the previous sections, the following example tries

[14]Here, we take the optimitic expected values of LCOS for Li-ion, lead-acid and vanadium redox flow batteries. The reasons for this is because costs were calculated for year 2030 and they are expected to decrease between 2030 and 2035 (see Jülch (2016)).

[15]In fact, from Table 7.1, average spot prices for scenario D - dry year, scenario D humid year, scenario E - dry year and scenario E - humid year are 95.12, 71.8, 188.9 and 137.43 [USD/MWh] respectively, which lead to an average of 123.3 [USD/MWh].

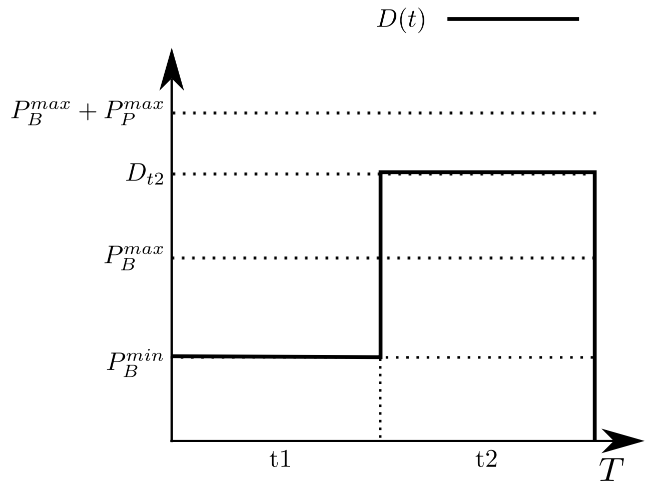
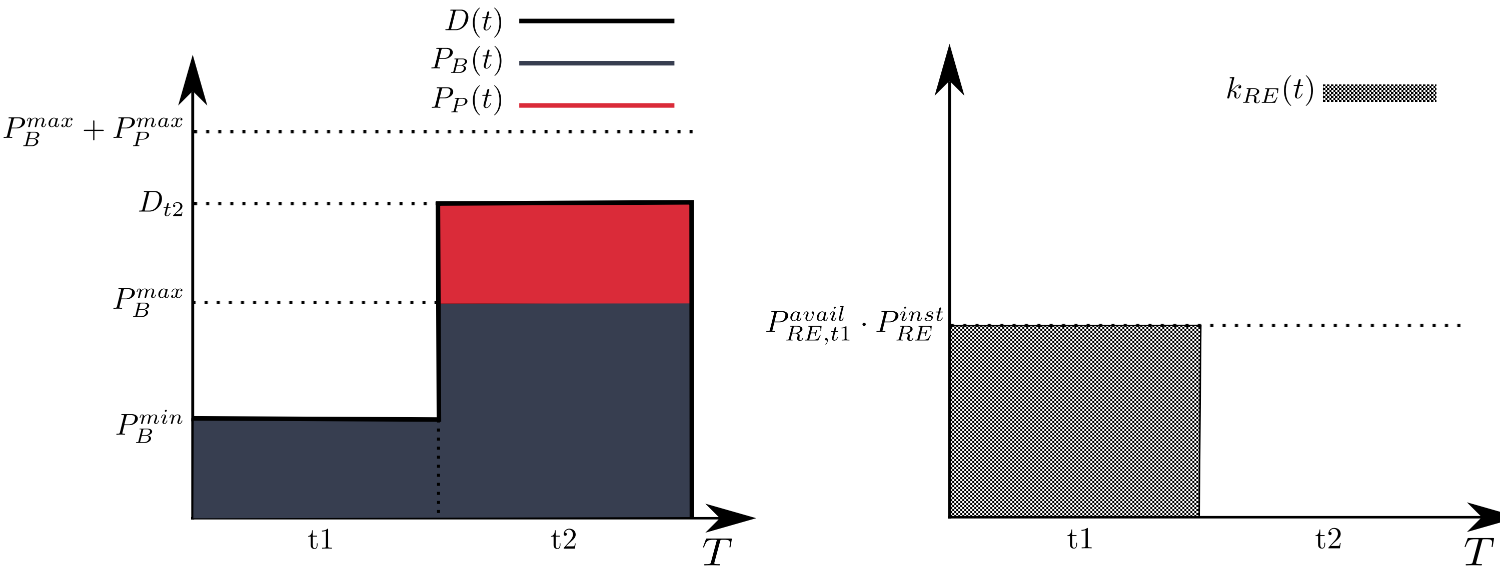


Figure 6.5: Baseline Demand for Example 6.4.

to emulates the dispatch in the case of (i) a non controllable renewable generation unit, (ii) a slow, cheap but restricted base technology like a coal generation unit and (iii) a fast and non restricted but more expensive generation technology like gas or diesel. Here, *MOT* stands for *Minimum Operational Time*, *MOL* stands for *Minimum Operating Levels*. See Section 3.3 for technical characteristics of conventional generation units.

Let's consider a 2-times horizon $\mathcal{T} = \{t1, t2\}$ and 3 generation units of different technologies: a renewable energy generation unit RE, a base generation unit B (e.g. coal) and a peaking generation unit P (e.g. gas or diesel). With this, $\mathcal{G} = \{B, P, RE\}$. Also, let's consider that the renewable energy generation unit RE has a zero variable cost ($c_{RE}^v = 0$), while the rest have a non-zero variable cost c_B^v and c_P^v for the base and peaking generation technologies respectively, with $0 < c_B^v < c_P^v$. Baseline demand is given by $\mathbf{D} = (D_{t1}, D_{t2}) \in \mathbb{R}_+$.

Following the notation introduced in the previous chapter, here we assume that both base and peaking generation units are thermal generation units without start-up costs ($c_B^{on} = c_P^{on} = 0$), shutdown costs ($c_B^{off} = c_P^{off} = 0$), load following costs ($c_B^{ramp} = c_P^{ramp} = 0$), minimum downtime ($\tau_B^{off} = \tau_P^{off} = 0$) and ramp rate limits restrictions ($\rho_B^{up} = \rho_B^{down} = \rho_P^{up} = \rho_P^{\text{down}} = +\infty$). We assume that the base generation unit has a non-zero minimum operational time $\tau_B^{on} = 2$, while minimum operational time for the peaking technology is assumed to be equal to zero ($\tau_P^{on} = 0$). Also, we consider that only the base technology has a non-zero minimum operational level $P_B^{min} > 0$, while the peaking generation technology is not restricted in this sense ($P_P^{min} = 0$). Both technologies have a non-infinite maximum power levels ($0 < P_B^{max}, P_P^{max} < +\infty$). On the other hand, the renewable generation technology is considered to be a solar or wind generation unit with a non zero installed capacity $P_{RE}^{inst} > 0$ but with a zero availability in time $t2$. This is: $\mathbf{P}_{RE}^{avail} = (P_{RE,t1}^{avail}, P_{RE,t2}^{avail})$ with $P_{RE,t1}^{avail} \geq 0$ and $P_{RE,2}^{avail} = 0$. Finally, we assume that $D_1 = P_B^{min}$ and that $P_B^{max} < D_2 \leq P_B^{max} + P_P^{max}$. With this, baseline demand can be illustrated as in Fig. 6.5.



(a) Optimal dispatch in the case without DR (b) Renewable energy curtailment without DR

Figure 6.6: Optimal dispatch and renewable energy curtailment in a case without DR.

6.4.1 Optimal Dispatch Without Demand Response

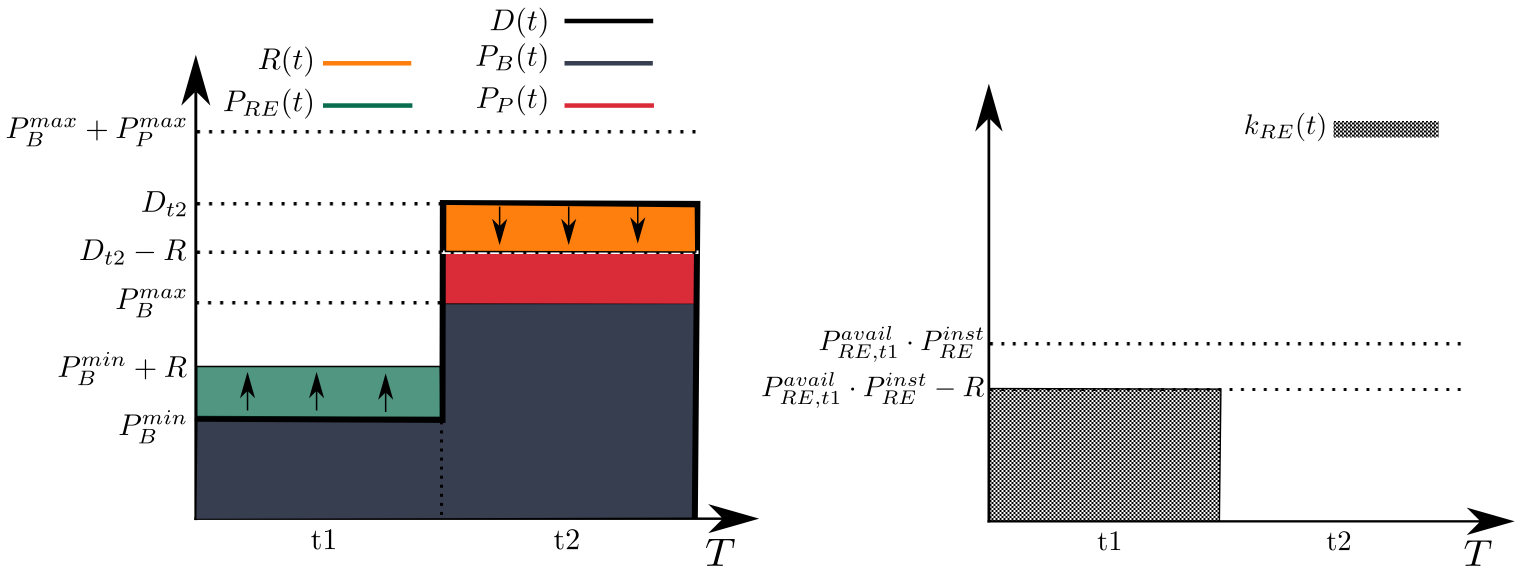
Without any demand flexibility integration, the unit commitment optimisation problem becomes

$$\min_{\{P_{g,t}, u_{g,t}\}_{t \in \mathcal{T}, g \in \mathcal{G}}} \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} c_g^v \cdot P_{g,t} \tag{6.25}$$

subject to Eqs. (5.11), (5.15), (5.16), (5.17), (5.18), (5.31), (5.32) and to the power balance constraint

$$\sum_{g \in \mathcal{G}} P_{g,t} = D_t, \quad \forall t \in \mathcal{T} \tag{6.26}$$

A detailed solution of the current problem can be found in Appendix C.3.1. However, it is easy to see that due to the minimum operational level and minimum operational time restriction of the base technology, the base generation unit will cover the total demand in the first period and will be operated at its maximum operational level in the second period. The peaking generation unit will cover the rest during the second period. The optimal dispatch solution is given by $P_{RE,t1} = P_{RE,t2} = 0$, $P_{B,t1} = D_{t1}$, $P_{B,t1} = P_B^{max}$, $P_{P,t1} = 0$, $P_{P,t2} = D_{t2} - P_B^{max}$ as shown in Fig. 6.6a. This means that the optimal solution involves a renewable energy curtailment equal to $k_{RE} = P_{t1}^{avail} \cdot P_{RE}^{inst} - P_{RE,t1} = P_{t1}^{avail} \cdot P_{RE}^{inst}$, as shown in Fig. 6.6b. This renewable energy curtailment is due to the minimum operational level (MOL) and minimum operational time (MOT) as it was described in Section 3.3.



(a) Optimal dispatch in the BAT case with DR and RE availability.

(b) RE curtailment in BAT case with DR and RE availability.

Figure 6.7: Optimal dispatch and renewable energy curtailment in the BAT case in the case with Demand Response and renewable energy availability.

6.4.2 Optimal Dispatch with DR Provided by Shiftable Demand

In the case of demand flexibility provided by shiftable demand, we consider the demand response disutility function $C_{DR}(\mathbf{R})$ from Eq. (5.1), assumptions (6.17), (6.18), ($\beta_c = +\infty$) and ($\beta_a \geq 0$) (BAT case study). With this, the DR-UC optimisation problem becomes

$$\min_{\{P_{g,t}, u_{g,t}, R_t\}_{t\in\mathcal{T}, g\in\mathcal{G}}} C_{DR}(\mathbf{R}) + \sum_{g\in\mathcal{G}} \sum_{t\in\mathcal{T}} c_g^v \cdot P_{g,t} \tag{6.27}$$

subject to Eqs. (5.8) (5.9), (5.10), (5.11), (5.15), (5.16), (5.17), (5.18), (5.31), (5.32).

A detailed solution can be found in Appendix C.3.2. In the case that there is enough renewable energy available, the optimal demand response adjustment is given by

$$R = \frac{c_P^v - 2\beta_a}{4 \cdot \Delta \cdot \beta} \tag{6.28}$$

and hence, renewable energy curtailment becomes $k_{RE} = P_{t1}^{avail} \cdot P_{RE}^{inst} - R$ as shown in Figs. 6.7a and 6.7b. In this case, in order to have a non-zero demand adjustment $R > 0$, the linear shiftable cost β_a should be

$$\beta_a < \frac{c_P^v}{2}, \tag{6.29}$$

which is exactly half the variable cost of the peaking technology (remember, that there are two Demand Response costs involved: decreasing and increasing demand).

On the other hand, in the case with no renewable energy available, the optimal demand

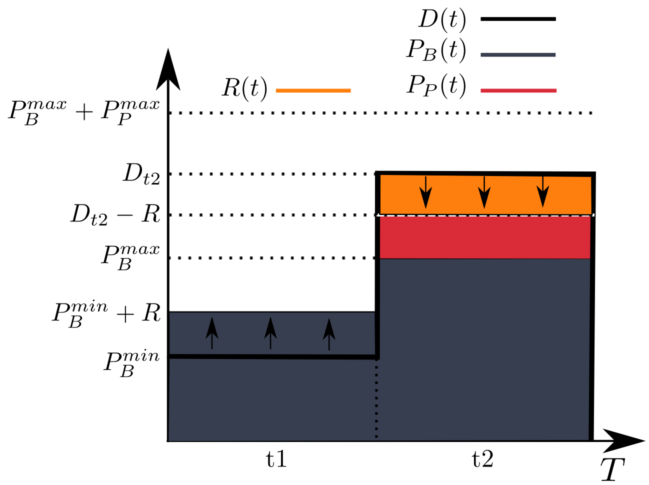


Figure 6.8: Optimal dispatch in the BAT case in the case without RE availability

response adjustment is given by

$$R = \frac{c_P^v - c_B^v - 2\beta_a}{4 \cdot \Delta \cdot \beta} \tag{6.30}$$

as shown in Fig. (6.8)

Here, in order to have a non-zero demand adjustment $R > 0$, the linear shiftable cost β_a, should be

$$\beta_a < \frac{c_P^v - c_B^v}{2}, \tag{6.31}$$

which is half the difference between the peaking technology and its alternative. Again, this value is divided by two because there are two costs involved in the Demand Response balance: one for decreasing, and one for increasing demand.

6.5 Limitations

There are some aspects of the current model and methodology that set some limits on the operation, and hence, on the impacts that can be observed. In the following, we identify some limitations that set a lower limit in terms of demand response benefits.

a) *Deterministic model:*

The current model is deterministic, and hence it considers a known future renewable energy availability, which is not the case in real operation. Hence, renewable energy curtailment levels identified in the results will correspond to a lower bound of possible renewable energy curtailment levels.

b) *One-bus system and no transmission restrictions:*

As no restriction is imposed in term of energy transmission (one-bus system), both the total requirements for flexibility and the value of demand-side response are underestimated. In fact, in some cases, balance provided by hydro reservoirs might not be enough in a case with transmission congestion (let's remember that in Chile, solar energy sources are located in the north, while big hydro reservoirs are located in the south). In this case, flexibility provided by local demand seems to be more attractive. Hence, demand response benefits identified in the results, will correspond to a lower bound of possible benefits.

c) *No secondary frequency regulation*

The current model does not considers a secondary (non primary) frequency regulation, and hence it does not consider spinning reserves nor standing reserves. This implies that operation results will correspond to a lower bound in terms of the optimal operation. Also, in this case, Demand Response could compete with conventional generation units in order to provide reserves. Hence, demand response benefits shown in the following results will correspond to a lower bound of its possible benefits.

d) *Hourly resolution and no primary frequency regulation:*

Intra-hour renewable energy non-controllable variability (e.g. shading effect in PV) increases the need and usage of primary reserves. Demand response is expected to reduce the need and use of primary reserves. Hence, by using an hourly resolution (and also a deterministic model), demand response benefits would be also bounded.

According to the above discussion, the following results will correspond to a lower bound in terms of demand response benefits.

Finally, as explained in Section 6.3.c, the chosen value for $\beta_{a,B}^{CUR}$ is equal to the average local marginal price of the BAU case, which averages the average spot prices of the results of the different combinations of scenarios and hydrologies (scenario D - dry year, scenario D - humid year, scenario E - dry year and scenario E - humid year) (See Table 7.1). A $\beta_{a,B}^{CUR}$ of 125 [USD/MWh] might underestimate the results for scenarios in which the average spot prices for the BAU case are lower (scenarios D), or overestimate the results for scenarios in which the average spot prices for the BAU case are higher (scenarios E). We consider that is important to analyse all scenarios with the same value of $\beta_{a,B}^{CUR}$ because it will be easier to compare results. Hence, a sensibility analysis section is introduced in order to asses the impact of changes in the $\beta_{a,B}^{CUR}$ value.

Chapter 7

Results and Discussion

In this chapter, we show and describe the results obtained from the simulations of the operation of the Chilean electricity system in the year 2035 with demand side flexibility modelled as in Chapter 5. The model was implemented in JuMP [1] by using the CPLEX solver and the supercomputing infrastructure of the NLHPC [2] laboratory. Every simulation was computed in a IBM System X iDataPlex dx360 M2 Server with 24 GB of RAM and 2 Intel(R) Xeon(R) CPU X5550 (2.66 GHz, 4 cores each) processors. The elapsed time range for each simulation was between 1.2 min and 18 hours, with an average elapsed time of 30 minutes. The developed code was released as free software with a GNU GPLv3 licence[3] and can be found in the Git repository of the project in *https://github.com/estebaniglesias/DemandResponse-UnitCommitment*.

The first section of this chapter shows the results of the operation of the Chilean electricity system without Demand Response (*Business as Usual (BAU)* case). Then, general results of each of the study cases are analysed (*Only storage (BAT)*, *Only curtailment (CUR)* and *Mixture of technologies (MIX)*) and compared with the BAU case. All results are presented for each combination of the two selected energy scenarios (D and E) and the two hydrologic situations (dry and humid year). Finally, a sensibility analysis section is introduced in order to assess the impact of different variable values in Demand Response participation, annual costs, spot price, capacity factors and total CO_2 emissions.

With respect to renewable energy curtailment, as the model does not have any preference between solar, wind and run-of-the-river energy, is does considers one technology over the other depending on how the solver is solving the problem, which is different for every variables combination. Hence, just the comparison of solar, wind and run-of-the-river curtailment separately does not allow us to conclude about renewable energy curtailment. In order to avoid this issue, in this chapter we introduce a *SWR curtailment* value which is equal to the overall curtailment of solar, wind and run-of-the-river generation units together[4].

[1]JuMP is a modeling language for mathematical optimization embedded in the Julia programming language. For more information visit https://github.com/JuliaOpt/JuMP.jl

[2]National Laboratory of High Performance Computing. See more in http://www.nlhpc.cl/en/about/

[3]See more in *https://www.gnu.org/licenses/quick-guide-gplv3.html*

[4]Is important to note that this is not the sum of the independent curtailment values in percentage. If

7.1 Business as Usual (BAU)

This section shows and describes the characteristics of the operation of a Chilean electricity system without Demand Response. These results are useful to later compare them with the operation of the case studies with DR incorporated.

	Scenario/Hydrology		D/dry	D/humid	E/dry	E/humid
Costs	Total cost	[MMUSD]	2813.54	2165.18	5554.58	4013.94
	On/Off cost	[MMUSD]	44.14	31.18	157.01	118.55
	Ramping cost	[MMUSD]	1.26	0.88	3.33	3.31
S.P	Spot price mean	[USD/MWh]	95.12	71.8	188.9	137.43
	Spot price std.	[USD/MWh]	34.8	28.0	111.75	89.02
Generation	Solar generation	[%]	14.37	14.37	24.53	24.67
	Wind generation	[%]	8.71	8.71	13.76	13.7
	RoR generation	[%]	16.57	17.93	13.19	14.15
	Dams generation	[%]	5.85	10.82	4.75	8.79
	Gas generation	[%]	17.12	11.44	12.44	10.21
	Coal generation	[%]	36.4	36.4	26.2	26.0
	Die. generation	[%]	1.0	0.3	5.17	2.46
Curt.	Solar curt.	[%]	0.0	0.0	2.54	2.01
	Wind curt.	[%]	0.0	0.02	1.92	2.32
	RoR curt.	[%]	0.0	0.0	1.99	2.85
	"S&W&RoR curt."	[%]	0.0	0.0	2.24	2.32
Cycles	Gas paid cycles		64.0	41.0	194.0	159.0
	Coal paid cycles		0.0	0.0	0.0	0.0
	Die. paid cycles		1.0	0.0	116.0	48.0
R. cost	Gas ramp. cost	[MMUSD]	0.44	0.23	0.22	0.16
	Coal ramp. cost	[MMUSD]	0.82	0.65	3.06	3.12
	Die. ramp. cost	[MMUSD]	0.0	0.0	0.06	0.02
	CO_2 emissions	[MMtonCO_2]	65.71	61.86	63.98	58.68

Table 7.1: Summary of results for the *Business as Usual* (BAU) case study.

The main observations are described in the following list:

a) *Dryer years are more costly. Also, in dry years thermal technologies replace hydro technologies in balancing the system:*

$\mathbf{P^S}$, $\mathbf{P^W}$ and $\mathbf{P^{RoR}}$ are the vectors of power generated by solar, wind and run-of-the-river generation units respectively, and $\mathbf{A^S}$, $\mathbf{A^W}$ and $\mathbf{A^{RoR}}$ are the vectors of available power for solar, wind and run-of-the-river generations units, then $k^S = \frac{\sum_{t\in\mathcal{T}} A_t^S - P_t^S}{\sum_{t\in\mathcal{T}} A_t^S}$, $k^W = \frac{\sum_{t\in\mathcal{T}} A_t^W - P_t^W}{\sum_{t\in\mathcal{T}} A_t^W}$ and $k^{RoR} = \frac{\sum_{t\in\mathcal{T}} A_t^{RoR} - P_t^{RoR}}{\sum_{t\in\mathcal{T}} A_t^{RoR}}$ will represent solar, wind and run-of-the-river curtailment, while $k^{SWR} = \frac{\sum_{t\in\mathcal{T}} (A_t^S - P_t^S) + (A_t^W - P_t^W) + (A_t^{RoR} - P_t^{RoR})}{\sum_{t\in\mathcal{T}} A_t^S + A_t^W + A_t^{RoR}}$ will represent the overall curtailment of solar and wind together. Also, for run-of-the-river generation units $g \in \mathcal{G}_{RoR}$ we use $A_{g,t}^{RoR} = min(\eta_g \cdot Q_{g,t}^{in}\,, \, P_g^{max})$.

From Table 7.1 it is observed that for each scenario (D or E), dry years are more expensive than humid years. This is not only because generation costs are being reduced in humid years due to hydrologic availability, but also due to the reduction of start-up/shutdown costs and load following costs in humid years[5]. This means that in dryer scenarios, thermal technologies replace hydro technologies in balancing the system. This is consistent with Matus et al. (2017).

b) *Spot price and spot price variability are higher in dry years:*

For each scenario, the average spot price and spot price variability increases in dry years, which is consistent with the observation found in the literature. As it can be observed from the percentage of generation per technology in Table 7.1, this is due to the replacement of energy from hydro technologies to flexible thermal technologies (i.e. gas and diesel. In fact, the generation of coal power plants barely change). For scenario E this can be also observed in Figs. 7.1a and 7.1b, where in the middle of the time horizon (between hour 300 and hour 400), the generation of diesel power plants in a dry year (Fig. 7.1a) are being replaced by hydro reservoirs generation during a humid year (Fig. 7.1b), reducing dramatically the spot price during the night.

c) *Renewable energy curtailment is higher in humid years:*

However, from the BAU case, it is observed that for each scenario, the SWR curtailment is more important for humid years. The reason is direct from the fact that in humid years, there is more availability for run-of-the-river generation units.

Also, from Figs. 7.1a and 7.1b it is observed that renewable energy curtailment occurs always when coal power plants are running at their minimum operational level, which is consistent with what was described in Chapter 3.

d) *CO_2 emissions are more important in scenario D despite the fact that demand is lower:*

From the generation section in Table 7.1, it can be observed that this is due to the high usage of coal power plants in scenario D. See more detailed analysis in section 7.3.5

Note that the results show that for scenario E, even during a humid year, there exist a 2.5% of diesel generation (5.2% during a dry year), which is higher than usual expectations[6] and drives up the spot price. We can see that this is due to the assumptions and data used (See Chapter 6) which leads to have less contribution of hydro reservoirs during the first season, and hence, force diesel generations to participate. In fact, the period considered in the simulations (and hence water inflow data) starts on January, which is always a dry season, even for the humid year (See hourly water inflow for both hydrologies in Section 6.1.3

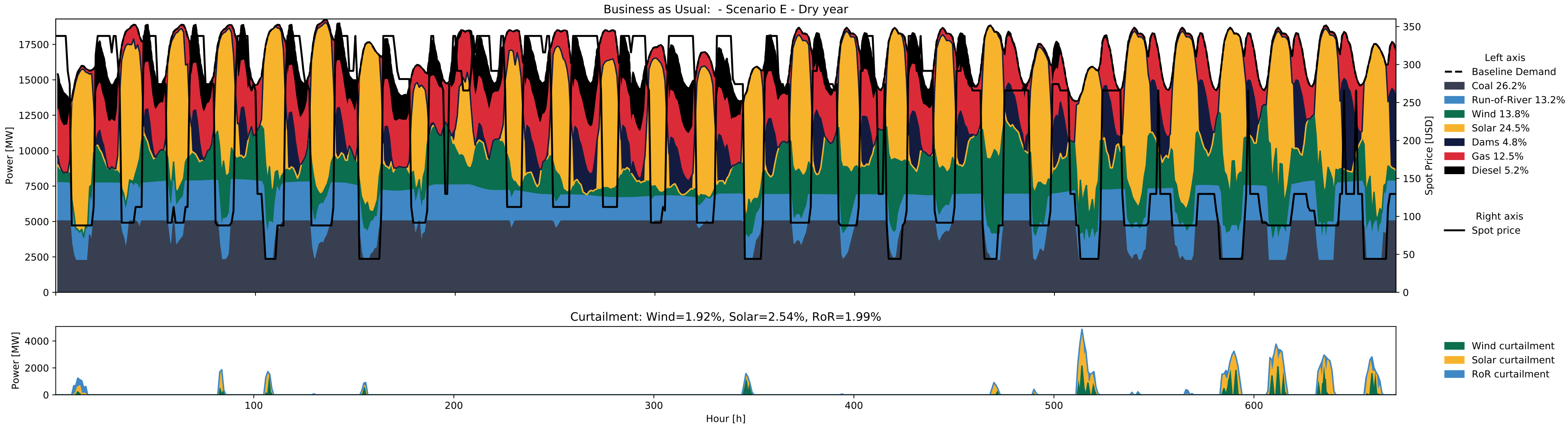
[5]However, the impact of start-up/shutdown costs and load following costs in total cost does not represent more than 3% of the total cost.

[6]For example, for similar conditions, in the PELP study, also for scenario E, diesel generation is expected to be 1.2% and 1.7% for a humid and dry year respectively (Matus et al. (2017)).

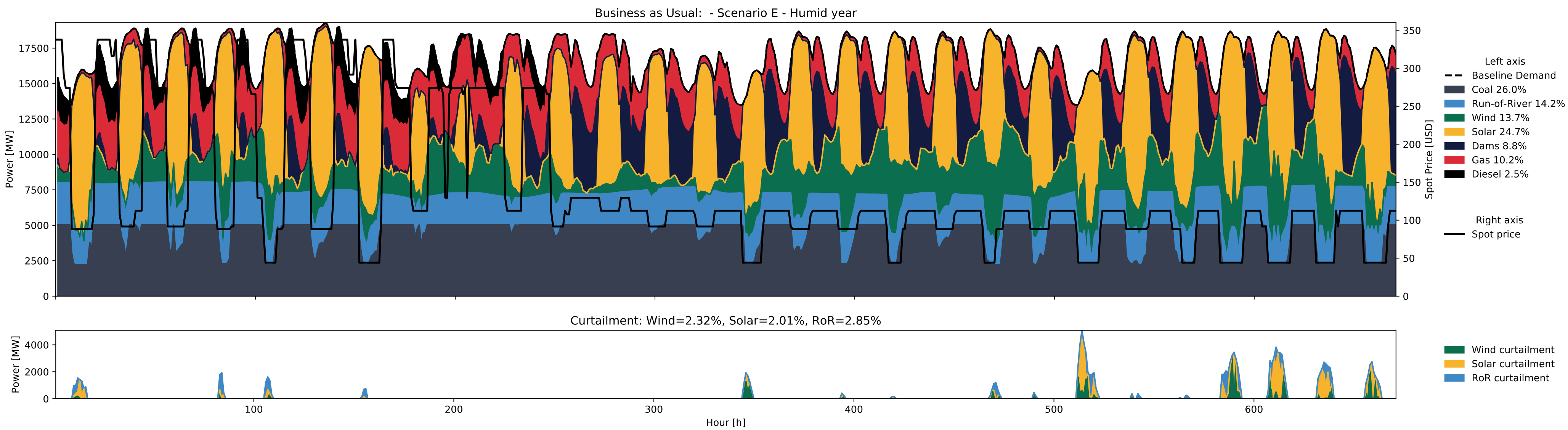
and Figs. 6.3 and 6.4) [7]. On the other hand it is assumed that the initial volume level for hydro reservoirs ($V_{g,0}$) is a characteristic of each hydro reservoir and that it does not depend on the hydrology of the year, leaving some hydro reservoirs to always start the year almost empty (See parameters in Appendix C).

In the following, Figs. 7.1a and 7.1b show the operation of the BAU study case for scenario E. The rest of the plots for the BAU study case can be found in Appendix A.1.

[7]In fact, in Chile the *hydrological year* is considered to start in April. As it is shown in Figs. 6.3 and 6.4, for a typical humid year, until mid April, water inflow is nearly similar than for a typical dry year.



(a) System operation for *Business as Usual* (BAU) case study, scenario E, dry year.



(b) System operation for *Business as Usual* (BAU) case study, scenario E, humid year.

Figure 7.1: System operation and spot price for *Business as Usual* case study, Sscenario E.

7.2 Cases with Demand Response: General Results

In this section, we show and describe the results obtained from the simulations of the base case in each of the 3 different study cases (BAT, CUR, MIX). As no sensibility analysis will be shown in this section[8], these results describe a general behaviour of the electricity system in the case of incorporating demand side flexibility in each of these study cases.

7.2.1 Only Shiftable Demand (BAT)

This section describes the general results for the base case of the Only shiftable demand (BAT) case study. As explained in section 6.3, for this case study, the base case is considered to be given by

$$\Delta_B = 0.001, \qquad \beta_{c,B}^{BAT} = +\infty, \qquad \beta_{c,B}^{BAT} = 50 \tag{7.1}$$

	Scenario/Hydrology		D/dry	D/humid	E/dry	E/humid
Costs	Total cost	[MMUSD]	2811.14 (↓ 0.1%)	2163.53 (↓ 0.1%)	5362.96 (↓ 3.4%)	3927.95 (↓ 2.1%)
	On/Off cost	[MMUSD]	44.14 (=)	31.18 (=)	129.97 (↓ 17.2%)	108.13 (↓ 8.8%)
	Ramping cost	[MMUSD]	1.08 (↓ 14.3%)	0.77 (↓ 12.5%)	2.66 (↓ 20.1%)	2.84 (↓ 14.2%)
S.P	Spot price mean	[USD]	93.87 (↓ 1.3%)	70.28 (↓ 2.1%)	173.18 (↓ 8.3%)	132.73 (↓ 3.4%)
	Spot price std.	[USD]	33.75 (↓ 3.0%)	25.25 (↓ 9.8%)	95.08 (↓ 14.9%)	77.41 (↓ 13.0%)
Generation	Solar generation	[%]	14.37 (=)	14.37 (=)	24.84 (↑ 0.3)	24.78 (↑ 0.1)
	Wind generation	[%]	8.71 (=)	8.71 (=)	13.72 (↓ 0.0)	13.66 (↓ 0.0)
	RoR generation	[%]	16.57 (=)	17.93 (=)	13.23 (↑ 0.0)	14.27 (↑ 0.1)
	Dams generation	[%]	5.85 (=)	10.82 (=)	4.75 (=)	8.79 (=)
	Gas generation	[%]	17.12 (↑ 0.0)	11.45 (↑ 0.0)	12.82 (↑ 0.4)	10.25 (↑ 0.0)
	Coal generation	[%]	36.5 (↑ 0.1)	36.5 (↑ 0.1)	26.8 (↑ 0.6)	26.4 (↑ 0.4)
	Die. generation	[%]	0.89 (↓ 0.1)	0.23 (↓ 0.1)	3.79 (↓ 1.4)	1.88 (↓ 0.6)
Curt.	Solar curt.	[%]	0.0 (=)	0.0 (=)	1.3 (↓ 1.2)	1.54 (↓ 0.5)
	Wind curt.	[%]	0.0 (=)	0.02 (=)	2.21 (↑ 0.3)	2.58 (↑ 0.3)
	RoR curt.	[%]	0.0 (=)	0.0 (=)	1.73 (↓ 0.3)	2.08 (↓ 0.8)
	"S&W&RoR curt."	[%]	0.0 (=)	0.0 (=)	1.65 (↓ 0.6)	1.96 (↓ 0.4)
Cycles	Gas paid cycles		64.0 (=)	41.0 (=)	173.0 (↓ 10.8%)	150.0 (↓ 5.7%)
	Coal paid cycles		0.0 (=)	0.0 (=)	0.0 (=)	0.0 (=)
	Die. paid cycles		1.0 (=)	0.0 (=)	68.0 (↓ 41.4%)	28.0 (↓ 41.7%)
R. cost	Gas ramp. cost	[MMUSD]	0.43 (↓ 2.3%)	0.23 (=)	0.19 (↓ 13.6%)	0.16 (=)
	Coal ramp. cost	[MMUSD]	0.65 (↓ 20.7%)	0.54 (↓ 16.9%)	2.44 (↓ 20.3%)	2.67 (↓ 14.4%)
	Die. ramp. cost	[MMUSD]	0.0 (=)	0.0 (=)	0.02 (↓ 66.7%)	0.01 (↓ 50.0%)
	CO_2 emissions	[MMtonCO_2]	65.77 (↑ 0.1%)	61.89 (↑ 0.0%)	63.75 (↓ 0.4%)	58.6 (↓ 0.1%)
DR	Max. PW adj.	[MW]	185.52 (1.4%)	212.49 (1.6%)	1224.87 (7.43%)	893.89 (5.05%)
	Max. EN shifted	[GWh]	1.48 (0.49%)	1.41 (0.47%)	9.68 (2.62%)	9.2 (2.49%)

Table 7.2: Summary of results for the *Only shiftable demand (BAT)* case study, base case scenario

[8]For sensibility analysis, see Section 7.3

A summary of the general results are shown in Table 7.2, where the value reduction or increment is shown in percentages with respect to the BAU case (Table 7.1)[9]. Also, in Table 7.2 the *Max. PW adj.* and *Max. EN shifted* indicators are introduced. The first indicator refers to the maximum power adjustment in the total time horizon, i.e., the maximum Demand Response participation. The percentage value shown besides is calculated with respect to the original baseline demand value at the time of the demand adjustment. On the other hand, the second indicator refers to the maximum amount of energy shifted within a day. The percentage value is calculated with respect to the total demand during that same day. The main observations are described in the following list.

a) *Demand Response participation reaches a maximum of 7.4% of the total demand, which is consistent with the literature.*

   Demand response participation in the case of DR provided by shiftable demand reaches a maximum of 1.6% and 7.4% of baseline demand for scenarios D and E respectively (Table 7.2). Also, for the same scenarios, maximum energy shifted is about 0.5% and 2.6% of daily energy demand. This values proves that the current approach of not imposing an upper bound on DR participation, but rather include a quadratic term in DR cost function, leads to reasonable results that are within the existing literature range in terms of DR participation[10].

b) *The impact of DR in costs is higher during dry years. It reduces total annual costs up to a 3.4%. Start-up/shutdown costs and load following costs are being reduced up to 17.2% and 20.1% respectively.*

   As shown in Table 7.2, for every scenario, the impact of DR provided by shiftable demand is greater in dry years. The higher value that intra-day balance has in dry years is due to the lack of water available to do the same job.

   In the case of scenario D, costs reduction are mainly due to the increment of energy provided by coal generation units and hence, the reduction of load following costs for this technology. This can be observed by comparing the first 200 hours of the operation of the BAU case of scenario D (Figs. A.1a and A.1b) with the BAT case for the same scenario (Figs. A.3a and A.3b). Here, intra-day balance provided by DR helps coal generation units to increase their participation as base technology (see below).

c) *Diesel generation is replaced by coal and gas.*

   The participation of diesel power plants decreases up to 42% in scenario D, and up to 27% in scenario E (Table 7.2[11]), increasing the usage of coal and gas generation units, as

[9] An upward pointing arrow (↑) refers to a value increment, whereas a downwards arrow (↓) refers to a value reduction.

[10] The models found in the literature generally impose an upper bound on DR participation of 5% of total demand (Walawalkar et al. (2008), Flores (2015)))

[11] In fact, a reduction of 0.1 parentage points from an original of 0.23 percentage points corresponds to a reduction of (0.1/0.24)=0.42 of total generation

well as a decreasing *SWR* curtailment. However, we can see that due to the quadratic term in the adjustment cost, and with the current costs assumptions, Demand Response is not cheap enough to completely eliminate diesel generation.

With regard to the increase of gas generation, it is observed that it occurs mainly in a dry year of scenario E, where gas generation units become valuable to also balance the system (in fact, while generation increase, paid cycles and ramping cost decrease), reducing its usage during the night and increasing its usage during the day. This can be observed by comparing the operation of hours 200-300 for BAU and BAT case in scenario E, dry year (Figs. 7.1a and 7.2a respectively).

d) *Total CO_2 emissions increase (scenario D) or are barely reduced (scenario E).*

Despite the fact that diesel generation is reduced, total CO_2 emissions are barely reduced (scenario E) or are even increased (scenario D). This is due the comparatively high value of emission factor for coal generation units compared with diesel generation units (coal generation units have a CO_2 emission factor 40% higher than diesel generation units[12].).

A similar phenomena is found in Mckenna and J Darby (2017), where the authors indicate that the carbon impact of Demand Response technologies may be negligible, or even negative for a case-study of domestic battery systems in the Irish power system. In this particular case, this effect is because CO_2 emissions factors are similar during peak and off-peak in the Irish power system, and the benefits are outweighed by losses in the battery system (See Hawkes (2014) for long-run marginal CO_2 emissions factors in national electricity systems).

Note that in the current model, no tax is imposed for CO_2 emissions. Including a carbon tax in the current DR model would be an interesting thing to evaluate in a future study. However, gas generation units are about 40 to 70 [USD] more expensive than coal generation units per unit of energy generated [MWh] (Table 6.3), which would require a carbon tax of about 57-86 [USD/tonCO_2] in order to reverse the merit of order between coal and gas generation units[13].

e) *Renewable energy curtailment is reduced up to 37% but it is not completely reduced.*

From Table 7.2 and Figs. 7.2a and 7.2b we can observe that renewable energy curtailment is not completely reduced (is reduced up to 37%, however). For instance, solar and wind curtailment between hours 500 and 650 in Figs. 7.2a and 7.2b are not being avoided by the use of Demand Response. A possible shift of demand in this situation would have been a reduction of energy during the night (and hence, reducing gas generation) and an increment of demand during the day (using the available wind and solar energy). How-

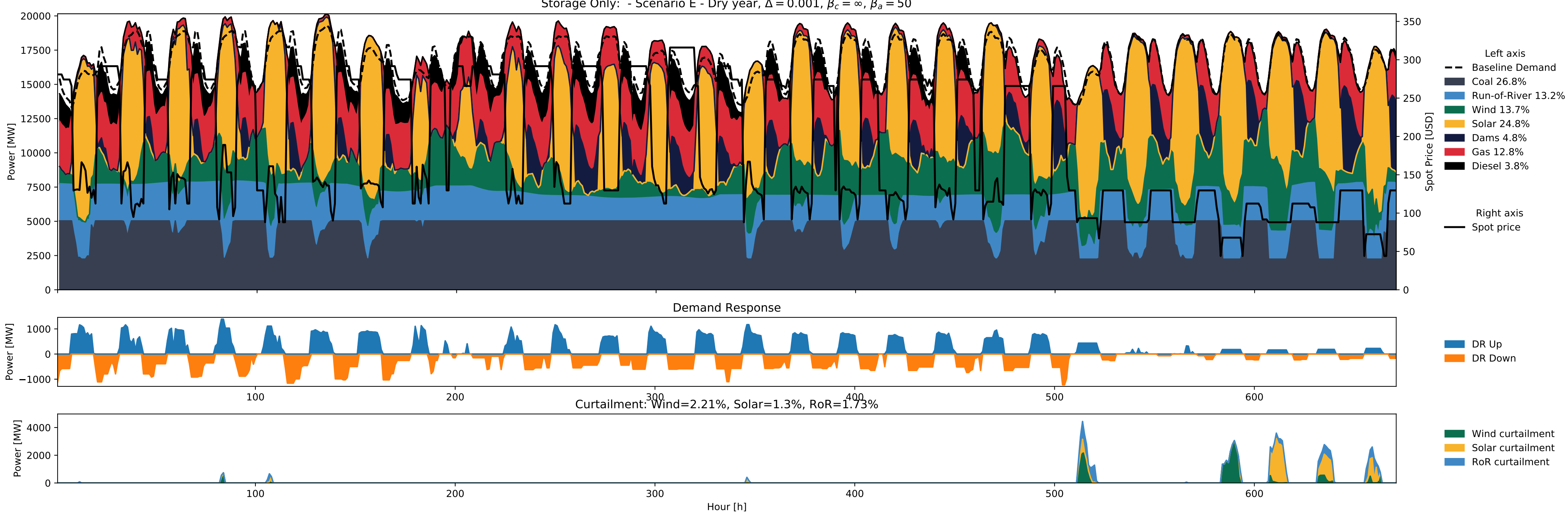
[12]See Table 6.4 for emission factor values.

[13]In fact, if c_c^v and c_g^v are the variable costs for coal and gas generation units respectively, e_c and e_g are their emissions factor and T is a given carbon tax, a carbon tax that makes coal generation units more expensive than gas can be calculated as the following. $c_c^v + \mathrm{e}_c \cdot T > c_g^v + \mathrm{e}_g \cdot T \quad \Rightarrow T > \frac{(c_g^v - c_c^v)}{(\mathrm{e}_c - \mathrm{e}_g)}$. Using $\mathrm{e}_c = 1.2$, $\mathrm{e}_g = 0.5$ and $c_c^v = 30$ and $c_g^v = 70$ for scenario D, and $c_c^v = 40$ and $c_g^v = 100$ for scenario E, leads a minimum carbon tax of 57 and 86 [USD/tonCO_2] for scenarios D and E respectively.

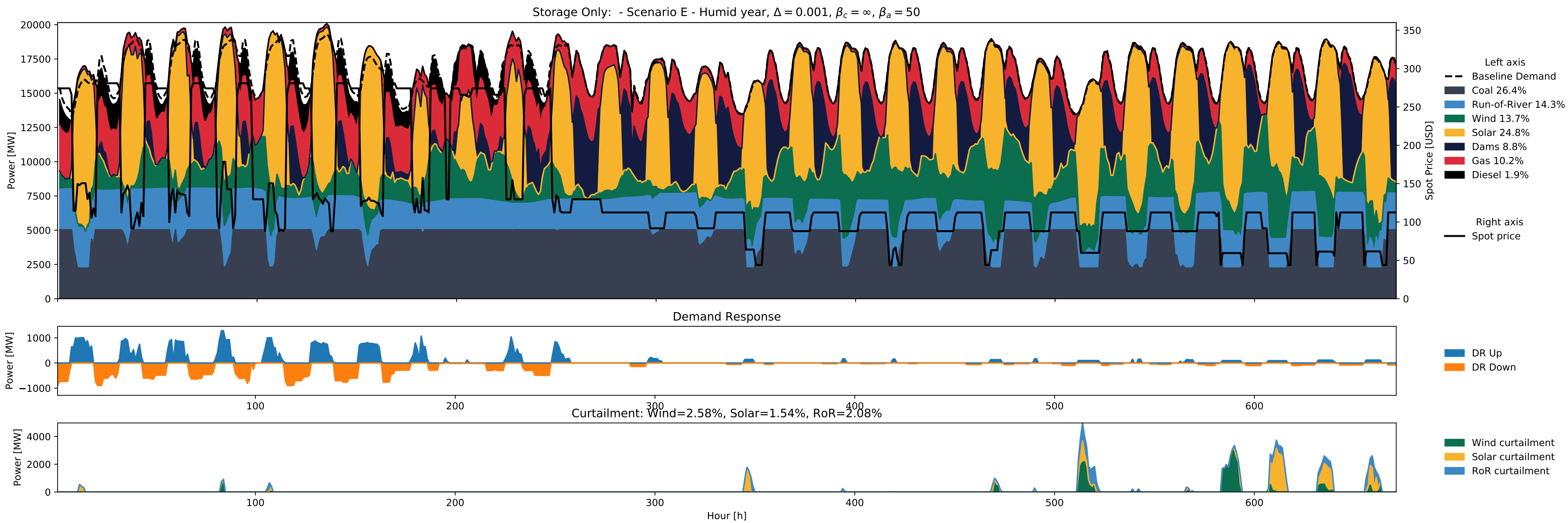
ever, the marginal cost of shifting demand from the night to the day is almost equal to the possible avoided cost by reducing gas generation (approx. 100 USD/MWh)[14]. In the next section, a sensibility analysis will be done to see how the reduction of demand adjustment cost impacts renewable energy curtailment.

In the following, Figs. 7.2a and 7.2b show the operation of the BAT study case for scenario E. The rest of the plots for the BAT study case can be found in Appendix A.2.

[14]Note that even with a linear demand adjustment cost, there is a cost of 50 USD/MWh involved in reducing demand, and an additional cost of 50 USD/MWh involved in increasing demand. On the other hand, the average cost of gas in this scenario 101.2 USD/MWh (see Table 6.3).



(a) System operation and spot price for the *Only shiftable demand (BAT)* case study, scenario E, dry year, base case.



(b) System operation and spot price for the *Only shiftable demand (BAT)* case study, scenario E, humid year, base case.

Figure 7.2: System operation and spot price for the *Only shiftable demand (BAT)* case study, scenario E, base case.

7.2.2 Only Adjustable Demand (CUR)

This section describes the general results for the base case of the *Only adjustable demand (CUR)* case study. As explained in Section 6.3, for this case study, the base case is considered to be given by

$$\Delta_B = 0.001, \qquad \beta_{c,B}^{CUR} = 0, \qquad \beta_{c,B}^{CUR} = 125. \tag{7.2}$$

	Scenario/Hydrology		D/dry	D/humid	E/dry	E/humid
Costs	Total cost	[MMUSD]	2804.39 (↓ 0.3%)	2161.46 (↓ 0.2%)	5316.94 (↓ 4.3%)	3906.51 (↓ 2.7%)
	On/Off cost	[MMUSD]	44.1 (↓ 0.1%)	31.18 (=)	144.0 (↓ 8.3%)	113.39 (↓ 4.4%)
	Ramping cost	[MMUSD]	1.26 (=)	0.88 (=)	3.26 (↓ 2.1%)	3.26 (↓ 1.5%)
S.P	Spot price mean	[USD/MWh]	88.17 (↓ 7.3%)	69.67 (↓ 3.0%)	166.8 (↓ 11.7%)	130.58 (↓ 5.0%)
	Spot price std.	[USD/MWh]	27.03 (↓ 22.3%)	23.48 (↓ 16.1%)	93.92 (↓ 16.0%)	75.94 (↓ 14.7%)
Generation	Solar generation	[%]	14.37 (=)	14.37 (=)	24.9 (↑ 0.4)	24.88 (↑ 0.2)
	Wind generation	[%]	8.71 (=)	8.71 (=)	13.45 (↓ 0.3)	13.42 (↓ 0.3)
	RoR generation	[%]	16.57 (=)	17.93 (=)	13.13 (↓ 0.1)	14.21 (↑ 0.1)
	Dams generation	[%]	5.85 (=)	10.82 (=)	4.75 (=)	8.79 (=)
	Gas generation	[%]	17.12 (↑ 0.0)	11.44 (↑ 0.0)	12.4 (↓ 0.0)	10.18 (↓ 0.0)
	Coal generation	[%]	36.4 (=)	36.4 (=)	26.2 (=)	26.0 (=)
	Die. generation	[%]	0.61 (↓ 0.4)	0.16 (↓ 0.1)	3.59 (↓ 1.6)	1.68 (↓ 0.8)
	DR curtailment	[%]	0.39 (↑ 0.4)	0.14 (↑ 0.1)	1.62 (↑ 1.6)	0.81 (↑ 0.8)
Curt.	Solar curt.	[%]	0.0 (=)	0.01 (↑ 0.0)	1.07 (↓ 1.5)	1.17 (↓ 0.8)
	Wind curt.	[%]	0.0 (=)	0.0 (↓ 0.0)	4.13 (↑ 2.2)	4.29 (↑ 2.0)
	RoR curt.	[%]	0.0 (=)	0.0 (=)	2.45 (↑ 0.5)	2.46 (↓ 0.4)
	"S&W&RoR curt."	[%]	0.0 (=)	0.0 (=)	2.24 (=)	2.32 (=)
Cycles	Gas paid cycles		64.0 (=)	41.0 (=)	193.0 (↓ 0.5%)	157.0 (↓ 1.3%)
	Coal paid cycles		0.0 (=)	0.0 (=)	0.0 (=)	0.0 (=)
	Die. paid cycles		0.0 (↓ 100.0%)	-0.0 (=)	67.0 (↓ 42.2%)	29.0 (↓ 39.6%)
R. cost	Gas ramp. cost	[MMUSD]	0.44 (=)	0.23 (=)	0.19 (↓ 13.6%)	0.16 (=)
	Coal ramp. cost	[MMUSD]	0.82 (=)	0.65 (=)	3.05 (↓ 0.3%)	3.09 (↓ 1.0%)
	Die. ramp. cost	[MMUSD]	0.0 (=)	0.0 (=)	0.02 (↓ 66.7%)	0.01 (↓ 50.0%)
	CO_2 emissions	[MMtonCO_2]	65.3 (↓ 0.6%)	61.72 (↓ 0.2%)	61.92 (↓ 3.2%)	57.65 (↓ 1.8%)
DR	Max. PW adj.	[MW]	153.66 (1.28%)	153.66 (1.17%)	718.52 (4.32%)	696.82 (4.28%)

Table 7.3: Summary of results for the *Only adjustable demand (CUR)* case study, base case scenario

A summary of the general results are shown in Table 7.3, where the *DR curtailment* indicator is added to the *Generation* section, referring to the demand reduction provided Demand Response. The main observations are described in the following list:

a) *Demand Response participation reaches a maximum level of 4.32% of total demand, which is consistent with the literature.*

   Demand response participation in the case of DR provided by shiftable demand reaches maximum of 1.3% and 4.3% of baseline demand for scenarios D and E respectively (Table 7.3). Similarly to the observation 7.2.1.a for the BAT study case, these values prove that the current approach of not imposing an upper bound on DR participation, but rather include a quadratic term in DR cost function, leads to reasonable results that are within the existing literature range in terms of DR participation [15].

b) *The impact of DR in costs is higher in dry years. Moreover, it does reduce total annual costs up to 4.3%, which are mainly due to costs reductions related to generation.*

   Similarly to observation 7.2.1.b, Demand Response participation becomes more valuable during dry years due to the replacement of expensive peaking generation units. In this context, costs reductions are mainly due to costs reduced in generation. For example, for a dry year in scenario E, start-up/shutdown costs and load following costs reduction are being reduced in 0.2% and 0.001% with respect to total annual costs.

   Also, total annual costs reduction in the case of Demand Response provided by adjustable demand (CUR) are higher than in the case of Demand Response provided by shiftable demand (BAT) with the current assumptions.

c) *Spot price is reduced up to 11.7%.*

   This reduction is due to the replacement of expensive diesel generation with coal generation, which also decreases spot price variability in at least 14% for all scenarios. From Figs. 7.1a and 7.3a it is observed that the maximum spot price is reduced from around 350 [USD/MWh] to lower than 300 [USD/MWh].

d) *Diesel generation is replaced by demand side curtailment. Demand Response competes with diesel generation units as peaking technologies.*

   As shown in Table 7.3, diesel generation is reduced up to 1.6 percentage points of the total demand (which corresponds to a reduction of 49.6% in diesel generation in that case). These reductions are always balanced by demand side curtailment, indicating that Demand Response competes with diesel generation units as peaking technologies reducing spot price during the night (See Figs. 7.3a and 7.3b).

e) *Renewable curtailment levels remain constant.*

   As Demand Response from adjustable demand provides no intra-day load balance, curtailment levels remain constant[16]

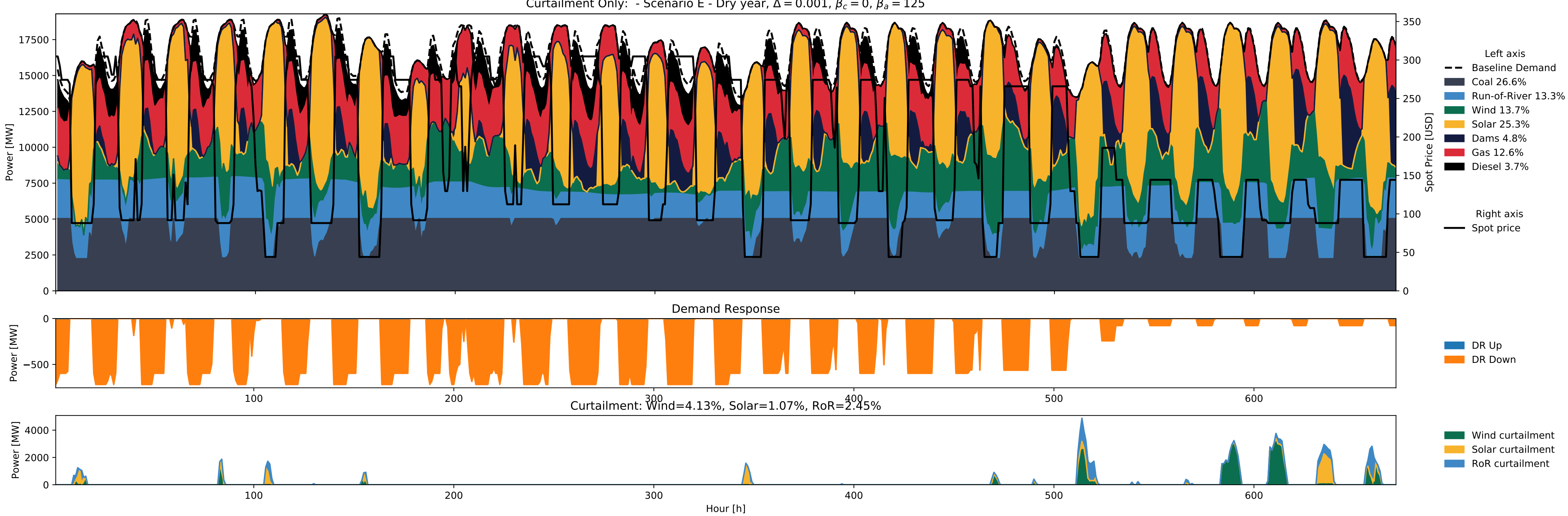
f) *CO_2 emissions are reduced up to a 3.2% which corresponds to an amount of 2 MMtonCO_2*

[15]The models found in the literature generally impose an upper bound on DR participation of 5% (Walawalkar et al. (2008), Flores (2015)))

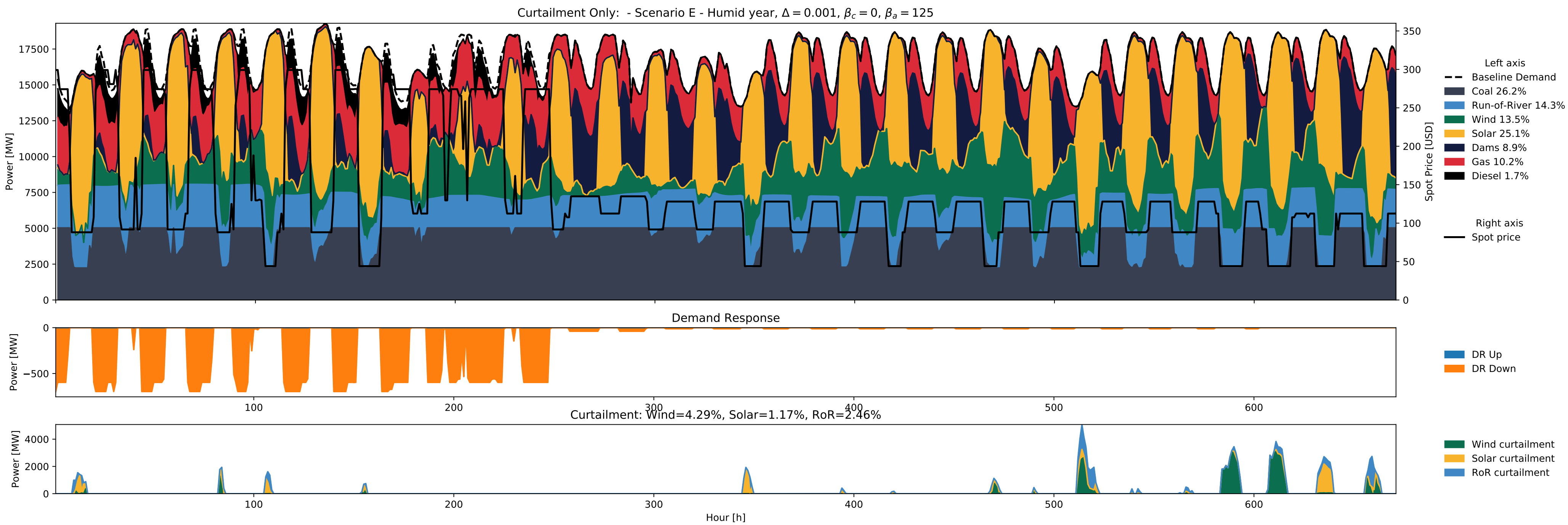
[16]Note that here we refer to the solar, wind and run-of-the-river (*SWR*) overall curtailment, and not to the particular solar, wind or run-of-the-river curtailment independently as explained in the beggining of this chapter.

This result is straightforward from the fact that DR in CUR study case replace peaking generation units by demand side curtailment that is assumed to have no carbon emissions. In particular, for scenario E during a dry year, CO_2 emissions are reduced up to a 3.2% corresponding to 2 MMtonCO_2.

In the following, Figs. 7.3a and 7.3b show the operation of the CUR study case for scenario E. The rest of the plots for the CUR study case can be found in Appendix A.3.



(a) System operation for *Only adjustable demand (CUR)* case study, scenario E, dry year, base case.



(b) System operation for *Only adjustable demand (CUR)* case study, scenario E, humid year, base case.

Figure 7.3: System operation and spot price for the *Only adjustable demand (CUR)* case study, scenario E, base case.

7.2.3 Mixture of Technologies (MIX)

This section describes the general results for the base case of the *Mixture of technologies (MIX)* case study. As explained in Section 6.3, for this case study, the base case is considered to be given by

$$\Delta_B = 0.001, \qquad \beta_{c,B}^{MIX} = 125, \qquad \beta_{a,B}^{MIX} = 50,$$

in which $\beta_{c,B}^{MIX}$ takes the base case value of the curtailment cost in CUR, and $\beta_{a,B}^{MIX}$ takes the base case value of the adjustment cost in BAT.

	Scenario/Hydrology		**D/dry**	**D/humid**	**E/dry**	**E/humid**
Costs	Total cost	[MMUSD]	2811.15 (↓ 0.1%)	2163.55 (↓ 0.1%)	5360.32 (↓ 3.5%)	3927.06 (↓ 2.2%)
	On/Off cost	[MMUSD]	44.14 (=)	31.2 (↑ 0.1%)	129.69 (↓ 17.4%)	108.85 (↓ 8.2%)
	Ramping cost	[MMUSD]	1.08 (↓ 14.3%)	0.77 (↓ 12.5%)	2.68 (↓ 19.5%)	2.84 (↓ 14.2%)
S.P	Spot price mean	[USD/MWh]	93.99 (↓ 1.2%)	70.51 (↓ 1.8%)	172.33 (↓ 8.8%)	132.34 (↓ 3.7%)
	Spot price std.	[USD/MWh]	33.65 (↓ 3.3%)	25.73 (↓ 8.1%)	94.38 (↓ 15.5%)	77.31 (↓ 13.2%)
Generation	Solar generation	[%]	14.37 (=)	14.37 (=)	24.84 (↑ 0.3)	24.78 (↑ 0.1)
	Wind generation	[%]	8.71 (=)	8.71 (=)	13.72 (↓ 0.0)	13.66 (↓ 0.0)
	RoR generation	[%]	16.57 (=)	17.93 (=)	13.23 (↑ 0.0)	14.27 (↑ 0.1)
	Dams generation	[%]	5.85 (=)	10.82 (=)	4.75 (=)	8.79 (=)
	Gas generation	[%]	17.11 (↓ 0.0)	11.45 (↑ 0.0)	12.81 (↑ 0.4)	10.25 (↑ 0.0)
	Coal generation	[%]	36.5 (↑ 0.1)	36.5 (↑ 0.1)	26.8 (↑ 0.6)	26.4 (↑ 0.4)
	Die. generation	[%]	0.89 (↓ 0.1)	0.23 (↓ 0.1)	3.76 (↓ 1.4)	1.87 (↓ 0.6)
	DR curtailment	[%]	0.0 (=)	0.0 (=)	0.05 (↑ 0.0)	0.02 (↑ 0.0)
Curt.	Solar curt.	[%]	0.0 (=)	0.0 (=)	1.31 (↓ 1.2)	1.54 (↓ 0.5)
	Wind curt.	[%]	0.0 (=)	0.0 (↓ 0.0)	2.21 (↑ 0.3)	2.59 (↑ 0.3)
	RoR curt.	[%]	0.0 (=)	0.01 (↑ 0.0)	1.73 (↓ 0.3)	2.08 (↓ 0.8)
	"S&W&RoR curt."	[%]	0.0 (=)	0.0 (=)	1.66 (↓ 0.6)	1.96 (↓ 0.4)
Cycles	Gas paid cycles		64.0 (=)	41.0 (=)	173.0 (↓ 10.8%)	151.0 (↓ 5.0%)
	Coal paid cycles		0.0 (=)	0.0 (=)	0.0 (=)	0.0 (=)
	Die. paid cycles		1.0 (=)	0.0 (=)	67.0 (↓ 42.2%)	28.0 (↓ 41.7%)
R. cost	Gas ramp. cost	[MMUSD]	0.43 (↓ 2.3%)	0.23 (=)	0.2 (↓ 9.1%)	0.16 (=)
	Coal ramp. cost	[MMUSD]	0.65 (↓ 20.7%)	0.54 (↓ 16.9%)	2.46 (↓ 19.6%)	2.67 (↓ 14.4%)
	Die. ramp. cost	[MMUSD]	0.0 (=)	0.0 (=)	0.02 (↓ 66.7%)	0.01 (↓ 50.0%)
	CO_2 emissions	[MMtonCO_2]	65.77 (↑ 0.1%)	61.89 (↑ 0.0%)	63.69 (↓ 0.5%)	58.58 (↓ 0.2%)
DR	Max. PW adj.	[MW]	185.52 (1.4%)	212.49 (1.6%)	1224.41 (7.42%)	893.37 (5.05%)
	Max. EN shifted.	[MWh]	1.48 (0.49%)	1.41 (0.47%)	9.75 (2.64%)	9.24 (2.5%)
	Max daily EN curt.	[GWh]	0.0 (0.0%)	0.0 (0.0%)	0.52 (0.13%)	0.38 (0.1%)

Table 7.4: Summary of results for the *Mixture of technologies (MIX)* case study, base case scenario

Table 7.4 shows a summary of the general results for this case study. Figs. 7.4a and 7.4b show the operation if the MIX study case for scenario E. The rest of the plots for the MIX study case can be found in Appendix A.4.

As it can be observed in Table 7.4 and Figs. 7.4a, 7.4b, A.7a and A.7b (and by comparing them with BAT results in Table 7.2 and Figs. 7.2a, 7.2b, A.3a and A.3b respectively), results for the base case of MIX case study are roughly the same as the results presented for the

BAT case study (Section 7.2.1). In fact, from Table 7.4, the maximum Demand Response curtailment occurs in scenario E during a dry year, reaching a maximum value of only 0.05%, which means that there is almost no energy curtailment, and hence, only intra-day energy balance. Also, daily energy curtailment reaches a maximum level of 520 MWh[17], which represent only a 0.13% of the original daily demand.

To understand why is this, first note that both case studies only differ in the β_c value. On one hand, Demand Response provided by shiftable demand was analysed imposing a β_c value of $\beta_c^{BAT} = +\infty$, while the *Mixture of technologies* case study uses a β_c value of $\beta_c^{MIX} = 125$. This means that the MIX case study is in fact a relaxation of the BAT case study in terms of the β_c value (which describes the quadratic cost of overall energy reduction within a specific day, as described in eq. (5.1)). Secondly, note that in the BAT simulation results it is observed that shiftable-Demand Response produces demand reduction during the night (avoiding the usage of diesel generation) and demand recovery (increment) during the day (mainly increasing coal generation levels). This demand increment involves (i) a quadratic adjustment cost given by $\beta_a^{BAT} = 50$ and (ii) generation cost given by an average coal variable cost of about $c^v = 30$ and $c^v = 40$ for scenarios D and E respectively (Table 6.3). This means that for the BAT case, at least linearly, the involved cost in recovering energy is about 80 and 90 [USD/MWh] for scenarios D and E respectively. In this context, an alternative energy curtailment with a linear cost of $\beta_c^{MIX} = 125$ it does not represent a better alternative, leading MIX operations to behave as the BAT case study.

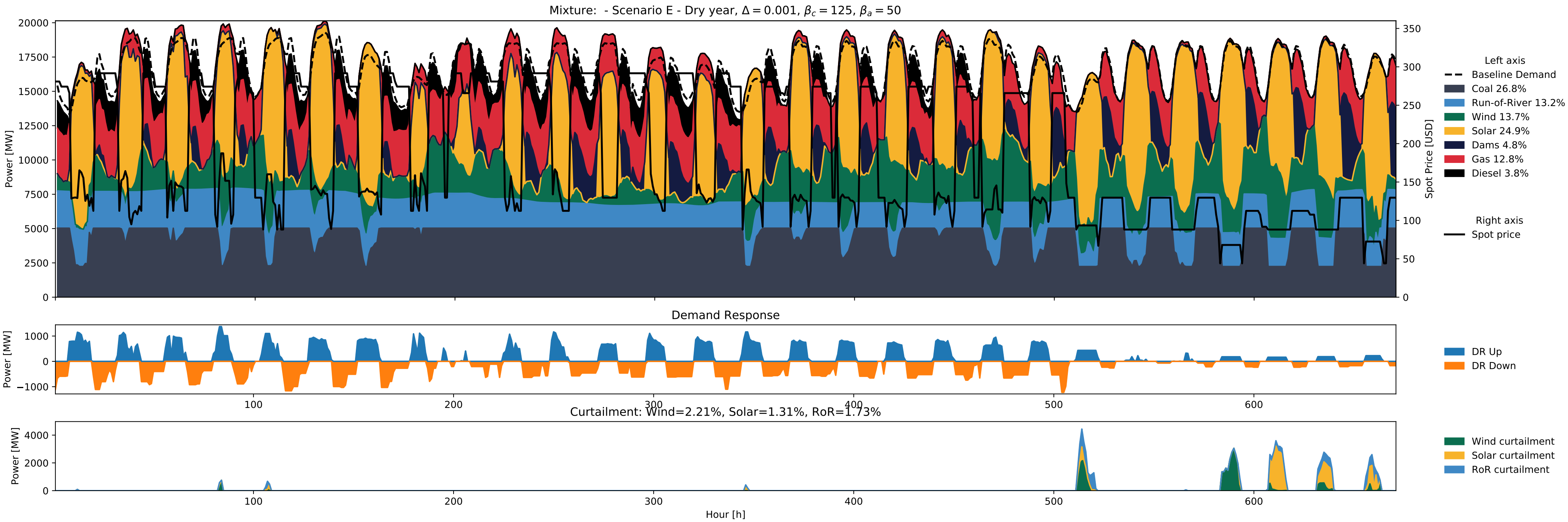
This highlights the fact that it is not straight forward to use the current DR participation model presented in this work to assess the impact of a situation in which demand flexibility is provided by a mixture of shiftable and adjustable demand. Moreover, note that while in CUR case study the only cost involved in curtailing demand is the hourly-dependent quadratic adjustment cost determined by $\beta_a^{CUR} = 125$, in the MIX case study, in order to curtail demand, there are two costs involved: (i) the quadratic adjustment cost determined by $\beta_a^{MIX} = 50$ and (ii) the quadratic curtailment cost of not recovering daily energy reduction determined by $\beta_c^{CUR} = 125$. Finally, the curtailment cost values quadratically the energy curtailed during the hole day, which is always higher (or equal) than the sum of quadratic hourly curtailment costs as in the case of CUR [18]. In order to emphasize this idea, Table 7.5 shows the results of a MIX case study simulation reducing β_c value up to 50 and hence using

$$\Delta_B = 0.001, \qquad \beta_c^{MIX} = 50, \qquad \beta_a^{MIX} = 50,$$

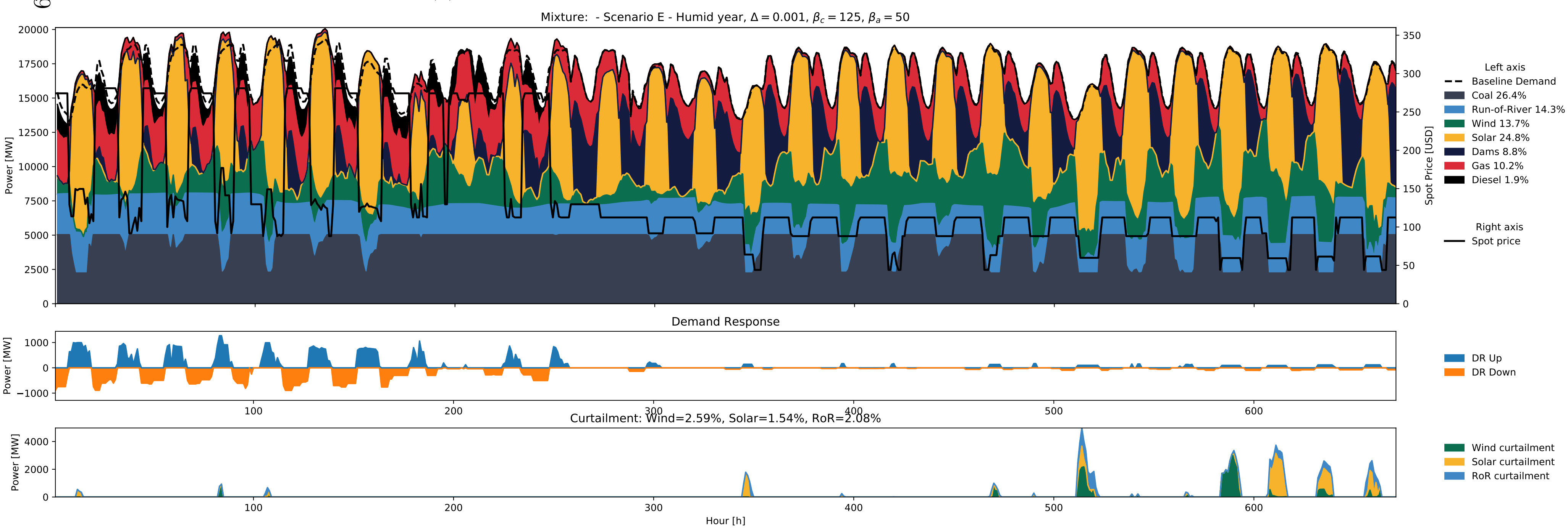
Here, it is observed that even if results are different and demand-side curtailment reaches a maximum of 0.26% of total demand, its participation is meaningless. Hence, in the following, sensibility analysis will be done for BAT and CUR case studies only.

[17]See parameter *Max daily EN curt.* in scenario E during a dry year

[18]$(\sum_t R_t)^2 = \sum_t R_t^2 + \sum_t \sum_{\tau \neq t} R_t \cdot R_\tau \ \geq \ \sum_t R_t^2$



(a) System operation for MIX case study, scenario E, dry year, base case.



(b) System operation for MIX case study, scenario E, humid year, base case.

	Scenario/Hydrology		D/dry	D/humid	E/dry	E/humid
Costs	Total cost	[MMUSD]	2807.1 (↓ 0.2%)	2161.46 (↓ 0.2%)	5337.15 (↓ 3.9%)	3916.2 (↓ 2.4%)
	On/Off cost	[MMUSD]	44.14 (=)	31.2 (↑ 0.1%)	131.02 (↓ 16.6%)	107.67 (↓ 9.2%)
	Ramping cost	[MMUSD]	1.07 (↓ 15.1%)	0.79 (↓ 10.2%)	2.7 (↓ 18.9%)	2.87 (↓ 13.3%)
S.P	Spot price mean	[USD/MWh]	92.86 (↓ 2.4%)	70.3 (↓ 2.1%)	166.85 (↓ 11.7%)	131.78 (↓ 4.1%)
	Spot price std.	[USD/MWh]	31.81 (↓ 8.6%)	22.92 (↓ 18.1%)	93.44 (↓ 16.4%)	77.1 (↓ 13.4%)
Generation	Solar generation	[%]	14.37 (=)	14.37 (=)	24.86 (↑ 0.3)	24.78 (↑ 0.1)
	Wind generation	[%]	8.71 (=)	8.71 (=)	13.71 (↓ 0.0)	13.66 (↓ 0.0)
	RoR generation	[%]	16.57 (=)	17.93 (=)	13.23 (↑ 0.0)	14.27 (↑ 0.1)
	Dams generation	[%]	5.85 (=)	10.82 (=)	4.75 (=)	8.79 (=)
	Gas generation	[%]	17.11 (↓ 0.0)	11.46 (↑ 0.0)	12.72 (↑ 0.3)	10.21 (↑ 0.0)
	Coal generation	[%]	36.5 (↑ 0.1)	36.5 (↑ 0.1)	26.8 (↑ 0.6)	26.3 (↑ 0.3)
	Die. generation	[%]	0.79 (↓ 0.2)	0.17 (↓ 0.1)	3.69 (↓ 1.5)	1.81 (↓ 0.6)
	DR curtailment	[%]	0.12 (↑ 0.1)	0.06 (↑ 0.1)	0.26 (↑ 0.3)	0.15 (↑ 0.2)
Curt.	Solar curt.	[%]	0.0 (=)	0.01 (↑ 0.0)	1.24 (↓ 1.3)	1.57 (↓ 0.4)
	Wind curt.	[%]	0.0 (=)	0.0 (↓ 0.0)	2.22 (↑ 0.3)	2.59 (↑ 0.3)
	RoR curt.	[%]	0.0 (=)	0.0 (=)	1.74 (↓ 0.2)	2.08 (↓ 0.8)
	"S&W&RoR curt."	[%]	0.0 (=)	0.0 (=)	1.63 (↓ 0.6)	1.97 (↓ 0.3)
Cycles	Gas paid cycles		64.0 (=)	41.0 (=)	176.0 (↓ 9.3%)	151.0 (↓ 5.0%)
	Coal paid cycles		0.0 (=)	0.0 (=)	0.0 (=)	0.0 (=)
	Die. paid cycles		1.0 (=)	0.0 (=)	66.0 (↓ 43.1%)	26.0 (↓ 45.8%)
R. cost	Gas ramp. cost	[MMUSD]	0.43 (↓ 2.3%)	0.22 (↓ 4.3%)	0.19 (↓ 13.6%)	0.16 (=)
	Coal ramp. cost	[MMUSD]	0.64 (↓ 22.0%)	0.56 (↓ 13.8%)	2.49 (↓ 18.6%)	2.7 (↓ 13.5%)
	Die. ramp. cost	[MMUSD]	0.0 (=)	0.0 (=)	0.02 (↓ 66.7%)	0.01 (↓ 50.0%)
	CO_2 emissions	[MMtonCO_2]	65.65 (↓ 0.1%)	61.81 (↓ 0.1%)	63.42 (↓ 0.9%)	58.42 (↓ 0.4%)
DR	Max. PW adj.	[MW]	218.73 (1.57%)	238.84 (1.8%)	1221.87 (7.41%)	929.45 (5.25%)
	Max. EN shifted.	[MWh]	1.66 (0.55%)	1.56 (0.52%)	10.0 (2.71%)	9.65 (2.61%)
	Max daily EN curt.	[GWh]	0.61 (0.19%)	0.6 (0.19%)	1.82 (0.46%)	1.64 (0.42%)

Table 7.5: Results of an even more optimistic *Mixture of technologies (MIX)* case study using
$\Delta_B = 0.001$, $\beta_c^{MIX} = 50$, and $\beta_{a,B}^{MIX} = 50$

7.3 Sensibility Analysis

This section describes the impact of the usage of different values of Δ and β_c in Demand Response participation, capacity factors, annual costs, spot price, and total CO_2 emissions for BAT and CUR case studies. As described in Section 6.3 for the BAT case study, the sensibility analysis is done using

$$\beta_c^{BAT} = \infty, \qquad \beta_a^{BAT} \in \{12.5, \quad 25, \quad 50, \quad 100, \quad 150\},$$

while, for the CUR case study, the sensibility analysis is done using

$$\beta_c^{CUR} = 0, \qquad \beta_a^{CUR} \in \{50, \quad 100, \quad 125, \quad 150, \quad 200, \quad 300\}.$$

Values for Δ are considered to be $\Delta \in \{0.001, 0.0036\}$ for both case studies.

7.3.1 Impacts in Demand Response Participation

Figures 7.5 and 7.6 show the maximum Demand Response adjustment values (*Max. PW adj.* indicator used in Tables 7.1, 7.2 and 7.3) for study cases BAT and CUR respectively, showing that in the most optimistic case ($\Delta = 0.001$ with $\beta_c^{BAT} = 12.5$ for BAT, and $\beta_c^{CUR} = 50$ for CUR) Demand Response reaches a maximum participation value of approximately 26% of total baseline demand in scenario E and 14% in scenario D in BAT. For the same values of β_c^{BAT} and β_c^{CUR}, when $\Delta = 0.0036$, maximum power adjustment reaches a maximum level of around 10 and 5% for in scenarios D and E respectively (again for BAT).

Recalling that in the existing literature, DR participation is considered to be within a range of 5-10% of total demand, it is reasonable to consider that if linear demand adjustment cost were as low as $\beta_c^{BAT} = 12.5$ and $\beta_c^{CUR} = 50$, then, the quadratic term Δ should be considered to be equal to $\Delta = 0.0036$. Hence, results of simulations using $\beta_c^{BAT} = 12.5$ and $\beta_c^{CUR} = 50$ should be analysed with caution. Taking this into account, these values proves that even in a optimistic scenario, the current approach of not imposing an upper bound on DR participation, but rather include a quadratic term in DR cost function, leads to reasonable results that are within the existing literature range in terms of DR participation.

On the other hand, Demand Response participation decreases drastically for β_c values higher than the base case values for both BAT and CUR case studies. In particular, for the BAT case study a value of $\bar{\beta}_c^{BAT} = 100$ [USD/MW] seems to be an upper limit for the adjustment cost. This is consistent with the variable cost of the diesel and coal generation units and the maximum value for β_a found in Eq. (6.29). In fact, following the notation introduced in Section 6.4, for scenario D, the peaking generation unit (diesel) has a variable cost of $c_P^v = 183$ [USD/MWh], while the base technology has a variable cost of around

$c^v_B = 27$ (Table 6.3)). With, this the maximum value for β_a in scenario D is[19]

$$\beta_a^{max,D} = \frac{c^P - c^B}{2} = \frac{183 - 27}{2} = 77.5 \tag{7.3}$$

For CUR case study the upper limit for the adjustment cost is observed to be $\bar{\beta}_c^{CUR} = 200$ [USD/MW] due to the same reason.

Hence, in the following, sensibility analysis results will be only shown for values of β_c up to 100 and 200 [USD/MW] for case studies BAT and CUR respectively.

[19] Another way to see this is that at least linearly, any shift of demand from the night to the day would involve at least cost of (i) 100 [USD/MW] for reducing demand during the night, (ii) 100 [USD/MWh] for increasing demand during the day, plus (iii) 30 or 40 [USD/MW] for increasing coal generation during the day for scenarios D and E respectively. For scenario D this sums 230 which is higher than the average cost of the peaking generation unit (183 [USD/MW], Table 6.3)

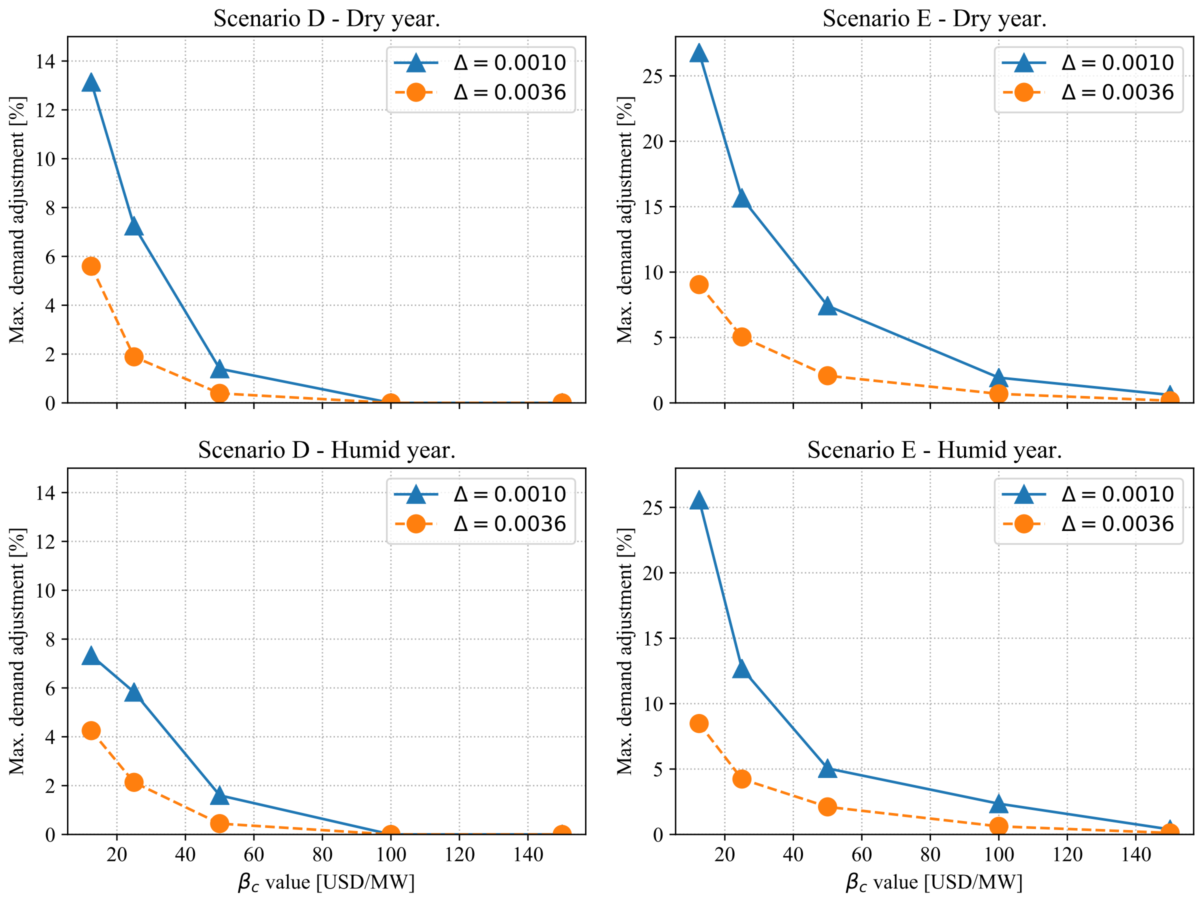


Figure 7.5: Maximum demand adjustment in *Only shiftable demand (BAT)* case study

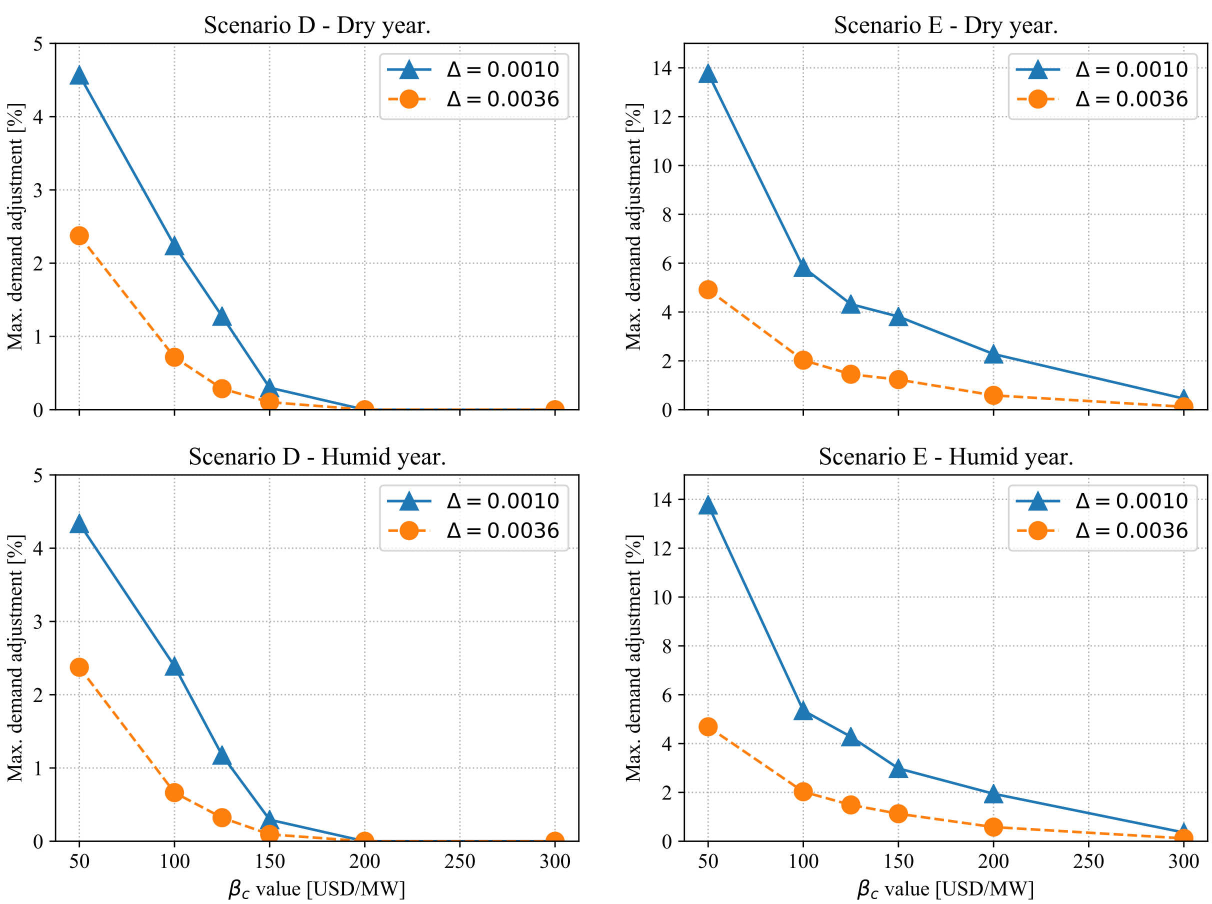


Figure 7.6: Maximum demand adjustment in *Only adjustable demand (CUR)* case study

7.3.2 Participation of Different Generation Technologies

This section shows the impact of different values of the β_c parameter in the participation of the different generation technologies through the usage of the *capacity factor* and *curtailment level* indicators. The *capacity factor* is the ratio between the actual energy produced by an energy generating unit, and the power it could have produced if it ran at its maximum power level during the whole time horizon (OpenEI (2012)). On the other hand, renewable energy *curtailment* is the difference between the power a given generation unit could produce given available resources, and the actual generation level. In the following, the *capacity factor* CF_X for generation technology $X \in$ {Dam, OCGT,CCGT, Coal, Diesel} is calculated as

$$CF_X = \frac{\sum_{t\in\mathcal{T}} \sum_{g\in\mathcal{G}_X} P_{g,t}}{T \cdot \sum_{g\in\mathcal{G}_X} P_g^{max}} \tag{7.4}$$

For solar, wind and run-of-the-river generation units, the *Solar, wind and run-of-the-river (SWR) curtailment level* k_{SWR} already introduced in the introduction of Chapter 7 is calculated as

$$k_{SWR} = \frac{\sum_{t\in\mathcal{T}} \left(\sum_{g\in\mathcal{G}_{RoR}} \left(\eta_g \cdot Q_{g,t}^{\text{in}} - P_{g,t}\right) + \sum_{g\in\mathcal{G}_S\cup\mathcal{G}_W} \left(P_g^{inst} \cdot P_{g,t}^{avail} - P_{g,t}\right)\right)}{\sum_{t\in\mathcal{T}} \left(\sum_{g\in\mathcal{G}_{RoR}} \eta_g \cdot Q_{g,t}^{\text{in}} + \sum_{g\in\mathcal{G}_S\cup\mathcal{G}_W} P_g^{inst} \cdot P_{g,t}^{avail}\right)} \tag{7.5}$$

With these definitions, capacity factors and SWR curtailment values were calculated for every simulation result. In order to better compare the changes in capacity factors by the usage of different values of the β_c parameter, Figs. 7.7a and 7.8a show (for the BAT and CUR case study respectively), the capacity factor difference with respect to the case without any Demand Response participation (BAU case) for conventional generation units. Similarly, Figs. 7.7b and 7.8b show SWR curtailment values for different values of β_c for the BAT and CUR case study respectively. Reference capacity factors values for the BAU case are shown in Table 7.6.

Scenario/Hydrology		**D/dry**	**D/humid**	**E/dry**	**E/humid**
Dams capacity factor	[%]	28.02	51.82	28.02	51.82
OCGT capacity factor	[%]	57.7	27.09	55.86	35.37
CCGT capacity factor	[%]	72.02	49.74	63.8	53.79
Coal capacity factor	[%]	98.3	98.47	86.99	86.56
Diesel capacity factor	[%]	5.62	1.66	21.78	10.37
SWR curtailment	[%]	0.0	0.0	2.24	2.32

Table 7.6: Capacity factor values for the *Business as Usual (BAU)* case study.

The main observations for Figs. 7.7a, 7.7b, 7.8a and 7.8b are described in the following list:

a) *Demand response provided by shiftable demand decreases diesel participation, increasing coal and gas generation unit's participation.*

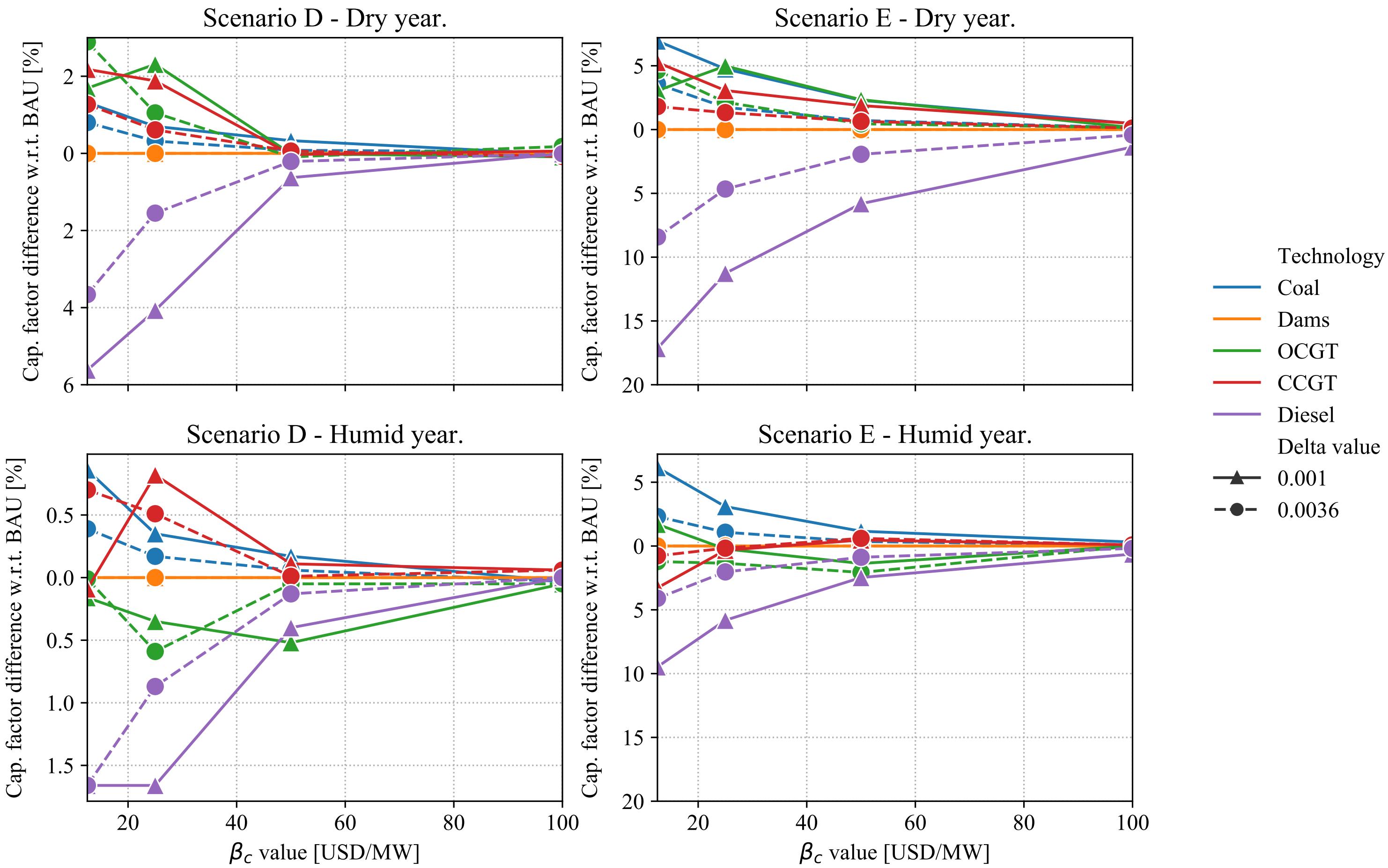
   As also noted in Observation 7.2.1.c, a lower cost for shifting demand can reduce diesel capacity factor up to a half because their generation is being replaced by coal and gas technologies (Fig.7.7a). For the scenario D in BAT, shiftable demand helps coal power plants to reach a capacity factor of almost 99%.

   On the other hand, for the case of Demand Response provided by adjustable demand (CUR), demand-response curtailment reduces diesel and gas generation unit's participation, keeping coal generation unit's participation constant (Fig. 7.8a).

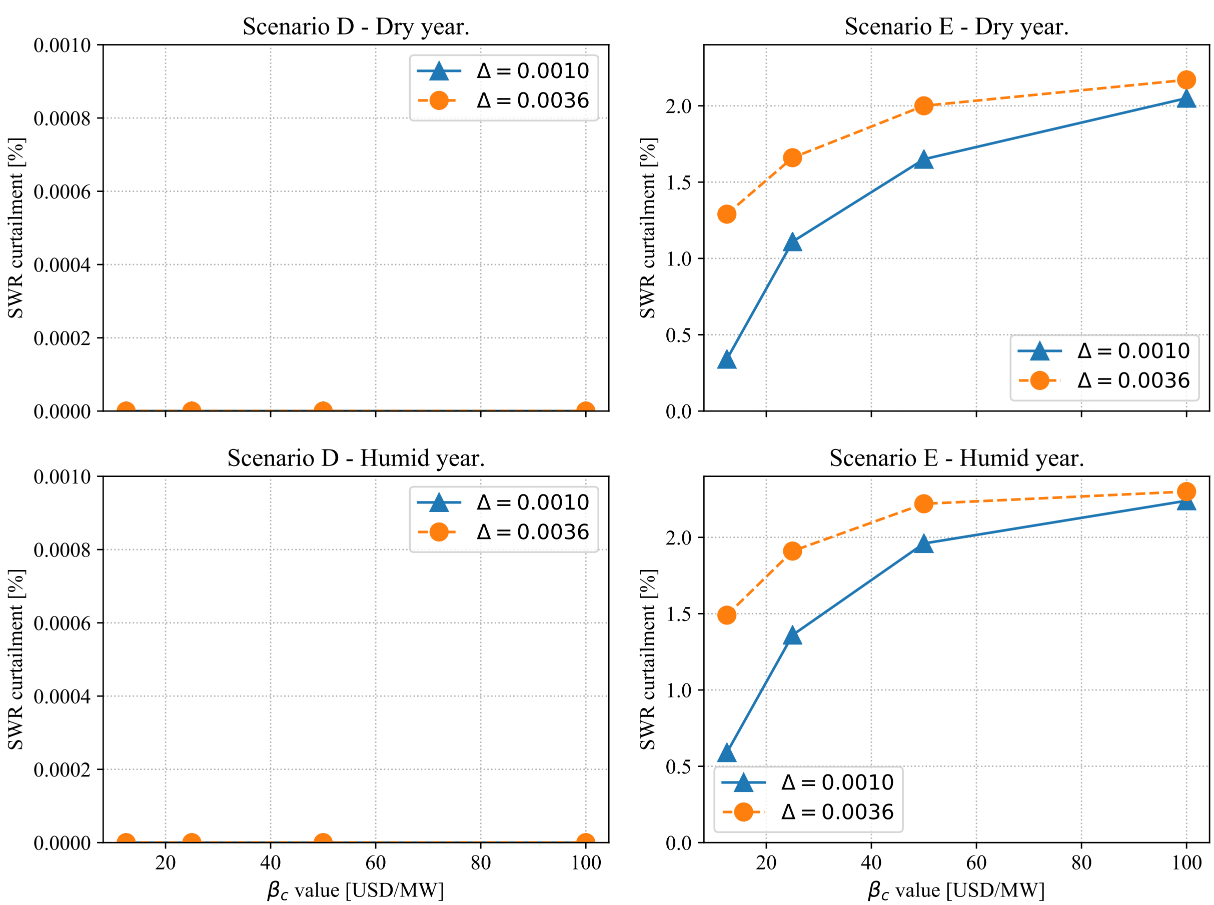
b) *A lower price for demand adjustment (β_c) in BAT case reduces SWR curtailment up to a half of its value of reference. Demand response provided only by adjustable demand does not reduces renewable energy curtailment.*

   From Fig. 7.8b it is observed that a lower price for demand adjustment help solar, wind and run of the river generation units to reduce their curtailment value.

   On the other hand, for CUR case, Demand Response participation does not help SWR curtailment to be reduced even in the most optimistic cases, which is direct from the fact that CUR does not provide demand balance, and hence, only reduces the generation of the peaking generation unit.

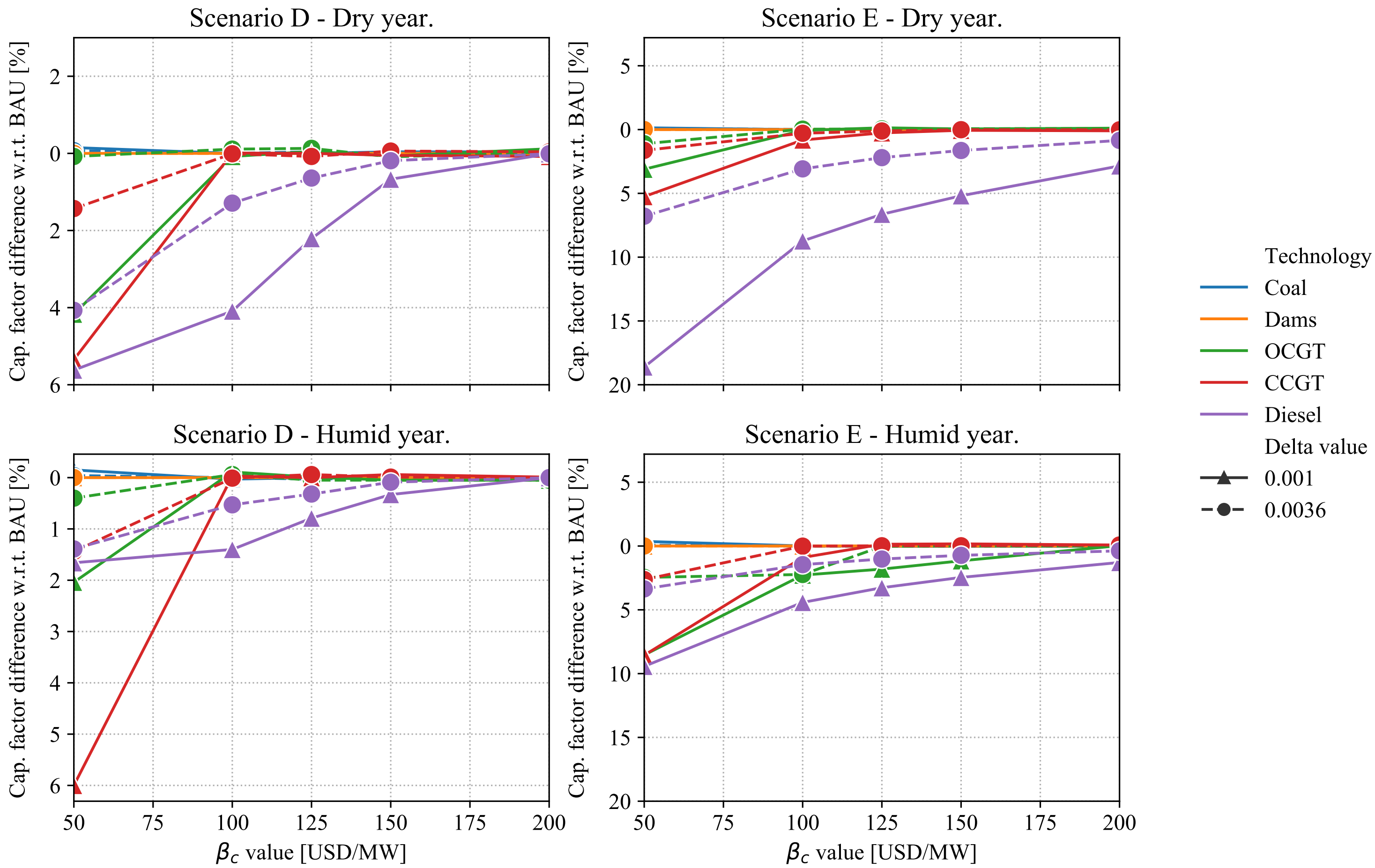


(a) Capacity factors of conventional generation units in *Only shiftable demand (BAT)* case study

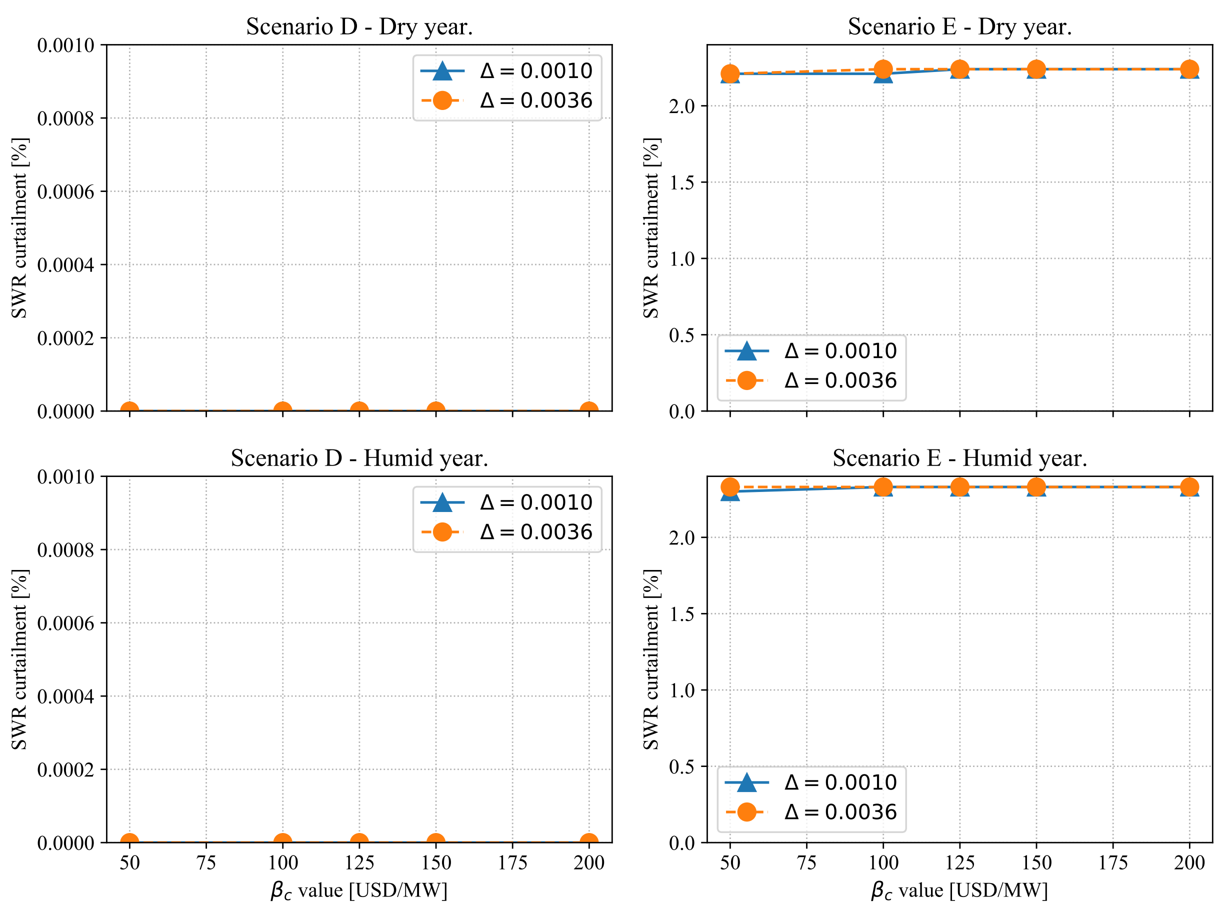


(b) Solar, wind and run-of-the-river curtailment value in *Only shiftable demand (BAT)* case study

Figure 7.7: Capacity factors and SWR curtailment in BAT case study



(a) Capacity factors of conventional generation units in *Only adjustable demand (CUR)* case study



(b) Solar, wind and run-of-the-river curtailment value in CUR case study

Figure 7.8: Capacity factors and SWR curtailment in CUR case study

7.3.3 Impacts in Costs

This section shows the impact of different values of the β_c parameter in annual costs. First, this section shows the impact in total costs, separated in load following costs, start-up/shutdown costs, generation costs per technology and Demand Response cost (payments to responsive demand) (Figs. 7.9a and 7.9b). As load following and start-up/shutdown costs are much lower than generation costs (Table 7.1), these results are later shown and described separately in Figs.7.10a and 7.10b (load following costs), and Figs. 7.11a and 7.11b (start-up/shutdown costs). In all figures, total cost rate reduction with respect to the BAU case is also shown in the right axis. The main observations are:

Total cost:

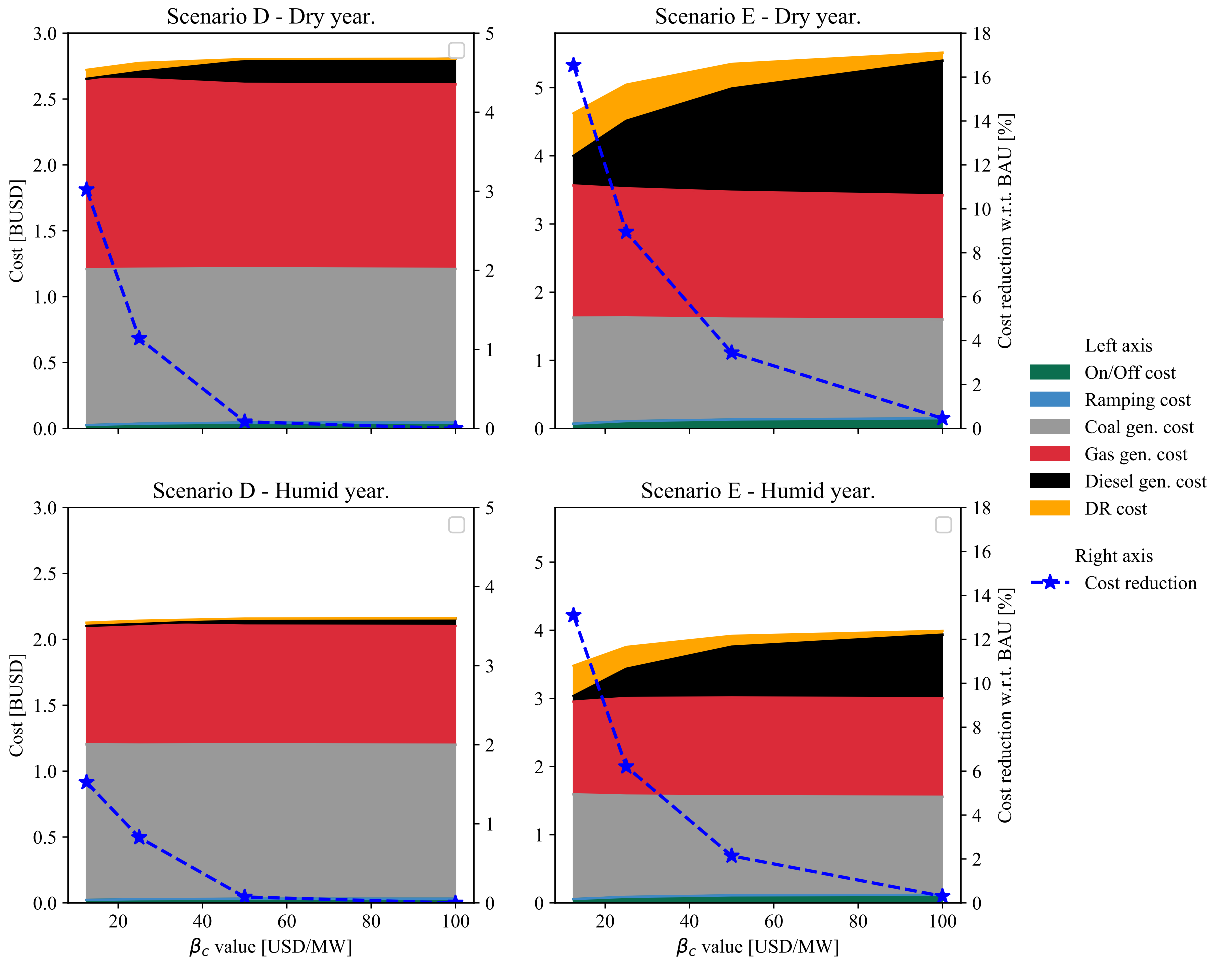
a) *Total annual cost is reduced with the reduction of adjustment cost for both case studies. Total annual costs can be reduced up to 16% and 5% in scenarios E and D respectively.*

b) *Annual costs reductions are mainly due to the reduction of diesel generation.*

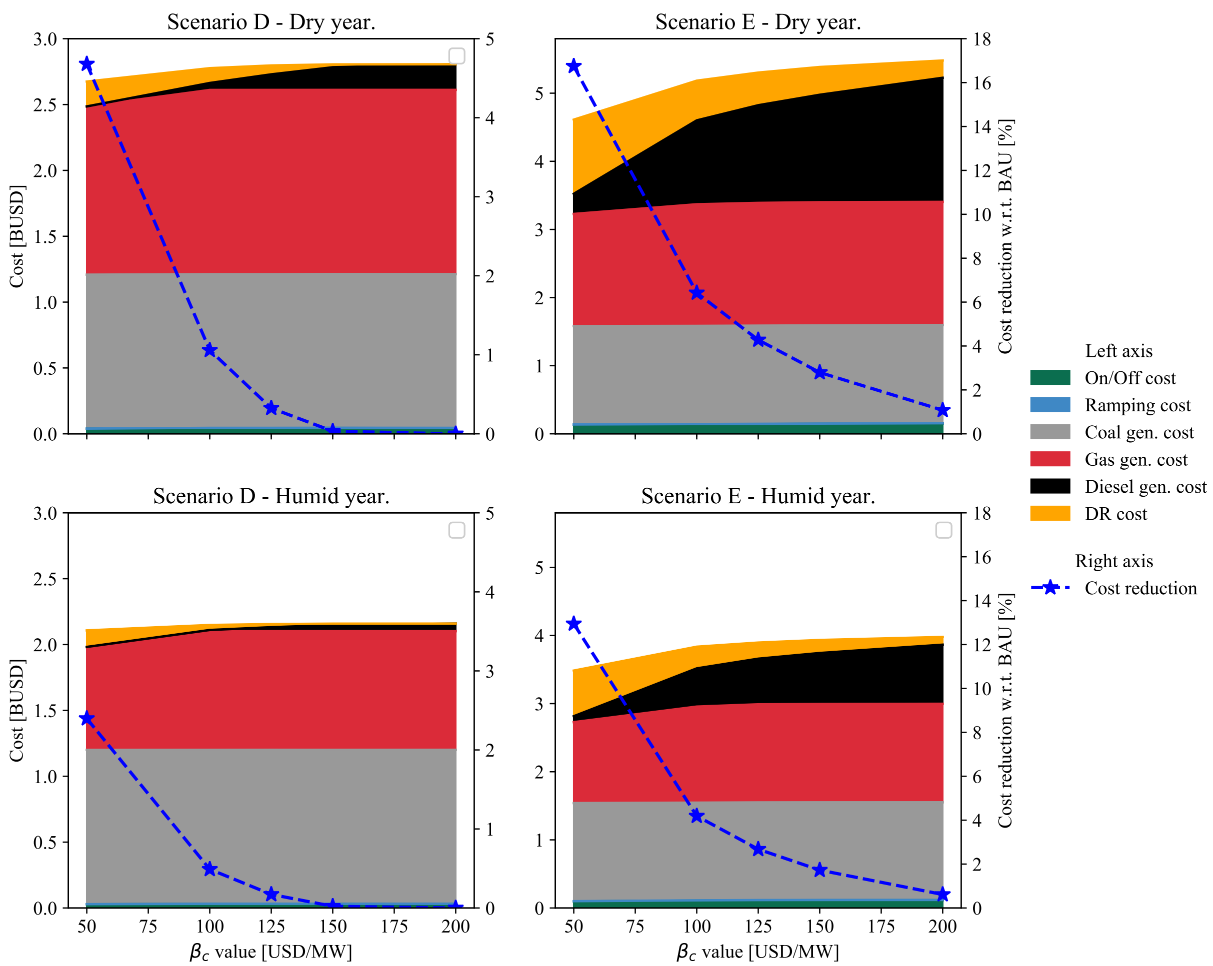
With respect to total annual costs reduction, the behaviour is roughly similar for both case studies: major costs reduction occurs in scenario E due to the major reduction of diesel generation costs (Figs. 7.9a and 7.9b). For the CUR case, the reason is direct from the fact that demand curtailment reduces diesel generation levels (Fig. 7.8a). For the BAT case, from Fig. 7.9a it can be observed that the replacement of diesel generation units with coal and gas (Observation 7.2.1.c) involves a cost increment of gas and coal generation cost which is negligible in comparison with the reduction of diesel generation cost[20].

With respect to scenario D, there is less impact in total generation cost because there is less diesel generation (less than 1% in BAU (Table 7.1)).

[20]This is due to the high difference in variable costs between diesel and coal. In fact, in scenario E, diesel generation units' variable cost is about 10 times the cost of coal generation units (See Table 6.3).



(a) Detailed total costs in *Only shiftable demand (BAT)* case study



(b) Detailed total costs in *Only adjustable demand (CUR)* case study

Figure 7.9: Detailed total costs

Load following cost:

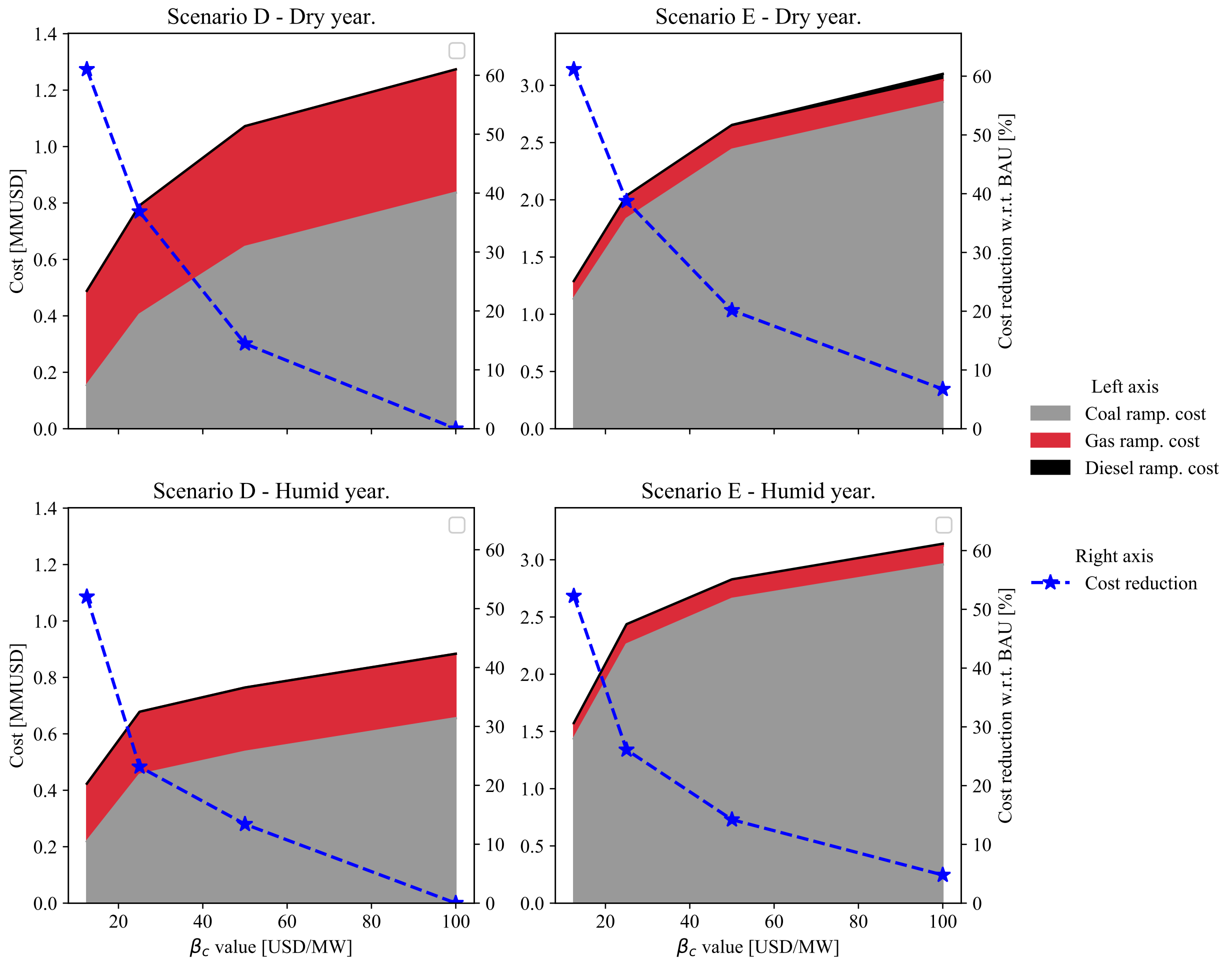
a) *Load following cost is reduced with the reduction of adjustment cost mainly in BAT case study. In particular, for this case study, load following cost can be reduced up to 60%.*

b) *Load following cost reduction is mainly due to the reduction of load following costs related to coal generation units.*

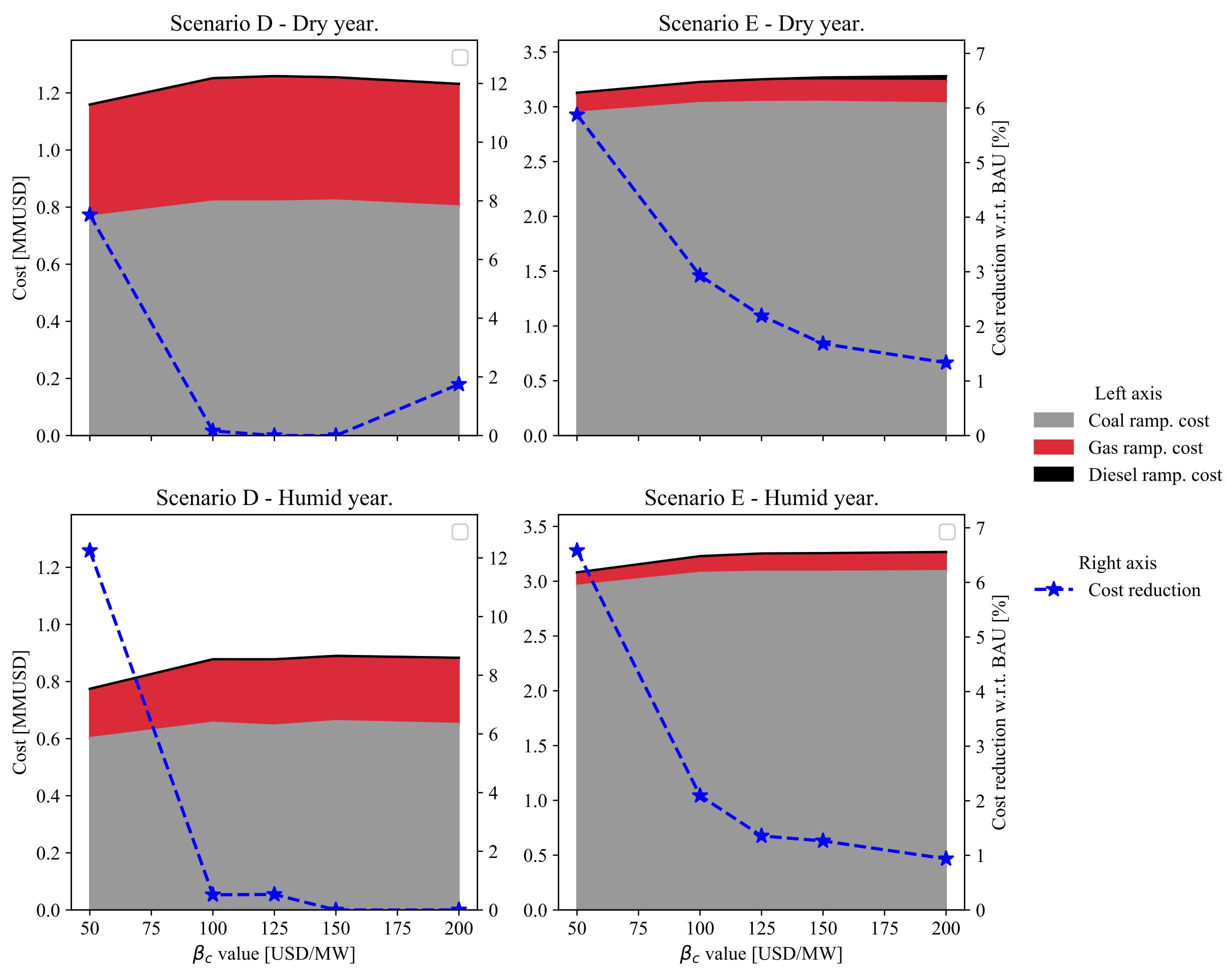
As observed in Fig. 7.10a, coal generation units are responsible for the majority of load following costs and their reduction. This, together with the increment of coal generation unit's capacity factor (Observation 7.3.2.a) reinforce the idea that coal power plants increase their position as a base technology with the help of DR.

c) *For CUR, there is little impact in load following cost.*

In the case of Demand Response provided by adjustable demand (CUR), there is little impact in load following costs due to the fact that coal generation units do not change their participation level (see changes in capacity factor in coal generation units in Fig. 7.8a).



(a) Detailed ramping costs in *Only shiftable demand (BAT)* case study



(b) Detailed load following in *Only adjustable demand (CUR)* case study

Figure 7.10: Detailed load following costs

Start-up/shutdown costs:

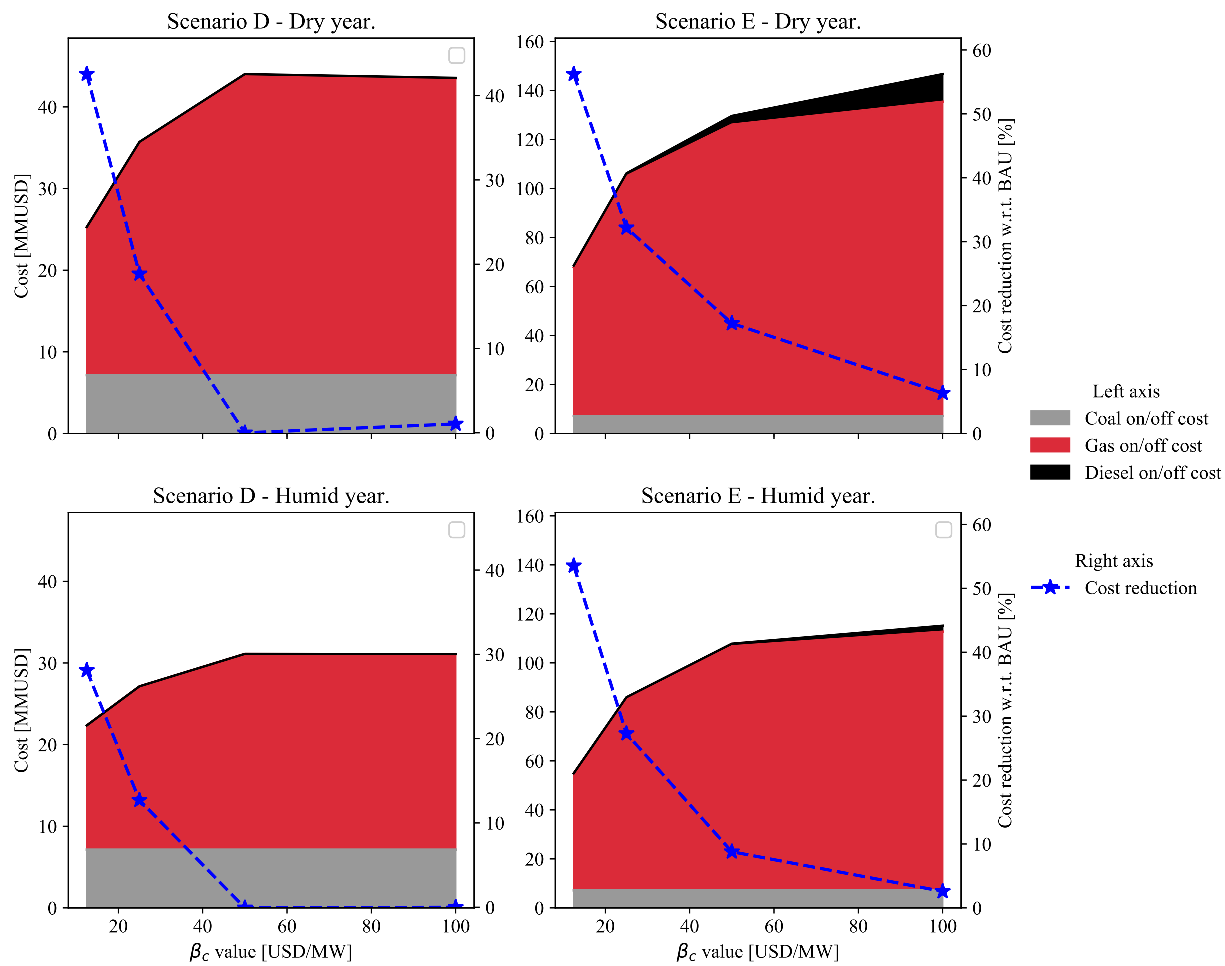
a) *The reduction of adjustment costs reduces start-up/shutdown costs both for BAT and CUR case study. For BAT case, start-up/shutdown cost can be reduced up to 43% in scenario D and up to 56% in scenario E. For CUR case study, start-up/shutdown cost reduction reaches levels of 12 and 14% for scenarios D and E respectively.*

b) *For all cases, costs reductions are due to the reduction of cycling operation levels of gas generation units.*

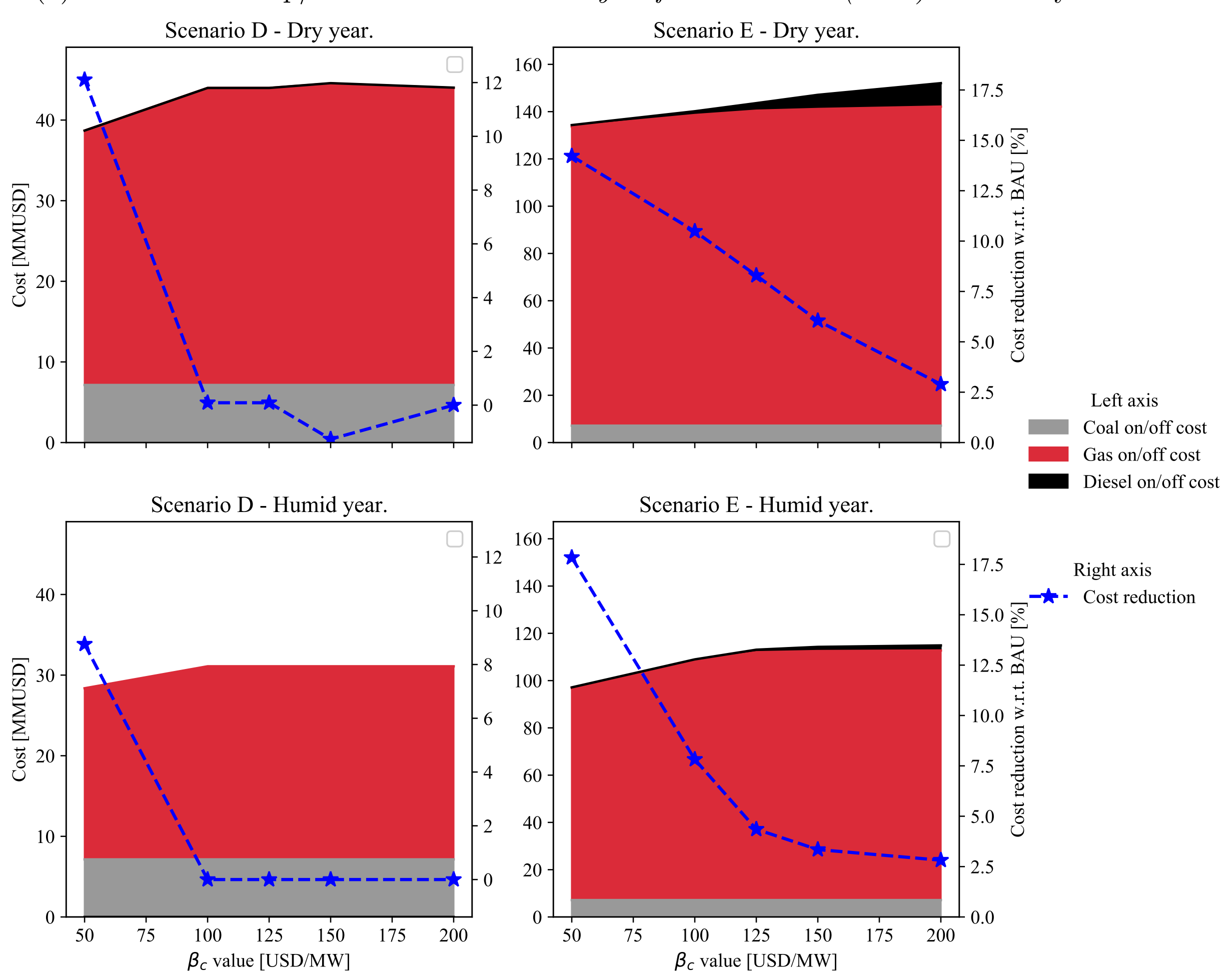
First, let's note that there are no changes in start-up/shutdown costs related to coal generation units. This is because coal generation units never shut down in the simulation[21]. Then, let's note that there is comparatively little start-up/shutdown costs related to diesel generation units, which is due to (i) diesel generation units' low participation (ii) few diesel generation units have non-zero start-up or shutdown cost (iii) non-zero diesel generation units' start-up or shutdown costs are much lower than those for gas generation units[22]. Hence, start-up/shutdown costs and its reduction are mainly due to gas generation units' participation.

[21]In fact, the quantity of cycles in the BAU case for coal generation units is 0 (Table 7.1).

[22]From Tables B.5 and B.7, average non-zero start-up cost for diesel generation units is $c\bar{on}_D = 7.542$ [USD] while for gas generation units is $c\bar{on}_G = 26.626$ [USD]. Also, from BAU results in Table 7.1, it can be observed that diesel generation units' cycling operation is always much lower than for gas generation units.



(a) Detailed start-up/shutdown costs in *Only shiftable demand (BAT)* case study



(b) Detailed start-up/shutdown costs in *Only adjustable demand (CUR)* case study

Figure 7.11: Detailed start-up/shutdown costs

7.3.4 Impacts in Spot Price

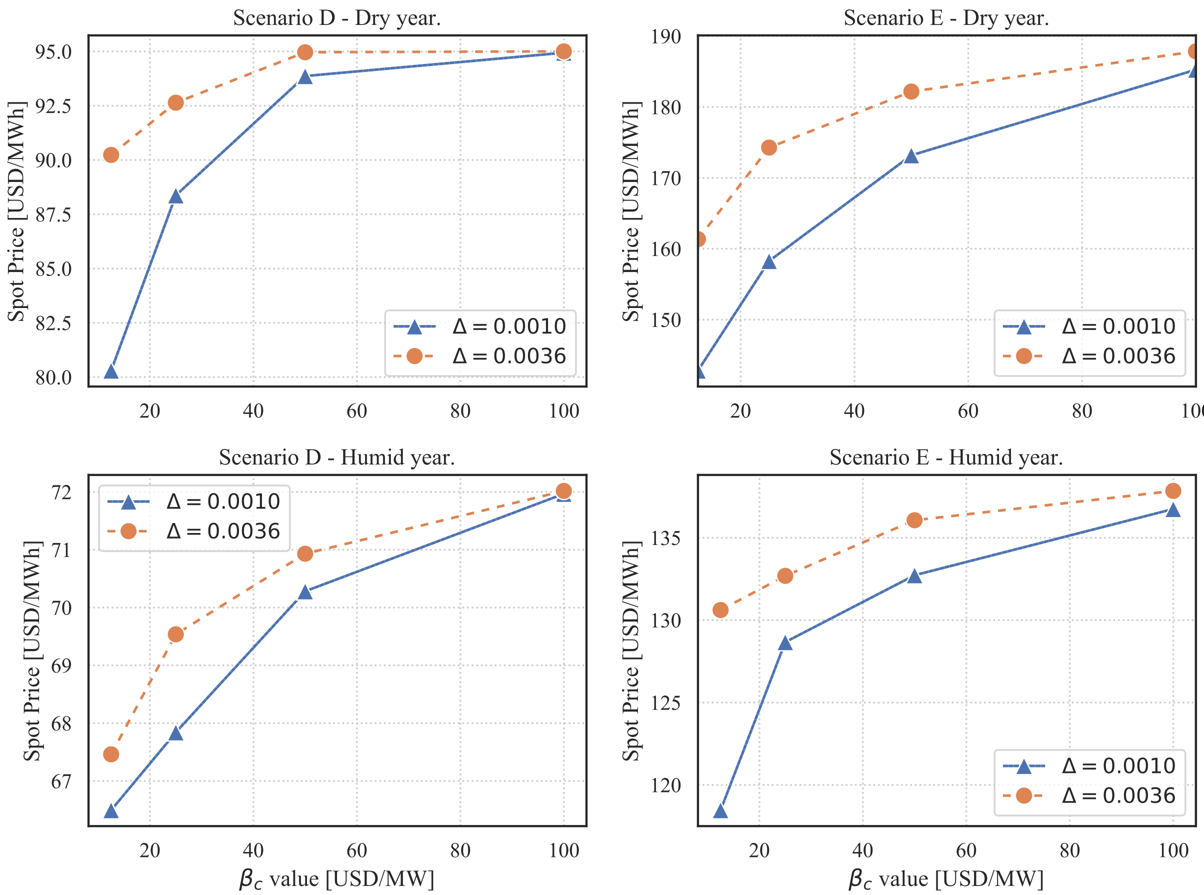
This section shows the impact of different values of the β_c parameter in spot price and spot price variability through the usage of the *spot price average value* and *spot price standard deviation* as shown in Figs. 7.12 and 7.13 respectively. The main observations are shown in the following list:

a) *Spot price average value and range decrease with a lower cost of Demand Response.*

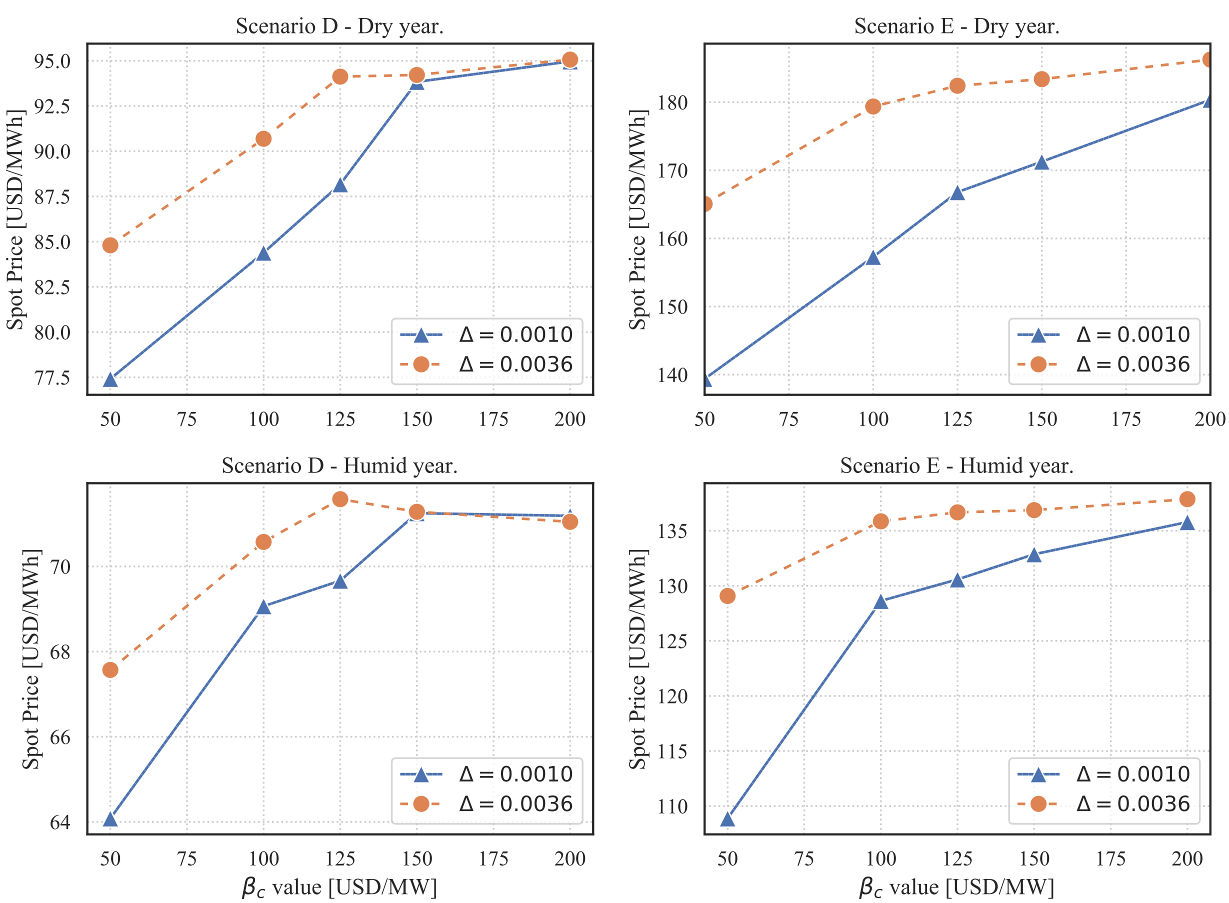
   As explained in the previous observations, this is mainly due to the reduction of diesel generation, which reduces the upper range of spot prices, hence, reducing spot price average value.

b) *Spot price standard deviation decreases with a lower cost of Demand Response*

   This is direct from the fact that the upper range of the spot price is reduced. Spot price variability reduction is important as it gives certainty about the future values of spot prices.

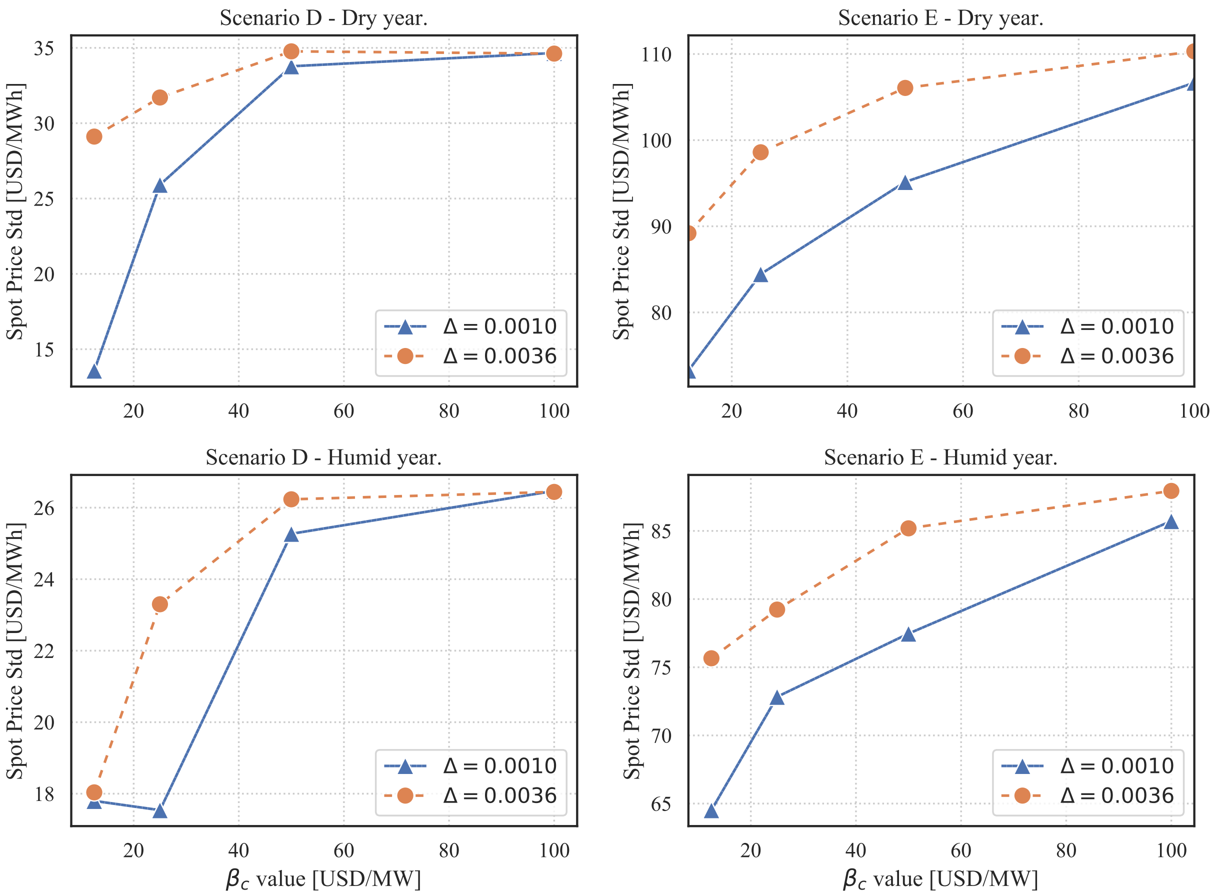


(a) Spot price average values in *Only shiftable demand (BAT)* case study

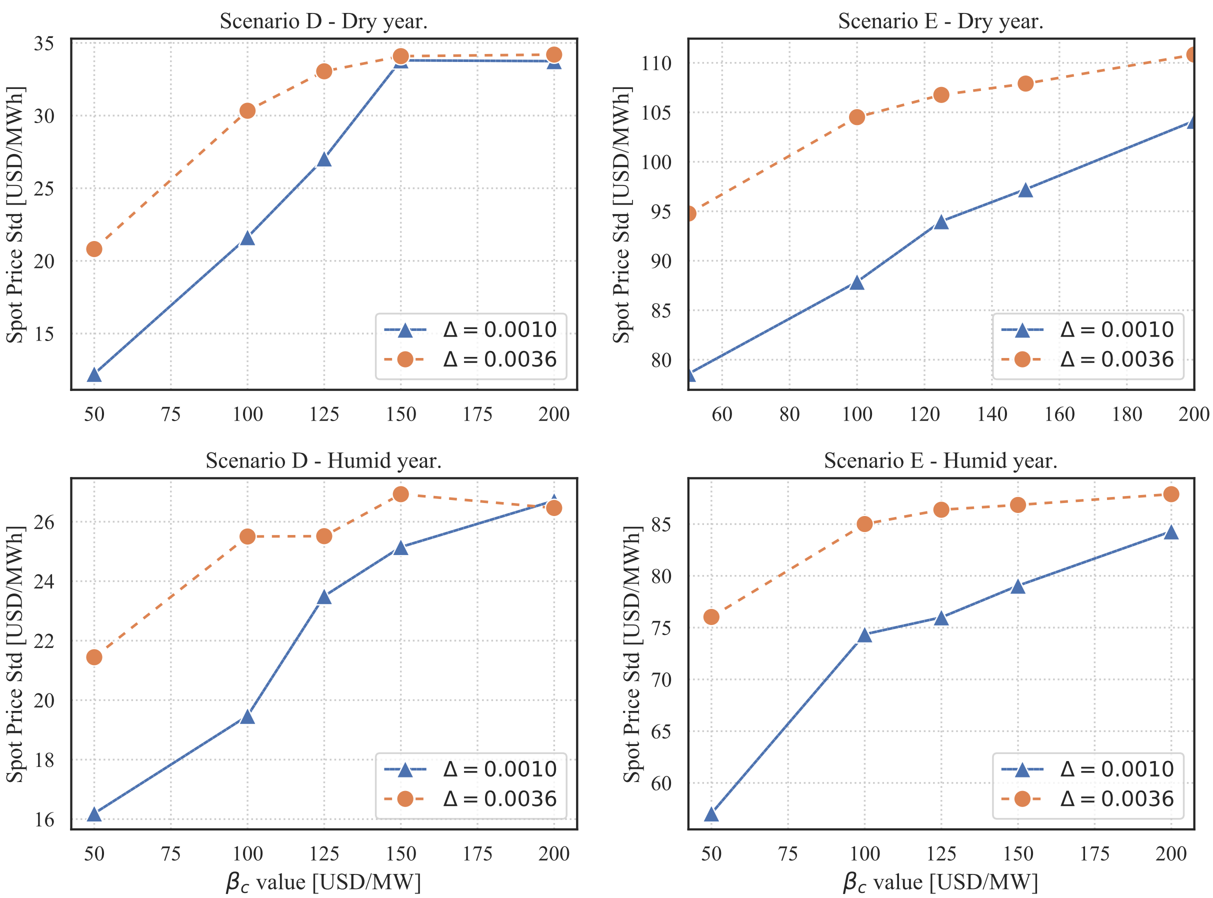


(b) Spot price average values in *Only adjustable demand (CUR)* case study

Figure 7.12: Spot price average values



(a) Spot price variability (std) in *Only shiftable demand (BAT)* case study



(b) Spot price variability (std) *Only adjustable demand (CUR)* case study

Figure 7.13: Spot price variability (std) values

7.3.5 CO_2 Emissions

This section shows the impact of different values of the β_c parameter in annual CO_2 emissions. In the following, Fig. 7.14 shows the total CO_2 emissions for different values of β_c, as well as the emissions for the case without Demand Response (BAU). More detailed results are shown in Fig. 7.15, where it is possible to compare emissions by different technologies (coal, gas and diesel). The main observations are described in the following:

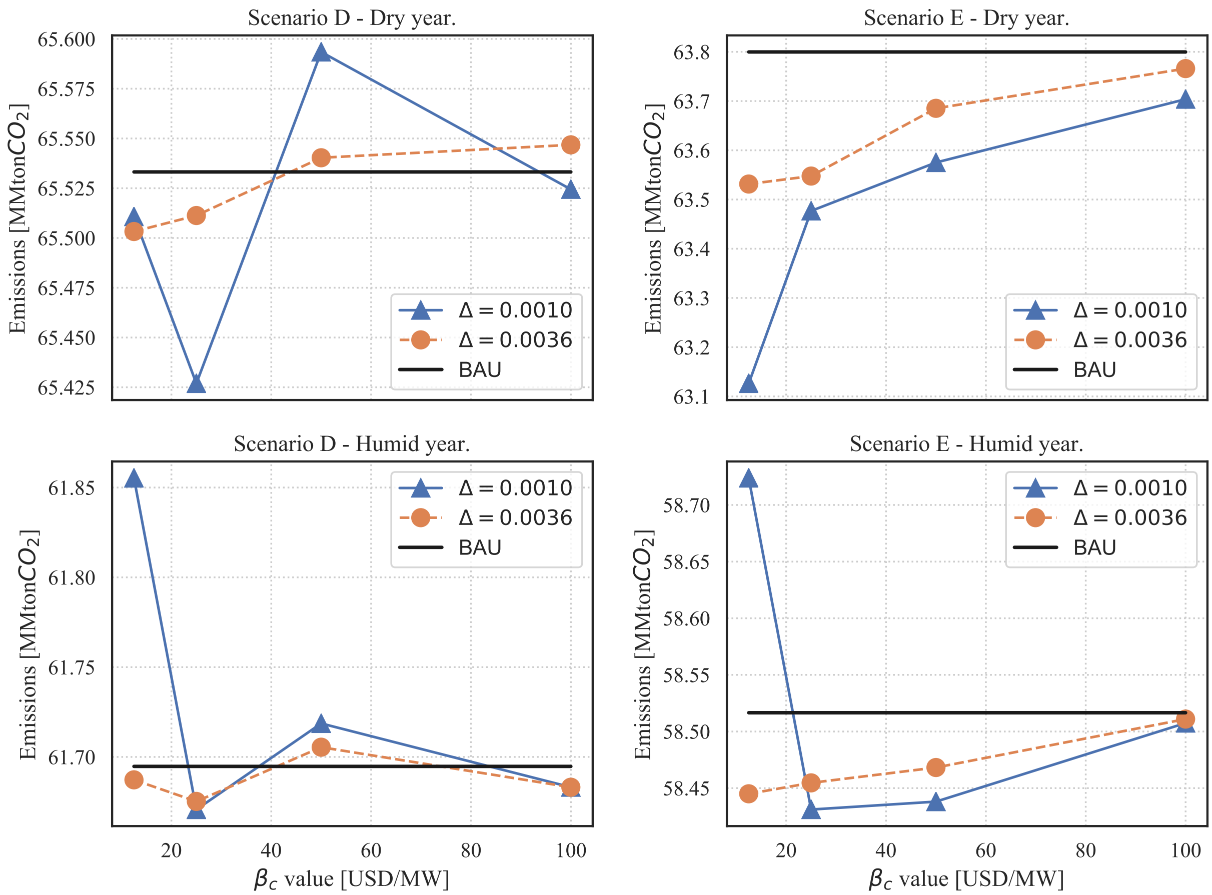
a) *When Demand Response is provided by shiftable demand (BAT), there is little impact in total CO_2 emissions.*

   From Fig. 7.14a it can be observed that with a reduction in Demand Response costs, CO_2 emissions can even increase up to 0.26% and 0.35% in scenarios D and E respectively. This is consistent with the fact that in the BAT case study, diesel generation is being replaced mainly by coal which has a CO_2 emission factor 44% higher.

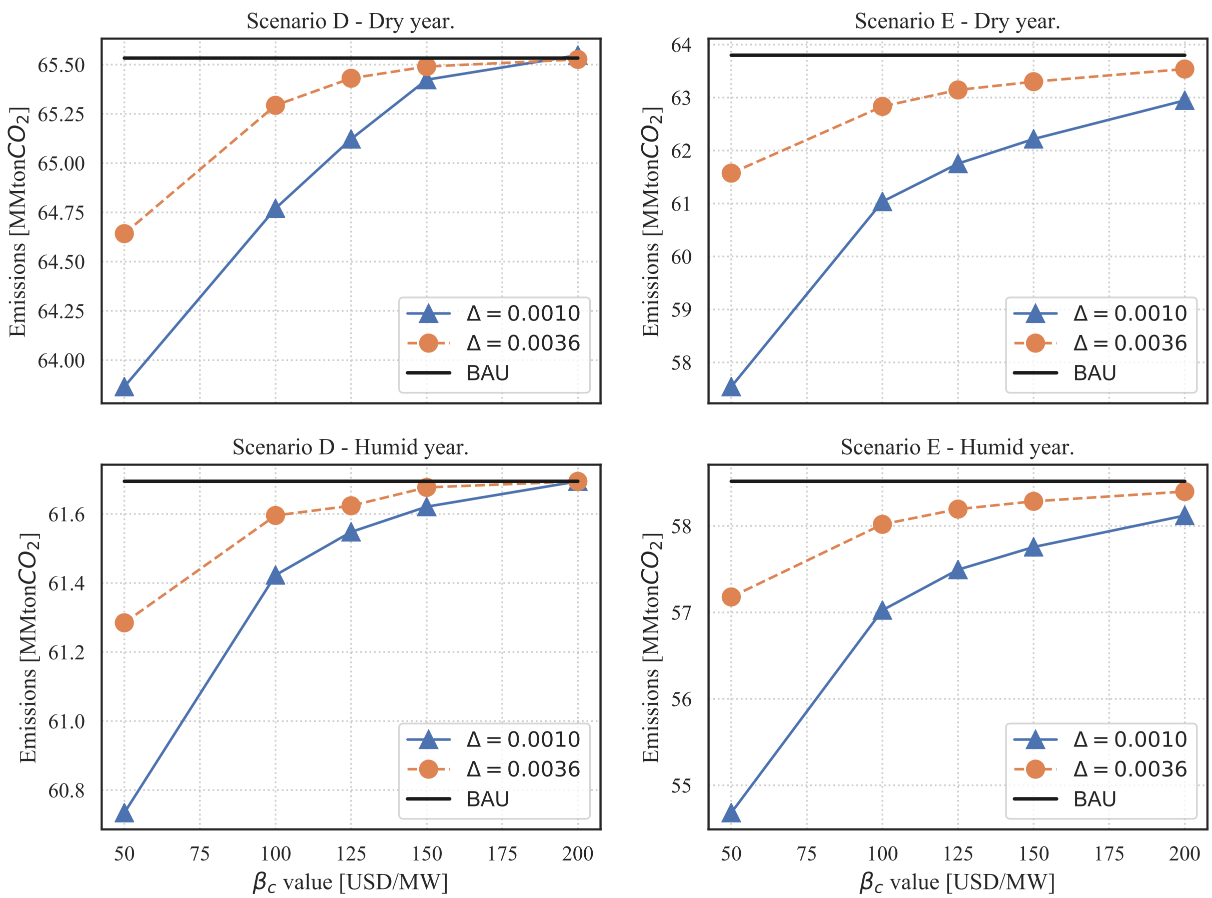
   An interesting thing to analyse in a further study would be the incorporation of a carbon tax in the current DR-UC model.

b) *When Demand Response is provided by adjustable demand, CO_2 emissions are reduced with lower values of β_c.*

   This is direct from the fact that in this case, Demand Response provides demand curtailment. Hence, lower thermal generation and emissions occur. In the most optimistic case, CO_2 emissions can be reduced up to 10.88%.

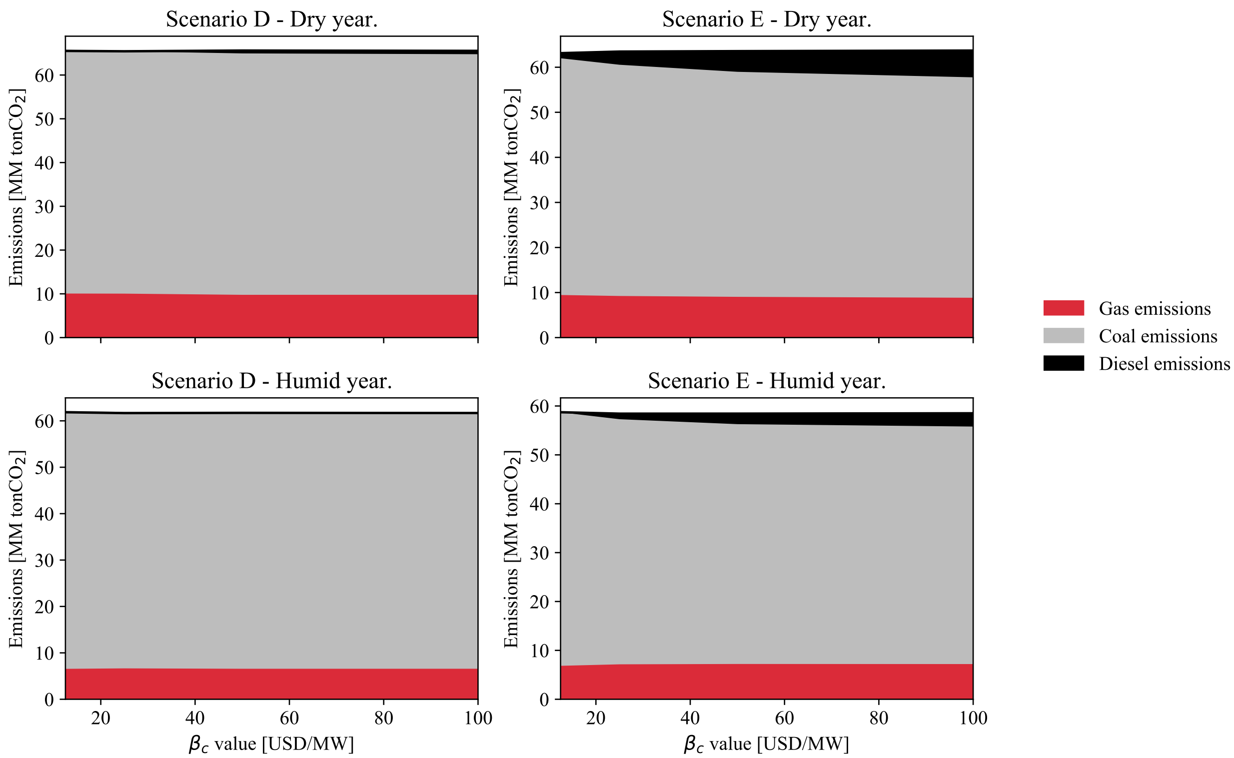


(a) CO_2 emissions in *Only shiftable demand (BAT)* case study

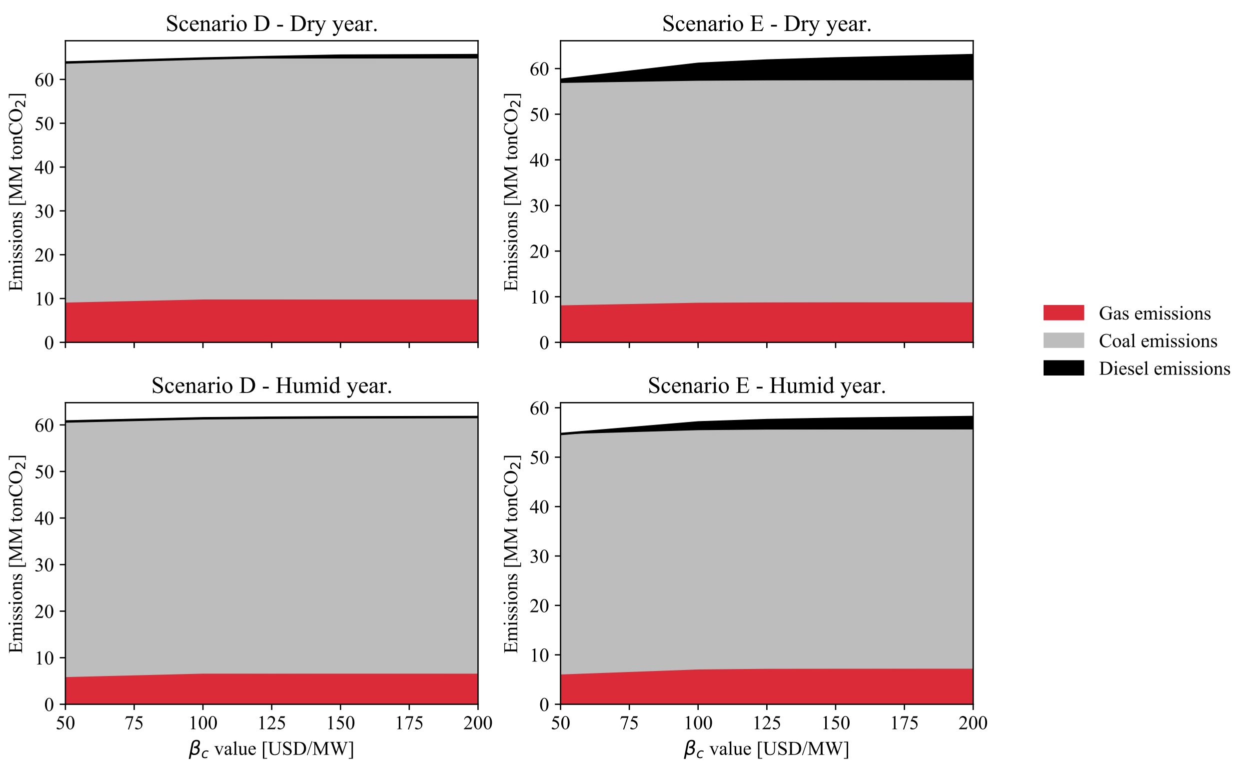


(b) CO_2 emissions in *Only adjustable demand (CUR)* case study

Figure 7.14: Detailed CO_2 emissions



(a) CO_2 emissions per technology in *Only shiftable demand (BAT)* case study



(b) CO_2 emissions per technology in *Only adjustable demand (CUR)* case study

Figure 7.15: Detailed CO_2 emissions per technology

Chapter 8

Conclusions

This thesis develops a deterministic Demand Response Unit Commitment (DR-UC) model, formulated as a mixed-integer nonlinear program (MINLP) by the use of a two-part quadratic disutility function that allows to assess the impact of demand-side flexibility provided both by shiftable and adjustable demand in a given electricity system with 5 different generation technologies (solar, wind, hydro reservoirs, run-of-the-river and thermal power plants). Unlike the rest of the literature, no restriction was imposed in terms of Demand Response participation levels. This problem was solved simulating the operation of the Chilean electricity system for different scenarios in the year 2035. With this, this study was able to assess the benefits that the incorporation of demand flexibility can provide to Chilean electricity market and to renewable energy incorporation. Finally, given the current model's limitations, Demand Response benefits shown in this study corresponds to a lower bound of its possible benefits to the system.

The main findings obtained from the results and the analyses made in this document are listed below.

- **The presented model is suitable to analyse the impact of Demand Response provided by adjustable or shiftable demand separately, but not for a mixture of them.**

  The results show that it is not straightforward to use the current DR-UC model to assess the impact of a situation in which demand flexibility is provided by a mixture of shiftable and adjustable demand (MIX case study). This implies that further models should be developed in order to assess the impact of Demand Response provided by a mixture of these technologies.

- **Demand response participation reaches levels which are consistent with the literature.**

  Given the values and assumptions used for the base case scenario in the current work, Demand Response participation in the Chilean electricity system reaches levels of 7.4% and 4.3% of total demand in the case of Demand Response provided by shiftable and adjustable demand respectively. This proves that the proposed model leads to reasonable results that are within the existing literature range in terms of Demand Response participation. Furthermore, in the most optimistic cases, Demand Response participation reaches a maximum value of 10% when $\Delta = 0.0036$.

- **There are no relevant impacts of Demand Response integration when levelized cost of storage or demand adjustment linear cost is higher than 200 [MW/MWh] ($\beta_a^{BAT} = 100$, $\beta_a^{CUR} = 200$).**

- **Demand response competes with diesel generation as peaking technology.**

  This is a general finding that includes two particular findings:

  - **Demand Response provided by adjustable (curtailable) demand reduces the participation of diesel generation as peaking technology.**

    Demand Response provided by adjustable demand mainly reduces the generation of the peaking and most expensive technology (diesel). Furthermore, when demand curtailment is cheaper, Demand Response also reduces gas generation.

  - **Demand Response provided by shiftable demand causes a replacement of diesel generation with renewable energy, gas and coal generation, reducing the participation of diesel as peaking technology.**

    Given the assumptions used for the base case scenario (levelized cost of storage equal to 100 USD/MWh), Demand Response provided by adjustable demand can reduce diesel generation up to 42%. Furthermore, in the most optimistic cases[1], Demand Response provided by shiftable demand can totally eliminate diesel generation. Depending on the scenario and costs assumptions, diesel generation is replaced by coal and/or gas generation.

  The foregoing findings open the discussion on how the actual capacity payment mechanism should change in order to give revenue certainty for peaking generation suppliers and ensure investment and resource adequacy. For example, it might be interesting to analyse how much should be the new value of the capacity payment[2] or if, in case of Demand Response provided by shiftable demand, responsive demand should receive part of the capacity payment due to the arbitrage of energy. Also, further study should be made on how a higher development of storage technologies and controllable shiftable-demand appliances would impact diesel generation risk and investment.

- **Renewable energy curtailment levels are reduced when Demand Response is provided by shiftable demand.**

  Demand response provided by shiftable demand can reduce renewable energy curtailment up to 27% in the base case scenario due to a reduction of diesel generation during

[1] Levelized cost of storage equal to 25 [USD/MWh]

[2] As explained in Section 2.2, currently, the capacity payment equals the capital cost of the peaking technology (diesel turbine).

the night and an increment of demand during the day when the renewable resource is available. Furthermore, renewable energy curtailment reduction can increase up to 50% in the most optimistic case. Demand response provided by adjustable (curtailable) demand does not reduce renewable energy curtailment levels.

- **Impacts of Demand Response are always higher in dry years.**

  In fact, Demand Response integration has more value in dry years due to the lack of water availability, and hence, a lack of energy balance provided by hydro reservoirs.

- **Total annual costs can be reduced up to 4.3% mainly due to the reduction of diesel generation.**

- **Demand Response provided by shiftable demand helps to reduce the start-up/shutdown cycling operation levels of gas generation units.**

  For the base case scenario, gas generation units reduce their start-up/shutdown cycling operation levels (and hence, start-up/shutdown cost) up to 11%. Cycling operation of diesel generation units are also being reduced, however, their impact in start-up/shutdown costs is negligible compared with gas generation units. There is no impact in coal generation units in terms of start-up/shutdown cycling operation because they do not do start-up/shutdown cycles, even in a case without Demand Response integration.

- **Demand response provided by shiftable demand helps to reduce the load following operation levels of coal and gas generation units.**

  This has an impact directly in the ramping costs. For the base case scenario, ramping costs are reduced up to 21% and 14% for coal and gas generation units respectively, which corresponds to a cost reduction of 0.67 MMUSD annually.

- **When Demand Response is provided by shiftable demand, there is little impact in total CO_2 emissions, or can even increase.**

  This is because diesel generation is being replaced mainly by coal which has a CO_2 emission factor 44% higher. Hence, despite the fact that the impact in cost is remarkable, it is not a major change in terms of CO_2 emissions, which can even increase up to 0.3%. An interesting thing to analyse in a further study would be the incorporation of a carbon tax in the current DR-UC model.

- **When Demand Response is provided by adjustable demand, CO_2 emissions are reduced up to 3.2%**

- **Demand response helps to reduce both spot price and spot price variability.** In the base case scenario, the average spot price is reduced up to 8.3% and 11.7% in the case of Demand Response provided by shiftable and adjustable demand respectively.

Spot price variability is reduced up to 15% and 23%

The previous listed findings include reductions of some of the undesired impacts of renewable energy penetration in the Chilean electricity system (renewable energy curtailment, cycling operation of thermal power plants). The findings also indicate that Demand Response can help to decrease spot price variability, and hence, decrease the revenue uncertainty that current developers of renewable energy projects face. Hence, it is possible to conclude that:

- **Demand-side flexibility integration in the Chilean electricity system would increase renewable energy integration and investment**

However, further research should be done, particularly on how this combination of lower renewable energy curtailment and lower spot price variability with lower spot prices might impact the development, risk, revenues, and hence, investment in renewable energy units.

8.1 Further Work

The main topics for further research identified in the current work are listed below:

- **Better identification of the costs involved in adjusting demand (β) in the Chilean electricity market.**

  Also, further research should be done on identifying the actual and future portion of adjustable and shiftable demand, as well as the future usage of thermal storage appliances, thermal heating, electric vehicles and other forms of energy storage in Chile.

- **Adapt the current DR-UC model to properly assess the impact of Demand Response provided by a mixture of shiftable and adjustable demand.**

- **Analyse how the capacity payments mechanism should change in the case of demand-side flexibility integration.**

  In particular, it is necessary to analyse how much should be the new value for the capacity payment, or if responsive demand should receive part of the capacity payment when doing arbitrage of energy (reducing demand during the night, and increasing demand during the day) and replacing diesel generation with, for example, coal.

- **Adapt the current DR-UC model to include a carbon tax, in order to analyse the impacts of Demand Response integration in CO_2 emissions in this scenario.**

- **Analyse how renewable energy investment would be affected in the case of demand-side flexibility integration.**

  Further research should be done analysing the impact of a combination of reduction of spot price variability, reduction of renewable energy curtailment and reduction spot price in renewable energy investments.

Nomenclature

Decision variables

$Q^{out}_{g,t}$ Outflow of reservoir g during time t $[hm^3/h]$.

$V_{g,t}$ Volume level of stored water in reservoir g at the end of hour t $[hm^3]$.

$OFF_{g,t}$ Shutdown binary variable of generator g in hour t ($OFF_{g,t} = 1$ if generator g was shut down in time t).

$ON_{g,t}$ Start-up binary variable of generator g in hour t ($ON_{g,t} = 1$ if generator g was started up in time t).

$P_{g,t}$ Power supplied by generator g in hour t [MW].

Q^t Final consumption in hour t [MW].

R^t Demand response in hour t [MW].

$u_{g,t}$ Binary state variable of power plant g in hour t ($u_{g,t} = 1$ if generator g is on in time t).

Parameters

α_a Quadratic adjustment cost parameter $[\$/MW^2]$.

α_c Quadratic demand curtailment cost parameter $[\$/MW^2]$.

β_a Linear adjustment cost parameter $[\$/MW]$.

β_c Linear demand curtailment cost parameter $[\$/MW]$.

Δ Quadratic factor.

$\mathbf{D}$ Vector of baseline demand.

$\mathbf{P}^{avail}_g$ Normalised power availability vector for solar or wind generator g.

$\mathbf{P}^{inst}_g$ Installed capacity of solar or wind generator g [MW].

ρ_g^{down} Hourly down ramp rate limit of generator g [MW].

ρ_g^{up} Hourly up ramp rate limit of generator g [MW].

τ_g^{off} Minimum downtime of generator g [h].

τ_g^{on} Minimum operation time of generator g [h].

c_g^{on} Shut-down cost of generator g [$].

c_g^{on} Start-up cost of generator g [$].

c_g^{ramp} Ramping cost of generator g [$].

c_g^{v} Variable cost of generator g [$/MW].

$C_{DR}(\cdot)$ Demand response disutility function [$].

$C_{g,t}^{gen}$ Generation cost of generator g in time t [$].

$C_{g,t}^{on/off}$ Start-up and shut-down cost (on/off cost) g in time t [$].

$C_{g,t}^{ramp}$ Load following (ramping) cost of generator g in time t [$/MW].

$C_{g,t}^{total}$ Total operational cost of generator g in time t [$].

g Generator $g \in \mathcal{G}$.

h_g Heat rate of thermal generator g ([MMBtu/MWh] for gas, [ton/MWh] for coal and [m^3/MWh] for diesel generation units).

h_g Heat rate of thermal generator g .

P_g^{max} Maximum power capacity of generator g [MW].

P_g^{min} Minimum power capacity of generator g [MW].

$p_{ff,g}$ Price of the fossil fuel of thermal generator g ([$/MBTu], [$/ton] and [$/$m^3$] for gas, coal and diesel generation units respectively).

$Q_{g,t}^{\text{in}}$ Water inflow of reservoir or run-of-the-river generation unit g during time t [hm^3/h].

$V_{g,0}$ Initial volume level of stored water in reservoir g at time $t = 0$ [hm^3].

V_g^{min} Minimum volume level of stored water of reservoir g [hm^3].

η_g Efficiency factor of hydro reservoir or run-of-the-river generation unit g [$(MW)/hm^3$].

D_t Baseline demand in hour t [MW].

Sets

$\mathcal{D}$ Set of days in the time horizon (e.g. days in a year).

$\mathcal{G}$ Set of power plants.

$\mathcal{G}_D$ Set of hydro reservoir power plants ($\mathcal{G}_D \subseteq \mathcal{G}$).

$\mathcal{G}_{RoR}$ Set of run-of-the-river power plants ($\mathcal{G}_{RoR} \subseteq \mathcal{G}$).

$\mathcal{G}_{SW}$ Set of solar and wind power plants ($\mathcal{G}_{SW} = \mathcal{G}_S \cup \mathcal{G}_W \subseteq \mathcal{G}$).

$\mathcal{G}_S$ Set of solar plants ($\mathcal{G}_S \subseteq \mathcal{G}$).

$\mathcal{G}_T$ Set of thermal power plants ($\mathcal{G}_T \subseteq \mathcal{G}$).

$\mathcal{G}_W$ Set of wind power plants ($\mathcal{G}_W \subseteq \mathcal{G}$).

$\mathcal{T}$ Set of hours in the time horizon (e.g. hours in a year).

$\mathcal{T}_{\mathrm{d}}$ Set of hours in the day d.

$\mathcal{Z}$ Set of solar and wind zones.

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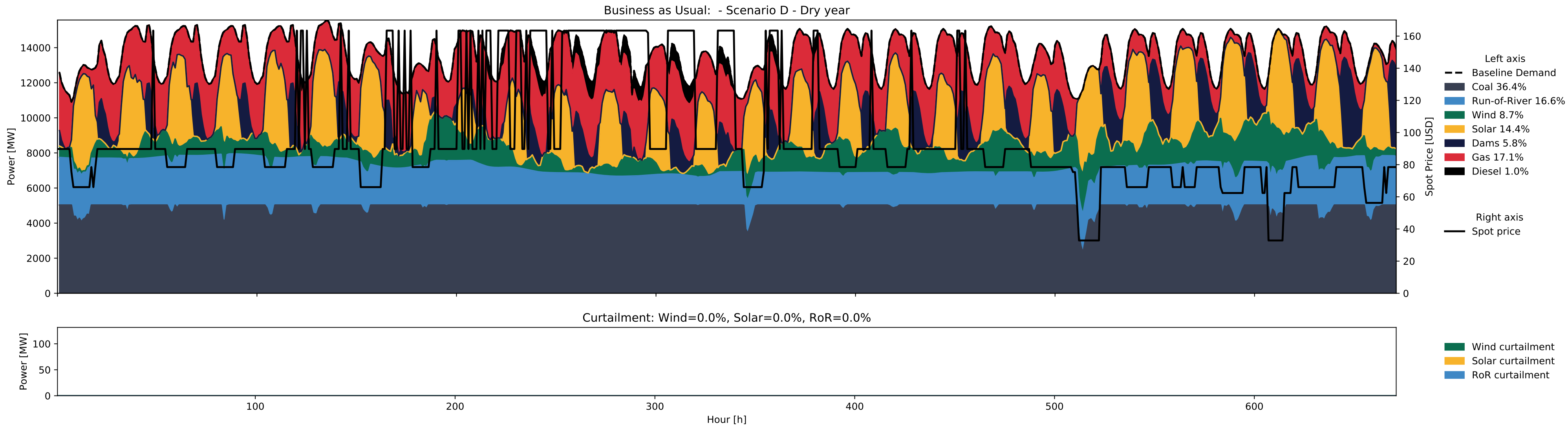
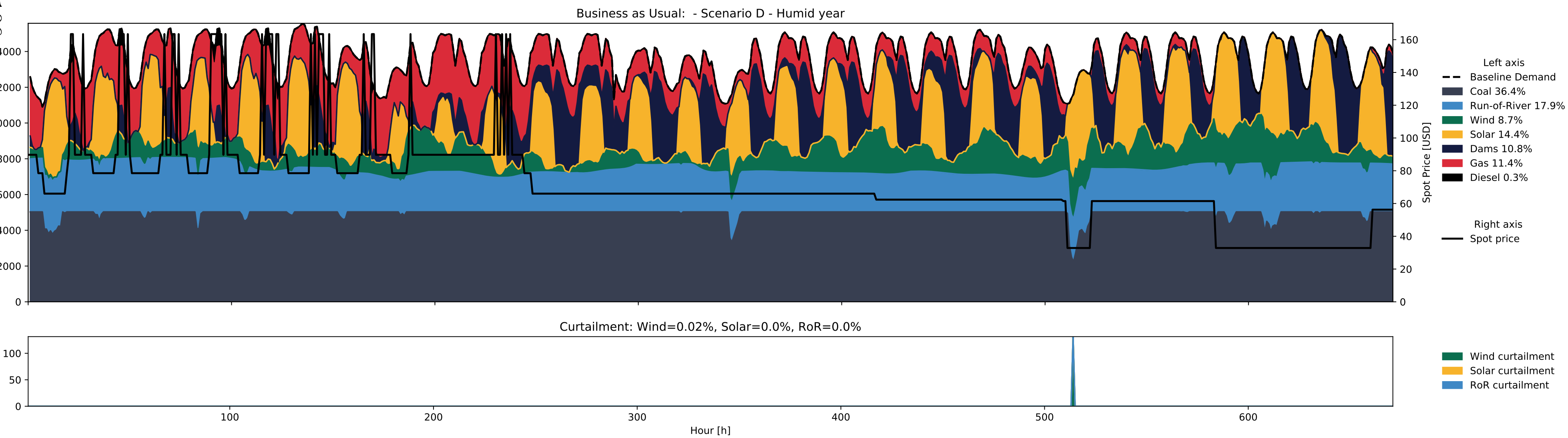
Appendix A

Base Case Figures

A.1 BAU Operation Figures

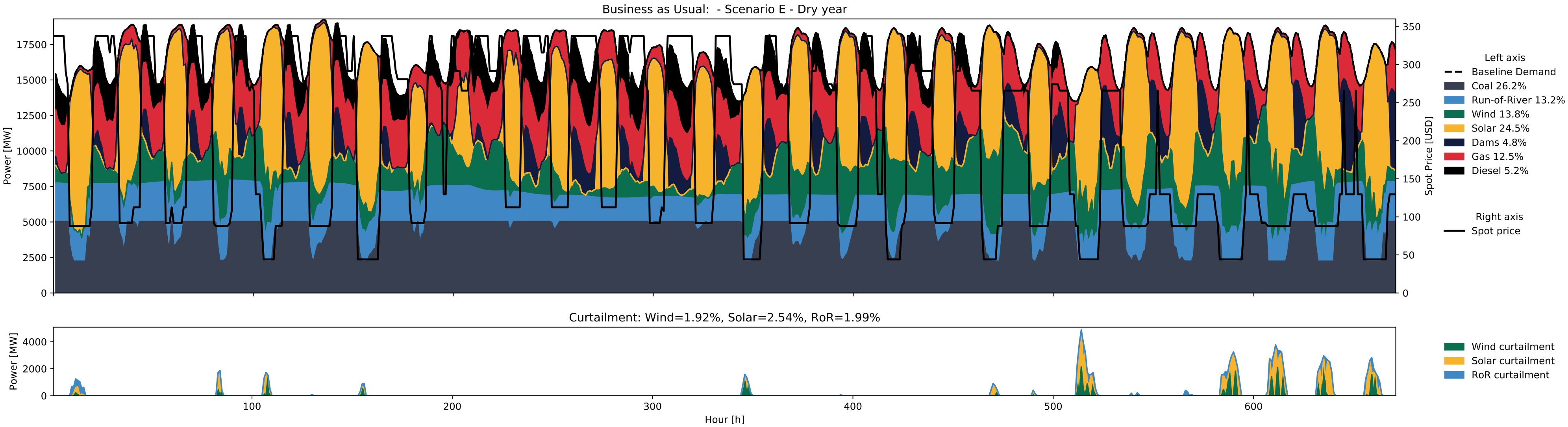


(a) BAU. Scenario D, dry year.

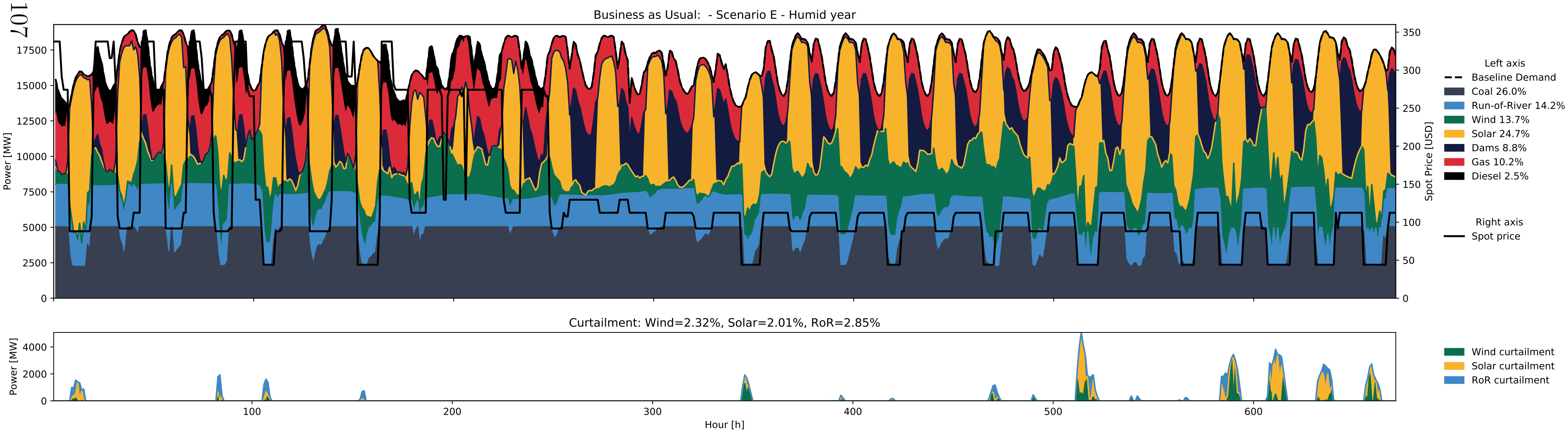


(b) BAU. Scenario D, humid year.

Figure A.1: System operation and spot price for *Business as Usual* case study, Scenario D



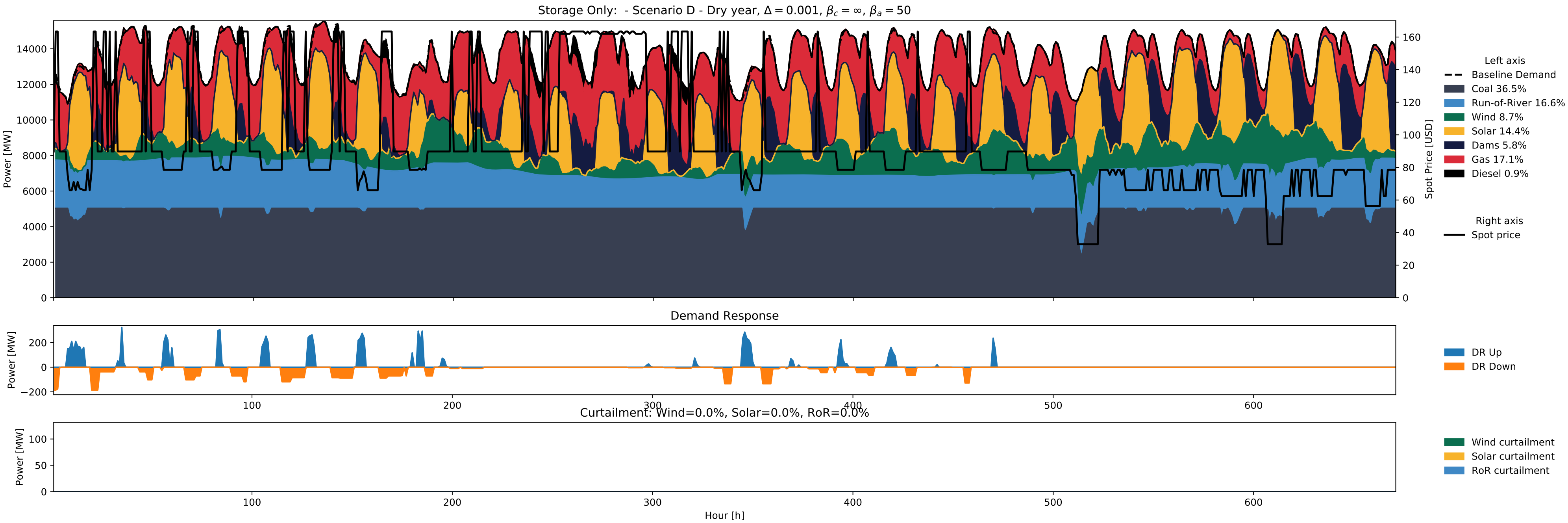
(a) BAU. Scenario E, dry year.



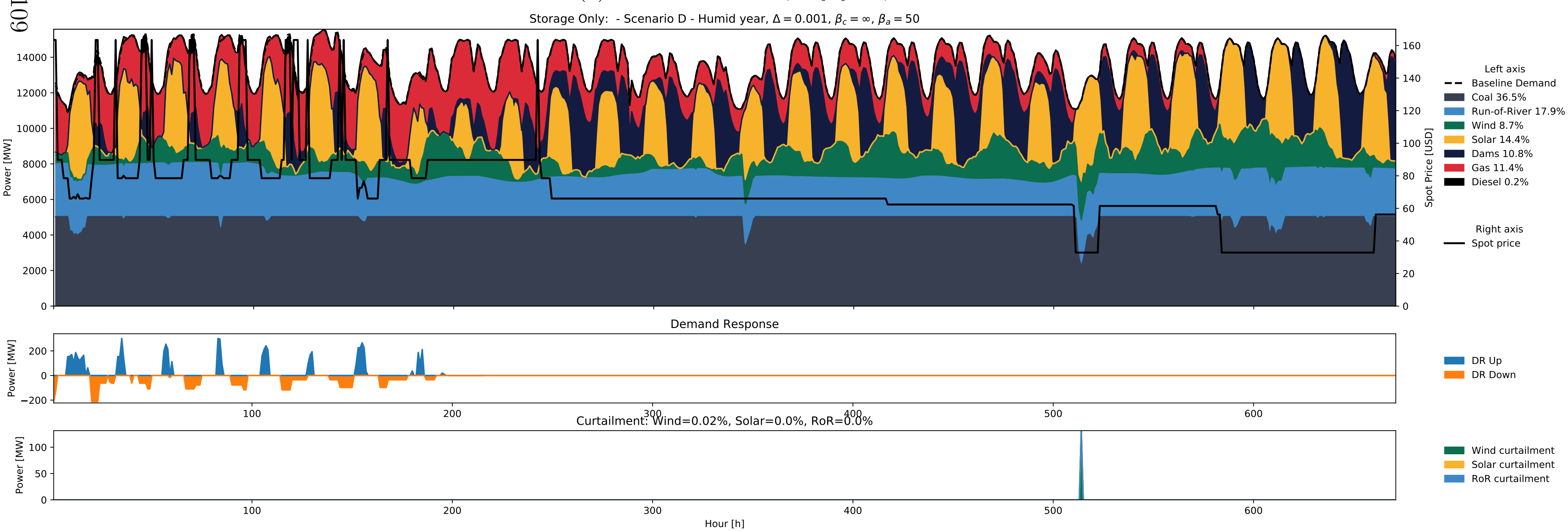
(b) BAU. Scenario E, humid year.

Figure A.2: System operation and spot price for *Business as Usual* case study, Scenario E

A.2 BAT Operation Figures

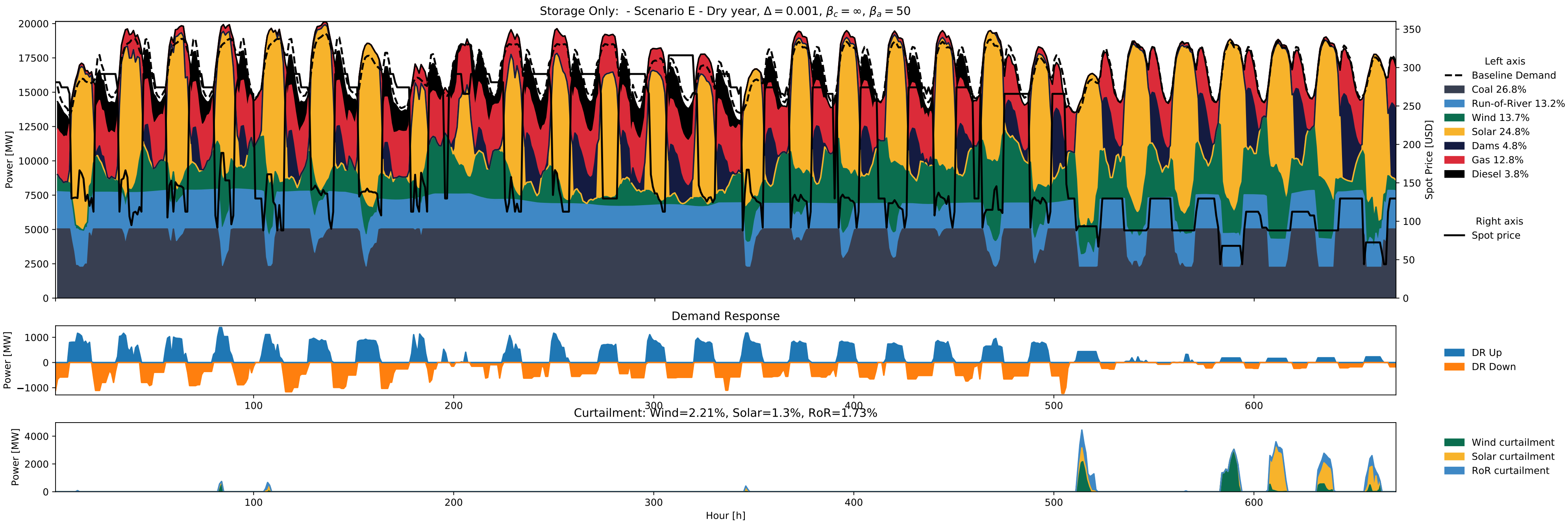


(a) BAT. Scenario D, dry year, base case.

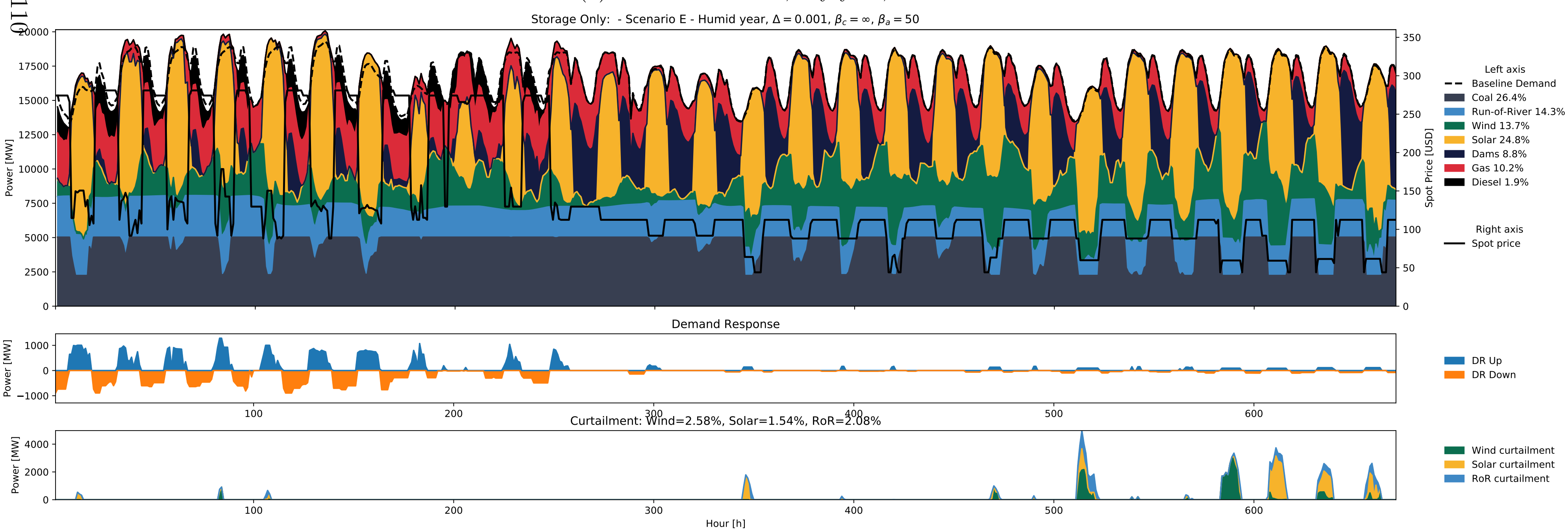


(b) BAT. Scenario D, humid year, base case.

Figure A.3: System operation and spot price for the *Only shiftable demand (BAT)* case study, scenario D, base case.



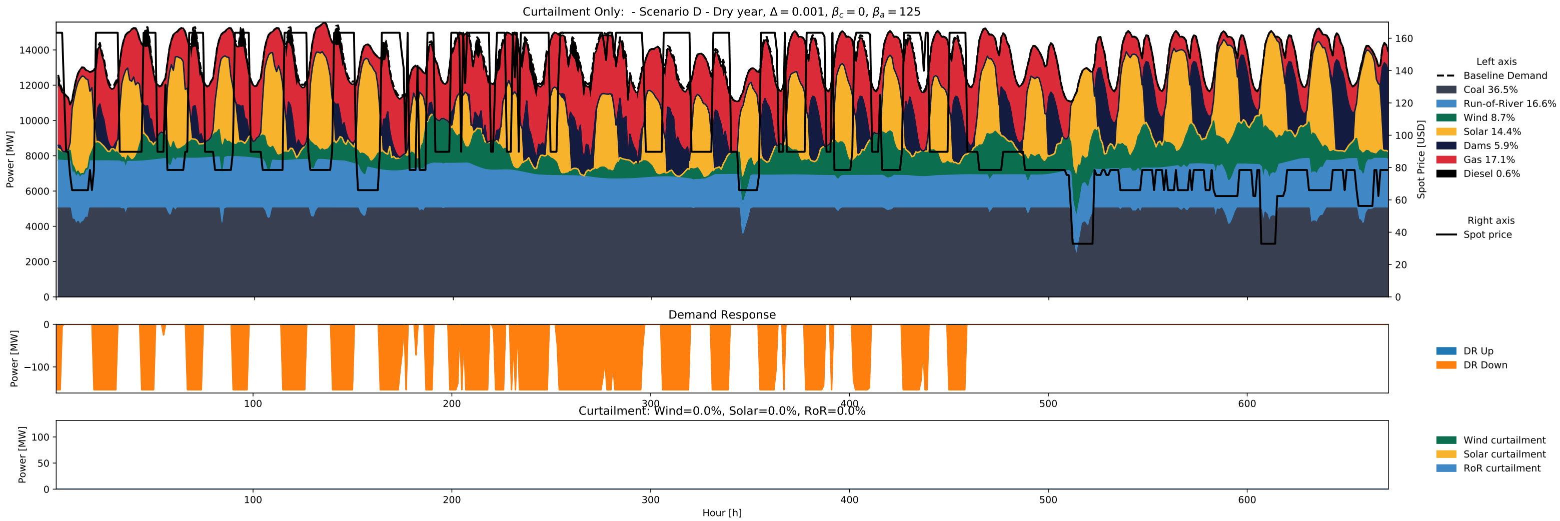
(a) BAT. Scenario E, dry year, base case.



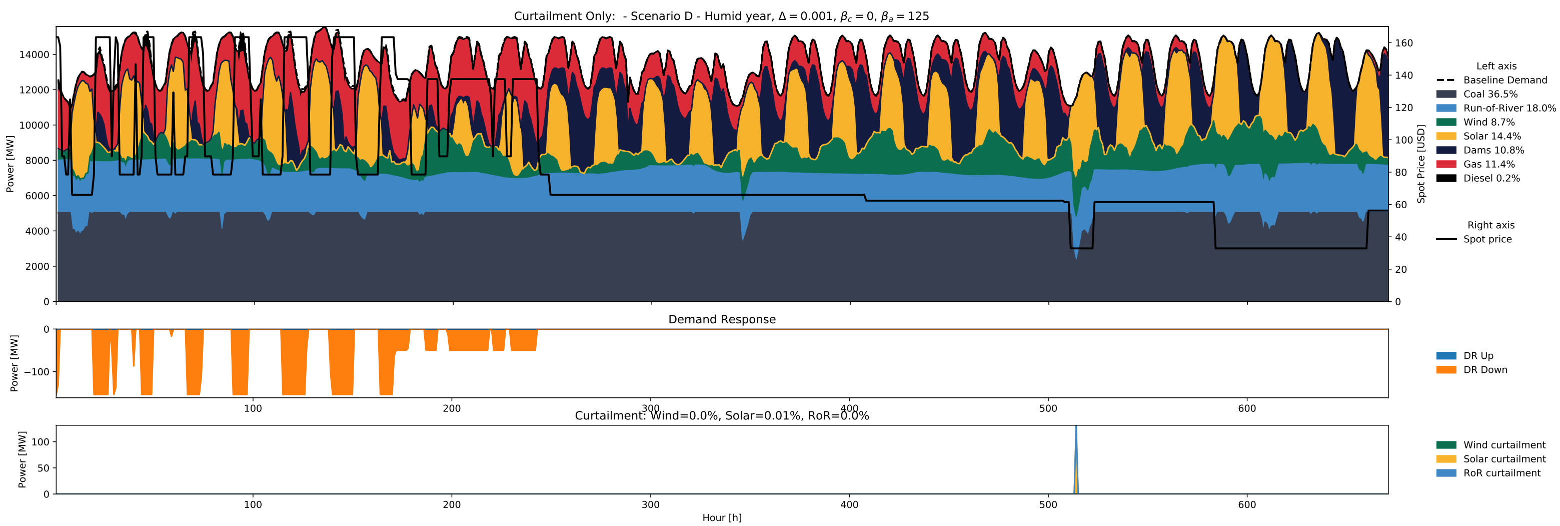
(b) BAT. Scenario E, humid year, base case.

Figure A.4: System operation and spot price for the *Only shiftable demand (BAT)* case study, scenario E, base case.

A.3 CUR Operation Figures

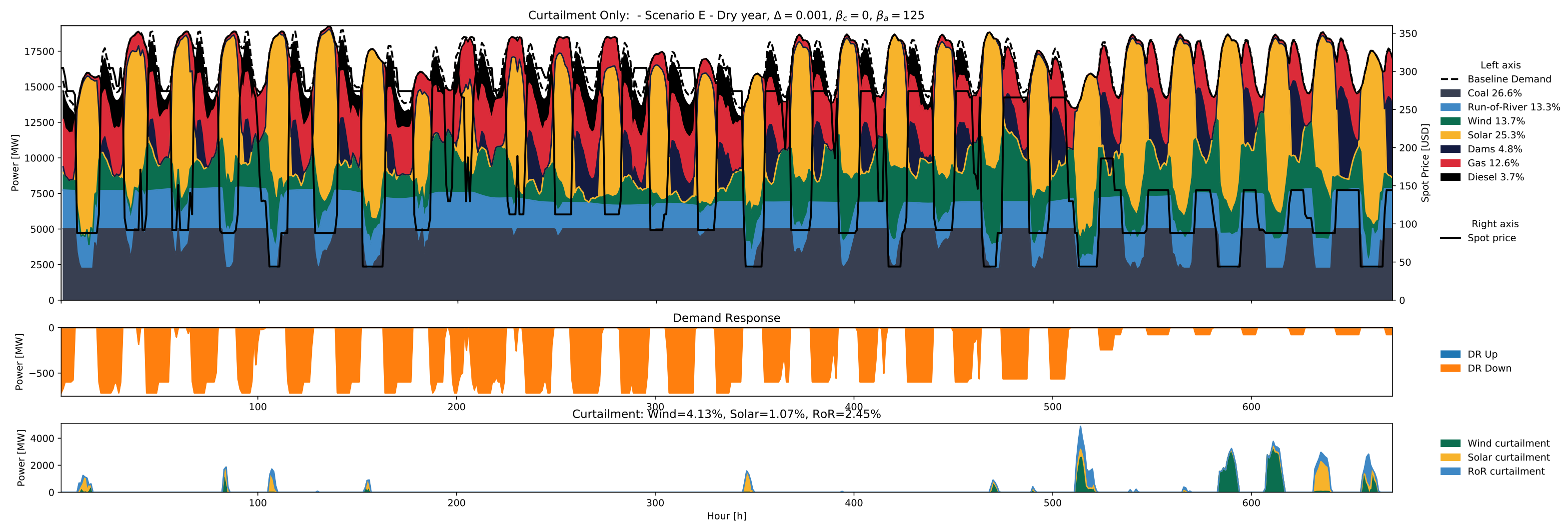


(a) System operation and spot price for *Only adjustable demand (CUR)* case study, scenario D, dry year, base case.

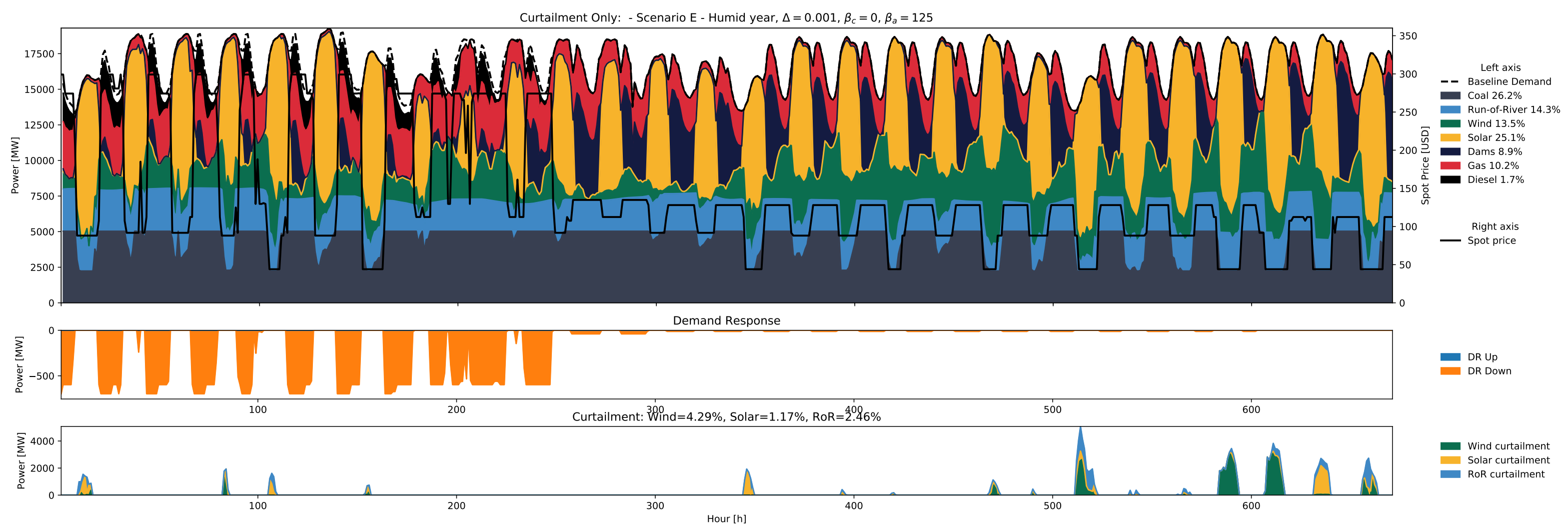


(b) System operation and spot price for *Only adjustable demand (CUR)* case study, scenario D, humid year, base case.

Figure A.5: System operation and spot price for the *Only adjustable demand (CUR)* case study, scenario D, base case.



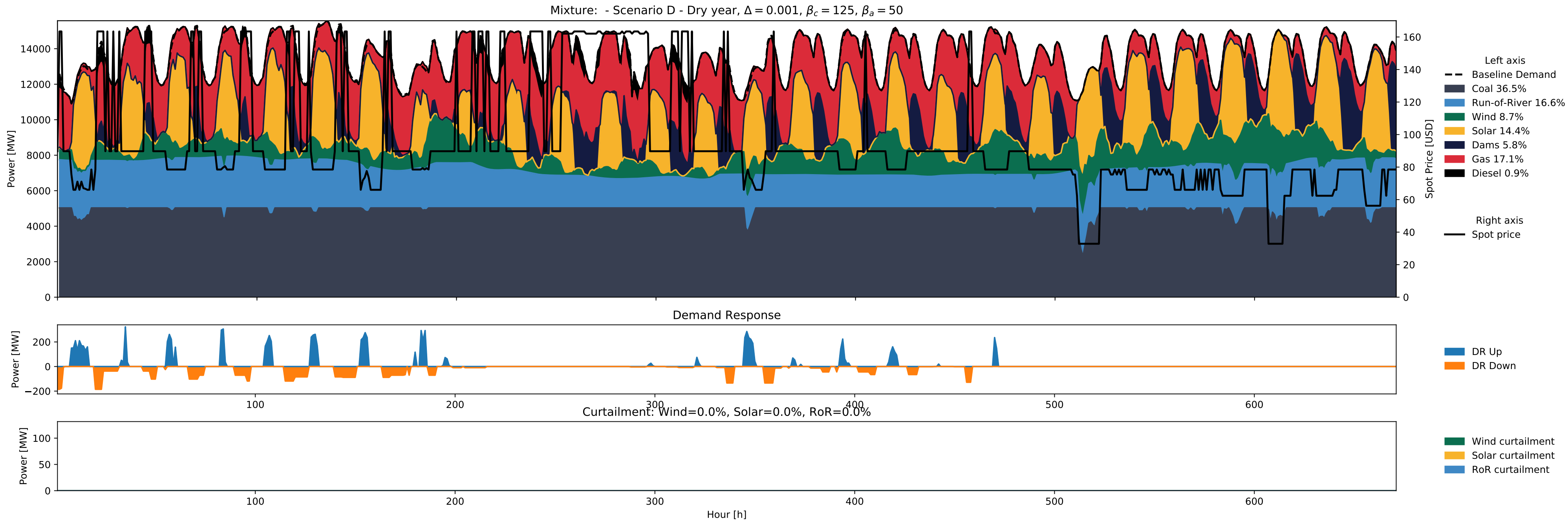
(a) System operation and spot price for *Only adjustable demand (CUR)* case study, scenario E, dry year, base case.



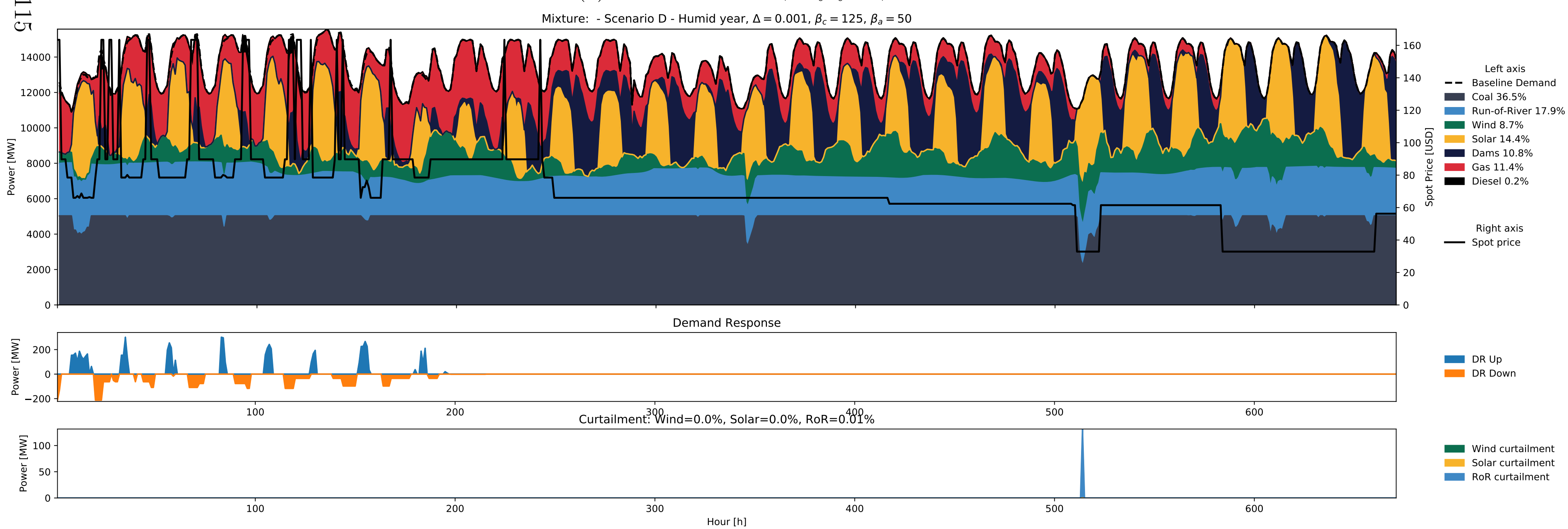
(b) System operation and spot price for *Only adjustable demand (CUR)* case study, scenario E, humid year, base case.

Figure A.6: System operation and spot price for the *Only adjustable demand (CUR)* case study, scenario E, base case.

A.4 MIX Operation Figures

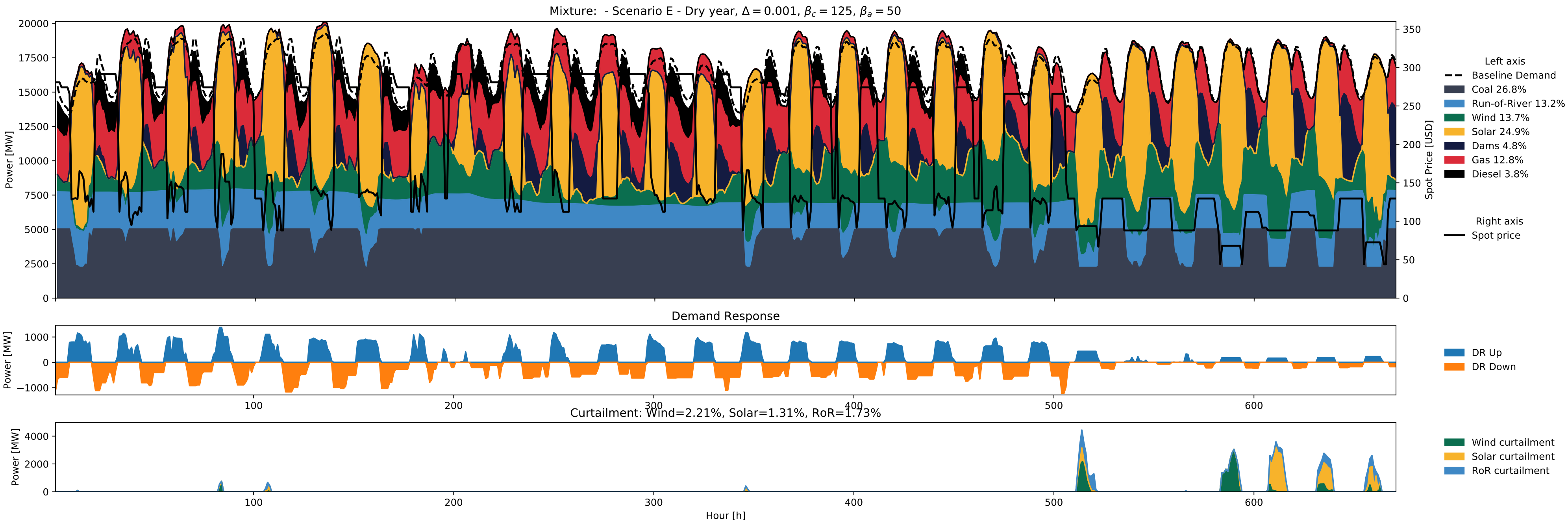


(a) MIX. Scenario D, dry year, base case .

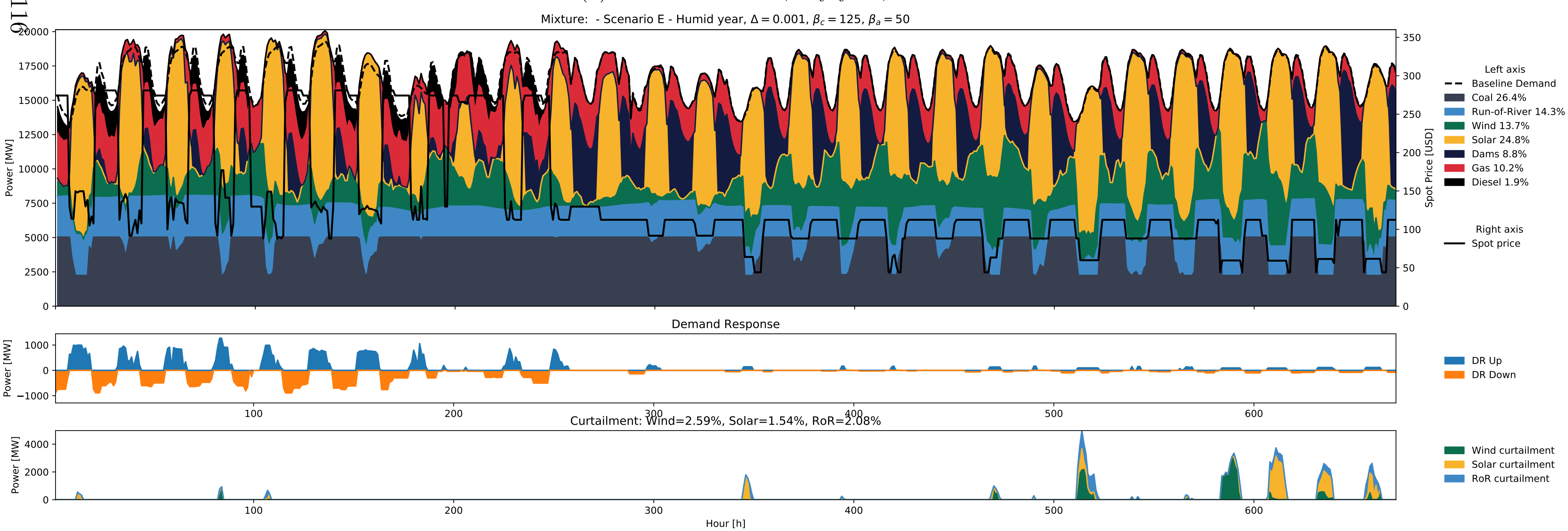


(b) MIX. Scenario D, humid year, base case.

Figure A.7: System operation and spot price for the *Mixture of technologies (MIX)* case study, scenario D, base case.



(a) MIX. Scenario E, dry year, base case.



(b) MIX. Scenario E, humid year, base case.

Figure A.8: System operation and spot price for the *Mixture of technologies (MIX)* case study, scenario E, base case.

Appendix B

Generation Units Parameters

In the following tables, columns **D** and **E** denotes if the generation unit is considered in scenario D or E respectively.

B.1 Solar Generation Units

Name	Type	Zone	P^{max}	in D?	in E?
Fv_andes_solar	PV	FV_SING	21.4	Y	Y
Fv_bolero_i	PV	FV_SING	84.0	Y	Y
Fv_bolero_ii	PV	FV_SING	42.0	Y	Y
Fv_bolero_iii	PV	FV_SING	20.0	Y	Y
Fv_calama_solar_1	PV	FV_SING	9.0	Y	Y
Fv_cerrodominador	PV	FV_SING	100.0	Y	Y
Fv_collahuasi04	PV	FV_SING	2738.0	Y	Y
Fv_finis_terrae	PV	FV_SING	138.0	Y	Y
Fv_granja_solar	PV	FV_SING	100.0	Y	Y
Fv_huatacondo	PV	FV_SING	98.0	Y	Y
Fv_jama_1	PV	FV_SING	30.0	Y	Y
Fv_jama_2	PV	FV_SING	22.4	Y	Y
Fv_la_huayca	PV	FV_SING	1.4	Y	Y
Fv_la_huayca_2	PV	FV_SING	8.2	Y	Y
Fv_lascar_i	PV	FV_SING	30.0	Y	Y
Fv_lascar_ii	PV	FV_SING	34.6	Y	Y
Fv_maria_elena	PV	FV_SING	67.7	Y	Y
Fv_nzaldivar04	PV	FV_SING	4172.0	N	Y
Fv_paruma	PV	FV_SING	21.4	Y	Y
Fv_pica_i	PV	FV_SING	0.6	Y	Y
Fv_pozo_almonte_2	PV	FV_SING	7.5	Y	Y
Fv_pozo_almonte_3	PV	FV_SING	16.0	Y	Y
Fv_puerto_seco	PV	FV_SING	9.0	Y	Y
Fv_pular	PV	FV_SING	28.9	Y	Y

Fv_quillagua_i	PV	FV_SING	23.0	Y	Y
Fv_quillagua_ii	PV	FV_SING	27.0	Y	Y
Fv_quillagua_iii	PV	FV_SING	50.0	Y	Y
Fv_san_pedro	PV	FV_SING	3.0	Y	Y
Fv_uribe_solar	PV	FV_SING	50.0	Y	Y
Fv_usya	PV	FV_SING	25.0	Y	Y
Fv_arica_solar_i	PV	FV_SIC_NORTE	18.0	Y	Y
Fv_arica_solar_ii	PV	FV_SIC_NORTE	22.0	Y	Y
Fv_carrera_pinto	PV	FV_SIC_NORTE	97.0	Y	Y
Fv_chanares	PV	FV_SIC_NORTE	35.0	Y	Y
Fv_conejo_i	PV	FV_SIC_NORTE	108.0	Y	Y
Fv_cordillerilla	PV	FV_SIC_NORTE	1.3	Y	Y
Fv_cumbres02	PV	FV_SIC_NORTE	3276.9	N	Y
Fv_diego_de_almagro	PV	FV_SIC_NORTE	36.0	Y	Y
Fv_divisadero	PV	FV_SIC_NORTE	65.0	Y	Y
Fv_el_aguila	PV	FV_SIC_NORTE	2.0	Y	Y
Fv_el_romero	PV	FV_SIC_NORTE	196.0	Y	Y
Fv_guanaco	PV	FV_SIC_NORTE	50.0	Y	Y
Fv_hornitos	PV	FV_SIC_NORTE	0.3	Y	Y
Fv_inca_de_varas_i	PV	FV_SIC_NORTE	60.0	Y	Y
Fv_inca_de_varas_ii	PV	FV_SIC_NORTE	60.0	Y	Y
Fv_javiera	PV	FV_SIC_NORTE	69.0	Y	Y
Fv_la_silla	PV	FV_SIC_NORTE	1.9	Y	Y
Fv_lalackama	PV	FV_SIC_NORTE	55.0	Y	Y
Fv_lalackama_2	PV	FV_SIC_NORTE	16.0	Y	Y
Fv_las_terrazas	PV	FV_SIC_NORTE	3.0	Y	Y
Fv_llano_de_llampos	PV	FV_SIC_NORTE	93.0	Y	Y
Fv_los_loros	PV	FV_SIC_NORTE	50.0	Y	Y
Fv_luz_del_norte	PV	FV_SIC_NORTE	141.0	Y	Y
Fv_malgarida_i	PV	FV_SIC_NORTE	28.0	Y	Y
Fv_pampa_camarones	PV	FV_SIC_NORTE	6.0	Y	Y
Fv_pampa_solar_norte	PV	FV_SIC_NORTE	90.6	Y	Y
Fv_pelicano	PV	FV_SIC_NORTE	100.0	Y	Y
Fv_pilar_los_amarillos	PV	FV_SIC_NORTE	2.2	Y	Y
Fv_salvador	PV	FV_SIC_NORTE	68.0	Y	Y
Fv_san_andres	PV	FV_SIC_NORTE	50.0	Y	Y
Fv_santa_cecilia	PV	FV_SIC_NORTE	3.0	Y	Y
Fv_sol_de_vallenar	PV	FV_SIC_NORTE	308.7	Y	Y
Fv_valle_solar	PV	FV_SIC_NORTE	74.0	Y	Y
Fv_valleland_solar	PV	FV_SIC_NORTE	74.0	Y	Y
Fv_alturas_de_ovalle	PV	FV_SIC_CENTRO	6.0	Y	Y
Fv_bellavista	PV	FV_SIC_CENTRO	3.0	Y	Y
Fv_chuchini	PV	FV_SIC_CENTRO	2.9	Y	Y
Fv_dona_carmen	PV	FV_SIC_CENTRO	40.0	Y	Y
Fv_el_boco_solar	PV	FV_SIC_CENTRO	3.0	Y	Y
Fv_el_divisadero	PV	FV_SIC_CENTRO	3.0	Y	Y
Fv_hormiga	PV	FV_SIC_CENTRO	2.5	Y	Y

Fv_la_chapeana	PV	FV_SIC_CENTRO	2.8	Y	Y
Fv_lagunilla	PV	FV_SIC_CENTRO	3.0	Y	Y
Fv_las_mollacas	PV	FV_SIC_CENTRO	2.8	Y	Y
Fv_lomas_coloradas	PV	FV_SIC_CENTRO	2.0	Y	Y
Fv_luna	PV	FV_SIC_CENTRO	3.0	Y	Y
Fv_pama	PV	FV_SIC_CENTRO	2.0	Y	Y
Fv_quilapilun	PV	FV_SIC_CENTRO	103.2	Y	Y
Fv_santa_julia	PV	FV_SIC_CENTRO	3.0	Y	Y
Fv_sdgx01	PV	FV_SIC_CENTRO	1.3	Y	Y
Fv_sol	PV	FV_SIC_CENTRO	3.0	Y	Y
Fv_tambo_real	PV	FV_SIC_CENTRO	2.9	Y	Y
Fv_til_til	PV	FV_SIC_CENTRO	3.0	Y	Y
Fv_alcones	PV	FV_SIC_SUR	50.0	Y	Y
Fv_cintac	PV	FV_SIC_SUR	2.5	Y	Y
Fv_esperanza	PV	FV_SIC_SUR	2.9	Y	Y
Fv_esperanza_ii	PV	FV_SIC_SUR	9.0	Y	Y
Fv_las_araucarias	PV	FV_SIC_SUR	0.1	Y	Y
Fv_marchigue_ii	PV	FV_SIC_SUR	9.0	Y	Y
Fv_nilhue	PV	FV_SIC_SUR	1.1	Y	Y
Fv_santiago	PV	FV_SIC_SUR	98.0	Y	Y
Fv_techos_de_altamira	PV	FV_SIC_SUR	0.2	Y	Y

Table B.1: Parameters of solar generation units.

B.2 Wind Generation Units

Name	**Type**	**Zone**	P^{max}	**in D?**	**in E?**
Eol_cerro_tigre	Wind	EOL_SING	145.7	Y	Y
Eol_ckani	Wind	EOL_SING	106.9	Y	Y
Eol_san_juan_iv	Wind	EOL_SING	32.7	Y	Y
Eol_san_juan_v	Wind	EOL_SING	26.1	Y	Y
Eol_san_juan_vi	Wind	EOL_SING	32.7	Y	Y
Eol_sierra_gorda	Wind	EOL_SING	110.9	Y	Y
Eol_tchamma	Wind	EOL_SING	148.9	Y	Y
Eol_valle_de_los_vientos	Wind	EOL_SING	88.0	Y	Y
Eol_cabo_leones_i	Wind	EOL_SIC_NORTE	114.3	Y	Y
Eol_cabo_leones_if	Wind	EOL_SIC_NORTE	62.4	Y	Y
Eol_cabo_leones_ii	Wind	EOL_SIC_NORTE	202.0	Y	Y
Eol_cabo_leones_iii	Wind	EOL_SIC_NORTE	135.1	Y	Y
Eol_san_juan	Wind	EOL_SIC_NORTE	183.0	Y	Y
Eol_sarco	Wind	EOL_SIC_NORTE	168.3	Y	Y
Eol_tal_tal	Wind	EOL_SIC_NORTE	98.0	Y	Y
Eolica_taltaleol01	Wind	EOL_SIC_NORTE	208.89	N	Y
Eolica_taltaleol03	Wind	EOL_SIC_NORTE	106.92	N	Y
Eolica_taltaleol04	Wind	EOL_SIC_NORTE	540.54	N	Y

Eolica_taltaleol05	Wind	EOL_SIC_NORTE	393.03	N	Y
Eolica_taltaleol07	Wind	EOL_SIC_NORTE	230.67	N	Y
Eolica_taltaleol09	Wind	EOL_SIC_NORTE	394.02	N	Y
Eolica_taltaleol10	Wind	EOL_SIC_NORTE	536.58	N	Y
Eolica_taltaleol11	Wind	EOL_SIC_NORTE	326.7	N	Y
Eol_canela_01	Wind	EOL_SIC_CENTRO	18.0	Y	Y
Eol_canela_02	Wind	EOL_SIC_CENTRO	59.4	Y	Y
Eol_el_arrayan	Wind	EOL_SIC_CENTRO	113.9	Y	Y
Eol_los_cururos	Wind	EOL_SIC_CENTRO	108.9	Y	Y
Eol_monte_redondo	Wind	EOL_SIC_CENTRO	47.5	Y	Y
Eol_punta_colorada	Wind	EOL_SIC_CENTRO	19.8	Y	Y
Eol_punta_palmeras	Wind	EOL_SIC_CENTRO	44.6	Y	Y
Eol_talinay_oriente	Wind	EOL_SIC_CENTRO	89.1	Y	Y
Eol_talinay_poniente	Wind	EOL_SIC_CENTRO	60.4	Y	Y
Eol_totoral	Wind	EOL_SIC_CENTRO	45.5	Y	Y
Eolica_lpalmas01	Wind	EOL_SIC_CENTRO	67.32	N	Y
Eolica_lpalmas02	Wind	EOL_SIC_CENTRO	381.15	N	Y
Eolica_pazucar01	Wind	EOL_SIC_CENTRO	57.42	N	Y
Eol_caman	Wind	EOL_SIC_SUR	148.5	Y	Y
Eol_coihue	Wind	EOL_SIC_SUR	213.8	Y	Y
Eol_esperanza	Wind	EOL_SIC_SUR	200.0	Y	Y
Eol_huajache	Wind	EOL_SIC_SUR	5.9	Y	Y
Eol_la_esperanza	Wind	EOL_SIC_SUR	10.4	Y	Y
Eol_las_penas	Wind	EOL_SIC_SUR	7.9	Y	Y
Eol_lebu	Wind	EOL_SIC_SUR	15.0	Y	Y
Eol_lomas_de_duqueco	Wind	EOL_SIC_SUR	45.7	Y	Y
Eol_los_buenos_aires	Wind	EOL_SIC_SUR	23.8	Y	Y
Eol_los_guindos	Wind	EOL_SIC_SUR	372.4	Y	Y
Eol_malleco	Wind	EOL_SIC_SUR	153.5	Y	Y
Eol_malleco_ii	Wind	EOL_SIC_SUR	98.0	Y	Y
Eol_negrete	Wind	EOL_SIC_SUR	35.6	Y	Y
Eol_negrete_cuel	Wind	EOL_SIC_SUR	32.7	Y	Y
Eol_puelche_sur	Wind	EOL_SIC_SUR	130.7	Y	Y
Eol_raki	Wind	EOL_SIC_SUR	8.9	Y	Y
Eol_renaico	Wind	EOL_SIC_SUR	87.1	Y	Y
Eol_san_gabriel	Wind	EOL_SIC_SUR	181.2	Y	Y
Eol_san_pedro	Wind	EOL_SIC_SUR	35.6	Y	Y
Eol_san_pedro_2	Wind	EOL_SIC_SUR	64.4	Y	Y
Eol_ucuquer_i	Wind	EOL_SIC_SUR	6.9	Y	Y
Eol_ucuquer_ii	Wind	EOL_SIC_SUR	10.9	Y	Y
Eolica_chiloe02	Wind	EOL_SIC_SUR	269.28	N	Y
Eolica_concepcion01	Wind	EOL_SIC_SUR	122.76	N	Y
Eolica_mulchen01	Wind	EOL_SIC_SUR	143.55	N	Y

Table B.2: Parameters of wind generation units.

B.3 Run-of-the-river Generation Units

Name	Type	Zone	P^{max}	η	in D?	in E?
Cenpas_sing_norte	RoR	ROR_1_PAN_DE_AZUCAR	14.44	1.9	Y	Y
Eq_minihidro_sic_centronorte	RoR	ROR_1_PAN_DE_AZUCAR	33.0	1.9	Y	Y
Alfalfal2	RoR	ROR_2_ALTO_JAHUEL	264.0	1.9	Y	Y
Eq_minihidro_sic_centro	RoR	ROR_2_ALTO_JAHUEL	48.0	1.9	Y	Y
Eq_pasada_sic_centro	RoR	ROR_2_ALTO_JAHUEL	779.0	1.9	Y	Y
Laslajas	RoR	ROR_2_ALTO_JAHUEL	267.0	1.9	Y	Y
Ancoa	RoR	ROR_3_ANCOA	27.0	1.9	Y	Y
Eq_minihidro_sic_centrosura	RoR	ROR_3_ANCOA	57.0	1.9	Y	Y
Eq_pasada_sic_centrosura	RoR	ROR_3_ANCOA	25.0	1.9	Y	Y
Hidroelectrica vii region 02	RoR	ROR_3_ANCOA	20.0	1.9	Y	Y
Hidroelectrica vii region 03	RoR	ROR_3_ANCOA	20.0	1.9	Y	Y
Lamina	RoR	ROR_3_ANCOA	34.0	1.9	Y	Y
Loscondores	RoR	ROR_3_ANCOA	150.0	1.9	Y	Y
Nuble	RoR	ROR_3_ANCOA	136.0	1.9	Y	Y
Riocolorado	RoR	ROR_3_ANCOA	15.0	1.9	Y	Y
Curillinque	RoR	ROR_4_ITAHUE	89.0	1.9	Y	Y
Elpaso	RoR	ROR_4_ITAHUE	60.0	1.9	Y	Y
Eq_pasada_sic_centro_tinguiririca	RoR	ROR_4_ITAHUE	318.0	1.9	Y	Y
Isla	RoR	ROR_4_ITAHUE	68.0	1.9	Y	Y
Lamontana01	RoR	ROR_4_ITAHUE	3.0	1.9	Y	Y
Lomaalta	RoR	ROR_4_ITAHUE	38.0	1.9	Y	Y
Sanignacio	RoR	ROR_4_ITAHUE	37.0	1.9	Y	Y
Abanico	RoR	ROR_5_CHARRUA	136.0	1.9	Y	Y
Angostura	RoR	ROR_5_CHARRUA	316.0	1.9	Y	Y
Antuco	RoR	ROR_5_CHARRUA	320.0	1.6	Y	Y
Eq_minihidro_sic_centrosurc	RoR	ROR_5_CHARRUA	8.0	1.9	Y	Y
Eq_pasada_sic_centrosurc	RoR	ROR_5_CHARRUA	126.0	1.9	Y	Y
Palmucho	RoR	ROR_5_CHARRUA	32.0	1.9	Y	Y
Picoiquen_itata	RoR	ROR_5_CHARRUA	39.0	1.9	Y	Y
Quilleco	RoR	ROR_5_CHARRUA	70.0	1.9	Y	Y
Rucue	RoR	ROR_5_CHARRUA	169.0	1.9	Y	Y
Carilafquen_malalcahuello	RoR	ROR_6_CARILAFQUEN	29.0	1.9	Y	Y
Lasnieves	RoR	ROR_6_CARILAFQUEN	7.0	1.9	Y	Y
Panguipulli	RoR	ROR_6_CARILAFQUEN	0.0	1.9	Y	Y
Sanpedro	RoR	ROR_6_CARILAFQUEN	170.0	1.9	Y	Y
Eq_minihidro_sic_sur	RoR	ROR_7_PUERTO_MONTT	115.0	1.9	Y	Y
Eq_pasada_sic_sur	RoR	ROR_7_PUERTO_MONTT	178.0	1.9	Y	Y
Chiburgo	RoR	ROR_8_COLBUN	19.0	1.9	Y	Y
Machicura	RoR	ROR_8_COLBUN	97.0	0.31	Y	Y

Table B.3: Parameters of run-of-the-river generation units.

B.4 Hydro Reservoirs

Name	**Type**	**Zone**	P^{max}	η	V_0	V^{min}	**in D?**	**in E?**
Rapel	Dam	RAPEL	350.0	0.61	358.57	272.3	Y	Y
Pehuenche	Dam	PEHUENCHE	457.46	1.74	116.91	106.6	Y	Y
Cipreses	Dam	CIPRESES	105.0	2.6	68.62	4.7	Y	Y
Eltoro	Dam	ELTORO	367.61	4.54	1149.05	431.0	Y	Y
Ralco	Dam	RALCO	539.15	1.44	417.88	409.4	Y	Y
Pangue	Dam	PANGUE	472.0	0.81	65.07	30.8	Y	Y
Canutillar	Dam	CANUTILLAR	169.0	1.9	108.39	89.9	Y	Y
Colbun	Dam	COLBUN	375.77	1.23	1039.51	381.6	Y	Y

Table B.4: Parameters of hydro reservoirs.

B.5 Gas Generation Units

In the following table, hr denote the heart rate value, which is expressed in [MMBtu/MWh] for all gas generation units; ef denote the emission factor ([tonCO_2/MWh]); c^v_D and c^v_E denote the variable cost in scenario D and E respectively ([USD/MWh]) calculated using the eq. (6.1).

Name	**Type**	P^{min}	P^{max}	ρ^{up}	ρ^{down}	τ^{on}	τ^{off}	c^{on}	c^{off}	c^{nf}	hr	c^{rp}	ef	**D**	**E**	c^v_D	c^v_E
Biocruz	OCGT	0.0	1.8	999	999	0	0	0	0	3.5	9.32	0.9	0.56	Y	Y	78.5	112.43
Cmpc_cordillera	OCGT	0.0	23.7	999	999	0	0	0	0	3.5	9.32	0.9	0.56	Y	Y	78.5	112.43
Cmpc_tissue	OCGT	0.0	4.0	999	999	0	0	0	0	3.5	9.32	0.9	0.56	Y	Y	78.5	112.43
Gas_atacama_cc1_gnl	CCGT	213.5	319.2	480	480	2	2	17903	17903	4.39	8.825	0.56	0.46	Y	Y	75.41	107.54
Gas_atacama_cc2_gnl	CCGT	213.5	318.8	480	480	2	2	17903	17903	4.39	8.825	0.56	0.46	Y	Y	75.41	107.54
Hbs_gnl	OCGT	0.0	3.5	999	999	0	0	0	0	3.5	9.32	0.9	0.56	Y	Y	78.5	112.43
Kelar	CCGT	200.6	511.8	999	999	3	5	27582	27582	1.69	10.943	0.56	0.46	Y	Y	89.75	129.59
Nehuenco_01_gnl	CCGT	252.1	331.3	600	600	4	8	18000	18000	2.9	7.28	0.56	0.46	Y	Y	61.48	87.99
Nehuenco_02_gnl	CCGT	245.0	367.6	600	600	4	8	26300	26300	2.4	6.69	0.56	0.46	Y	Y	56.24	80.59
Nueva_renca_gnl	CCGT	234.2	358.0	600	600	40	2	12539	12539	5.55	7.06	0.56	0.46	Y	Y	62.36	88.07
San_isidro_01_cc	CCGT	259.4	322.0	600	600	2	2	61170	61170	9.21	7.06	0.56	0.46	Y	Y	66.02	91.73
San_isidro_02_cc	CCGT	259.4	373.9	600	600	2	2	39327	39327	9.21	7.06	0.56	0.46	Y	Y	66.02	91.73
Tg3_gnl	OCGT	0.0	36.8	999	999	0	0	0	0	3.5	9.32	0.9	0.56	Y	Y	78.5	112.43
U16_gnl	OCGT	117.0	339.6	870	870	4	4	18865	18865	3.5	9.32	0.9	0.56	Y	Y	78.5	112.43

Table B.5: Parameters of gas generation units.

B.6 Coal Generation Units

In the following table, hr denote the heart rate value, which is expressed in [ton/MWh] for all coal generation units; ef denote the emission factor ([tonCO_2/MWh]); c_D^v and c_E^v denote the variable cost in scenario D and E respectively ([USD/MWh]) calculated using the eq. (6.1).

Name	**Type**	P^{min}	P^{max}	ρ^{up}	ρ^{down}	τ^{on}	τ^{off}	c^{on}	c^{off}	c^{nf}	hr	c^{rp}	ef	**D**	**E**	c_D^v	c_E^v
Ang_i	Coal	121.68	246.1	121	300	48	48	35232	35232	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Ang_ii	Coal	121.68	250.5	141	300	48	48	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Bocamina_01	Coal	65.8	121.0	120	120	72	48	19533	19533	7.35	0.38	2.02	1.27	Y	Y	32.85	44.04
Bocamina_02	Coal	211.9	319.3	211	211	72	48	145747	145747	4.3	0.38	2.02	1.27	Y	Y	29.8	40.99
Campiche	Coal	98.7	241.4	300	300	24	168	0	0	5.55	0.38	2.02	1.27	Y	Y	31.05	42.24
Cochrane_1	Coal	75.94	233.6	159	159	48	48	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Cochrane_2	Coal	75.94	233.6	159	159	48	48	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Cta	Coal	83.8	159.2	83	83	72	48	21874	21874	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Cth	Coal	83.8	159.7	83	83	48	48	20845	20845	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Ctm1	Coal	79.0	147.1	180	180	48	120	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Ctm2	Coal	79.0	152.5	180	180	48	120	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Cttar	Coal	90.52	147.0	90	180	48	48	19186	19186	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Curico	Coal	0.0	2.0	999	999	0	0	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Guacolda_01	Coal	55.22	141.5	120	120	4	8	0	0	1.0	0.4	2.02	1.27	Y	Y	27.84	39.62
Guacolda_02	Coal	55.22	141.5	120	120	4	8	29177	29177	1.0	0.4	2.02	1.27	Y	Y	27.84	39.62
Guacolda_03	Coal	52.98	135.7	120	120	4	4	0	0	2.1	0.38	2.02	1.27	Y	Y	27.6	38.79
Guacolda_04	Coal	53.75	137.6	120	120	4	4	0	0	2.0	0.38	2.02	1.27	Y	Y	27.5	38.69
Guacolda_05	Coal	53.72	130.4	120	120	4	4	0	0	2.0	0.38	2.02	1.27	Y	Y	27.5	38.69
Iem	Coal	170.0	371.3	816	816	48	48	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Nto1	Coal	56.14	120.5	180	180	48	48	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Nto2	Coal	55.83	124.7	180	180	48	48	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Nueva_ventanas	Coal	97.8	246.5	300	300	24	168	0	0	5.55	0.38	2.02	1.27	Y	Y	31.05	42.24
Santa_maria	Coal	221.8	338.6	221	221	120	48	257646	257646	3.0	0.35	2.02	1.27	Y	Y	26.48	36.8
U12	Coal	44.28	80.4	240	240	24	48	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
U13	Coal	44.28	79.1	240	240	24	48	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8

U14	Coal	66.27	126.4	300	300	24	48	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
U15	Coal	66.66	122.8	120	120	24	48	0	0	2.0	0.35	2.02	1.27	Y	Y	25.48	35.8
Ventanas_01	Coal	56.2	112.3	180	180	24	168	0	0	2.18	0.42	2.02	1.27	Y	Y	30.36	42.74
Ventanas_02	Coal	111.8	206.5	180	180	24	168	0	0	1.38	0.4	2.02	1.27	Y	Y	28.22	40.0

Table B.6: Parameters of coal generation units.

B.7 Diesel Generation Units

In the following table, hr denote the heart rate value, which is expressed in $[m^3/MWh]$ for all diesel generation units; ef denote the emission factor ([tonCO_2/MWh]); c_D^v and c_E^v denote the variable cost in scenario D and E respectively ([USD/MWh]) calculated using the eq. (6.1).

Name	P^{min}	P^{max}	ρ^{up}	ρ^{down}	τ^{on}	τ^{off}	c^{on}	c^{off}	c^{nf}	hr	c^{rp}	ef	**D**	**E**	c_D^v	c_E^v
Andes_generacion_tg	0.0	29.9	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Antilhue_tg	0.0	96.9	999	999	0	0	0	0	2.8	0.3375	0.56	0.88	N	Y		327.25
Biomar	0.0	2.4	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Calle_calle	0.0	12.9	999	999	0	0	0	0	21.69	0.2875	0.56	0.88	Y	Y	190.51	298.07
Candelaria_ca_01_diesel	59.7	124.0	600	600	0	0	5000	5000	2.8	0.4	0.56	0.88	Y	Y	237.69	387.33
Candelaria_ca_02_diesel	59.7	127.3	600	600	0	0	5000	5000	2.8	0.4	0.56	0.88	Y	Y	237.69	387.33
Canete	0.0	4.0	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Cardones	69.7	151.5	660	660	0	8	15346	15346	24.41	0.3	0.56	0.88	N	Y		312.81
Casablanca_1	0.0	1.6	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Casablanca_2	0.0	0.9	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Cementos_bio_bio	0.0	13.5	999	999	0	0	0	0	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Cenizas	0.0	13.8	999	999	0	0	0	0	13.81	0.2875	0.56	0.88	N	Y		290.19
Chiloe	0.0	8.9	999	999	0	0	0	0	39.27	0.35	0.56	0.88	N	Y		375.73
Chufken	0.0	1.6	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Chuyaca	0.0	14.9	999	999	0	0	0	0	21.63	0.3125	0.56	0.88	N	Y		322.04
Cog_aconcagua	0.0	76.2	999	999	0	0	0	0	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Colihues	0.0	21.8	999	999	0	0	0	0	22.18	0.2625	0.56	0.88	Y	Y	176.32	274.53

Colmito	24.9	57.4	999	612	0	0	1500	1500	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Con_con	0.0	2.2	999	999	0	0	0	0	42.28	0.3	0.56	0.88	Y	Y	218.44	330.68
Constitucion_elektragen	0.0	8.9	999	999	0	0	0	0	39.27	0.35	0.56	0.88	N	Y		375.73
Contulmo	0.0	0.8	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Coronel_tg_diesel	0.0	46.2	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Ctm3	0.0	248.3	480	480	2	2	0	0	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Cummins	0.0	0.7	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Curacautin	0.0	2.4	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Curauma	0.0	2.5	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Degan	0.0	35.6	999	999	0	0	0	0	33.3	0.275	0.56	0.88	Y	Y	194.78	297.66
Deutz	0.0	1.9	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Diego_de_almagro_tg	0.0	22.8	999	999	0	0	0	0	6.63	0.425	0.56	0.88	N	Y		415.19
Dona_carmen	0.0	47.5	999	999	0	0	0	0	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Eagon	0.0	2.4	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
El_penon	0.0	80.2	999	999	0	0	0	0	28.0	0.275	0.56	0.88	Y	Y	189.48	292.36
El_salvador_tg	0.0	23.6	999	999	0	0	0	0	43.48	0.425	0.56	0.88	N	Y		452.04
Emelda_01	0.0	32.9	999	999	0	0	0	0	14.5	0.3625	0.56	0.88	N	Y		362.98
Emelda_02	0.0	35.6	999	999	0	0	0	0	14.5	0.3875	0.56	0.88	N	Y		387.01
Esperanza	0.0	21.8	999	999	0	0	0	0	28.2	0.26	0.56	0.88	Y	Y	180.88	278.14
Espinos	0.0	122.4	999	999	0	0	0	0	26.4	0.275	0.56	0.88	Y	Y	187.88	290.76
Estandartes	0.0	1.6	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Estandartes_7_12	0.0	4.8	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Gmar	0.0	8.3	999	96	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Horcones_tg_diesel	0.0	24.1	999	999	0	0	0	0	10.0	0.4375	0.56	0.88	N	Y		430.58
Huasco_tg	0.0	57.4	999	999	0	0	0	0	3.5	0.272862439	0.56	0.88	N	Y		265.81
Inacal	0.0	6.6	999	999	0	0	0	0	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Ingenova	0.0	2.0	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Jce	0.0	0.8	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Laguna_verde	0.0	52.2	999	999	0	0	0	0	7.86	0.5125	0.56	0.88	N	Y		500.54
Laguna_verde_tg	0.0	17.8	999	999	0	0	0	0	11.42	0.325	0.56	0.88	Y	Y	202.26	323.85
Las_vegas	0.0	2.1	999	999	0	0	0	0	31.74	0.3	0.56	0.88	Y	Y	207.9	320.14
Lebu	0.0	2.4	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06

Linares	0.0	0.4	999	999	0	0	0	0	44.43	0.275	0.56	0.88	Y	Y	205.91	308.79
Lonquimay	0.0	1.2	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Los__alamos	0.0	0.8	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Los__guindos	64.7	136.6	600	600	4	1	3635	3635	3.25	0.3	0.56	0.88	N	Y		291.65
Los__pinos	29.6	103.1	999	999	0	1	1000	1000	4.5	0.2875	0.56	0.88	Y	Y	173.32	280.88
Los__vientos	59.7	130.7	600	600	2	1	11329	11329	2.95	0.3375	0.56	0.88	N	Y		327.4
Louisiana__pacific	0.0	6.0	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
M1ar	0.0	2.9	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
M2ar	0.0	2.8	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Maiq	0.0	5.6	999	999	0	0	0	0	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Maule	0.0	5.9	999	999	0	0	0	0	39.27	0.35	0.56	0.88	N	Y		375.73
Miiq	0.0	2.8	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Mimb	0.0	27.6	180	6	0	0	0	0	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Msiq	0.0	5.8	999	999	0	0	0	0	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Nehuenco__9b__01__diesel	0.0	133.7	999	999	0	0	0	0	4.3	0.4125	0.56	0.88	Y	Y	246.53	400.84
Newen	0.0	12.9	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Nueva__aldea__02__diesel	0.0	9.9	999	999	0	0	0	0	12.0	0.3625	0.56	0.88	N	Y		360.48
Olivos	0.0	111.3	999	999	0	0	0	0	30.4	0.2875	0.56	0.88	Y	Y	199.22	306.78
Placilla	0.0	3.0	999	999	0	0	0	0	28.37	0.3	0.56	0.88	Y	Y	204.53	316.77
Portada	0.0	3.0	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Punta__colorada	0.0	16.8	999	999	0	0	0	0	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Quellon__02	0.0	7.9	999	999	0	0	0	0	28.3	0.3125	0.56	0.88	N	Y		328.71
Quintay	0.0	3.0	999	999	0	0	0	0	28.97	0.3	0.56	0.88	Y	Y	205.13	317.37
Quintero__1__diesel	0.0	120.4	999	999	0	0	0	0	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Quintero__2__diesel	0.0	123.9	999	999	0	0	0	0	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Renca	0.0	91.1	999	999	0	0	0	0	3.64	0.4625	0.56	0.88	N	Y		448.25
San__francisco__tg	0.0	25.4	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
San__gregorio	0.0	0.4	999	999	0	0	0	0	44.43	0.275	0.56	0.88	Y	Y	205.91	308.79
San__lorenzo	0.0	61.4	999	999	0	0	0	0	24.1	0.425	0.56	0.88	N	Y		432.66
Santa__lidia	59.7	137.6	600	600	2	1	10698	10698	3.53	0.325	0.56	0.88	N	Y		315.96
Suiq	0.0	4.0	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Taltal__01__diesel	74.9	108.9	600	600	0	0	16770	16770	6.75	0.3125	0.56	0.88	N	Y		307.16

Taltal_02_diesel	74.9	108.9	600	600	0	0	16770	16770	6.75	0.3125	0.56	0.88	N	Y		307.16
Tamaya	0.0	90.6	999	999	0	0	0	0	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Teno	0.0	58.4	999	999	0	0	0	0	28.0	0.275	0.56	0.88	Y	Y	189.48	292.36
Termopacifico	0.0	80.4	999	999	0	0	0	0	24.22	0.23	0.56	0.88	Y	Y	159.28	245.32
Tg1	0.0	24.4	600	600	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Tg2	0.0	24.6	600	600	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Tg3d	0.0	36.8	600	600	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Tgiq	0.0	23.3	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Tgtar	0.0	23.4	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Totoral	0.0	3.0	999	999	0	0	0	0	33.43	0.3	0.56	0.88	Y	Y	209.59	321.83
Trapen	0.0	80.2	999	999	0	0	0	0	28.0	0.275	0.56	0.88	Y	Y	189.48	292.36
U10	13.5	35.6	360	360	8	24	1733	1733	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
U11	13.5	35.6	360	360	8	24	1733	1733	3.5	0.272862439	0.56	0.88	Y	Y	163.73	265.81
Ujina_ug1	0.0	6.4	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Ujina_ug2	0.0	6.4	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Ujina_ug3	0.0	6.4	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Ujina_ug4	0.0	6.4	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Ujina_ug5	0.0	8.5	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Ujina_ug6	0.0	8.5	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Watts	0.0	2.4	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Yungay_01_diesel	0.0	51.9	999	999	0	0	0	0	22.7	0.35	0.56	0.88	N	Y		359.16
Yungay_02_diesel	0.0	51.6	999	999	0	0	0	0	22.7	0.3125	0.56	0.88	N	Y		323.11
Yungay_03_diesel	0.0	52.9	999	999	0	0	0	0	22.7	0.3375	0.56	0.88	N	Y		347.15
Yungay_04_diesel	0.0	40.7	999	999	0	0	0	0	57.8	0.375	0.56	0.88	N	Y		418.3
Zofri_1	0.0	0.9	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06
Zofri_2	0.0	5.1	999	999	0	0	0	0	3.5	0.3375	0.56	0.88	Y	Y	201.68	327.95
Zofri_2_5	0.0	5.1	999	999	0	0	0	0	3.5	0.3375	0.56	0.88	Y	Y	201.68	327.95
Zofri_3	0.0	4.7	999	999	0	0	0	0	3.5	0.3375	0.56	0.88	Y	Y	201.68	327.95
Zofri_6	0.0	0.4	999	999	0	0	0	0	3.5	0.27	0.56	0.88	Y	Y	162.05	263.06

Table B.9: Parameters of diesel generation units.

Appendix C

Grouped Generation Units Parameters

Given the grouping methodology explained in sections 6.1.3 and 6.1.4, run-of-the-river generation units were grouped in 8 equivalent units, while solar and wind generation units were grouped in 4 groups each. The final group of generation units used for the simulations are described in the following:

C.1 Generation Units for Scenario D

C.1.1 Scenario D: Grouped solar generation units

Name	**Type**	**Zone**	P^{max}
Fv_sing	PV	FV_SING	7978.1
Fv_sic_norte	PV	FV_SIC_NORTE	5260.9
Fv_sic_centro	PV	FV_SIC_CENTRO	192.4
Fv_sic_sur	PV	FV_SIC_SUR	172.8

Table C.1: Parameters of grouped solar generation units in scenario D.

C.1.2 Scenario D: Grouped wind generation untis

Name	**Type**	**Zone**	P^{max}
Eol_sing	Wind	EOL_SING	691.9
Eol_sic_norte	Wind	EOL_SIC_NORTE	963.1
Eol_sic_centro	Wind	EOL_SIC_CENTRO	607.1
Eol_sic_sur	Wind	EOL_SIC_SUR	1888.9

Table C.2: Parameters of grouped wind generation units in scenario D.

C.1.3 Scenario D: Grouped run-of-the-river generation units

Name	**Type**	**Zone**	P^{max}	η
Pas1	RoR	ROR_1_PAN_DE_AZUCAR	81.29	3.8
Pas2	RoR	ROR_2_ALTO_JAHUEL	1334.73	7.6
Pas3	RoR	ROR_3_ANCOA	777.61	17.1
Pas4	RoR	ROR_4_ITAHUE	431.0	13.3
Pas5	RoR	ROR_5_CHARRUA	1109.29	16.8
Pas6	RoR	ROR_6_CARILAFQUEN	354.8	7.6
Pas7	RoR	ROR_7_PUERTO_MONTT	133.98	3.8
Pas8	RoR	ROR_8_COLBUN	115.0	1.31

Table C.3: Parameters of grouped run-of-the-river generation units in scenario D.

C.1.4 Scenario D: Hydro reservoirs

Name	**Type**	**Zone**	P^{max}	η	V_0	V^{min}
Rapel	Dam	RAPEL	350.0	0.61	358.57	272.3
Pehuenche	Dam	PEHUENCHE	457.46	1.74	116.91	106.6
Cipreses	Dam	CIPRESES	105.0	2.6	68.62	4.7
Eltoro	Dam	ELTORO	367.61	4.54	1149.05	431.0
Ralco	Dam	RALCO	539.15	1.44	417.88	409.4
Pangue	Dam	PANGUE	472.0	0.81	65.07	30.8
Canutillar	Dam	CANUTILLAR	169.0	1.9	108.39	89.9
Colbun	Dam	COLBUN	375.77	1.23	1039.51	381.6

Table C.4: Parameters of hydro reservoirs in scenario D.

C.1.5 Scenario D: Gas generation units

In the following table, hr denote the heart rate value, which is expressed in [MMBtu/MWh] for all gas generation units; ef denote the emission factor ([tonCO_2/MWh]); c^v denote the variable cost ([USD/MWh]) calculated using the eq. (6.1).

Name	**Type**	P^{min}	P^{max}	ρ^{up}	ρ^{down}	τ^{on}	τ^{off}	c^{on}	c^{off}	c^{nf}	hr	c^{rp}	ef	c^v
Gas_atacama_cc1_gnl	CCGT	213.5	319.2	480	480	2	2	17903.0	17903.0	4.39	8.82	0.56	0.46	75.41
Gas_atacama_cc2_gnl	CCGT	213.5	318.8	480	480	2	2	17903.0	17903.0	4.39	8.82	0.56	0.46	75.41
Gnlca_equiv	OCGT	0.0	69.8	999	999	0	0	0.0	0.0	0.0	0.0	0.9	0.56	78.5
Kelar	CCGT	200.6	511.8	999	999	3	5	27582.0	27582.0	1.69	10.94	0.56	0.46	89.75
Nehuenco_01_gnl	CCGT	252.1	331.3	600	600	4	8	18000.0	18000.0	2.9	7.28	0.56	0.46	61.48
Nehuenco_02_gnl	CCGT	245.0	367.6	600	600	4	8	26300.0	26300.0	2.4	6.69	0.56	0.46	56.24
Nueva_renca_gnl	CCGT	234.2	358.0	600	600	40	2	12539.0	12539.0	5.55	7.06	0.56	0.46	62.36
San_isidro_01_cc	CCGT	259.4	322.0	600	600	2	2	61170.0	61170.0	9.21	7.06	0.56	0.46	66.02
San_isidro_02_cc	CCGT	259.4	373.9	600	600	2	2	39327.0	39327.0	9.21	7.06	0.56	0.46	66.02
U16_gnl	OCGT	117.0	339.6	870	870	4	4	18865.0	18865.0	3.5	9.32	0.9	0.56	78.5

Table C.5: Parameters of gas generation units in scenario D.

C.1.6 Scenario D: Coal generation units

In the following table, hr denote the heart rate value, which is expressed in [ton/MWh] for all coal generation units; ef denote the emission factor ([tonCO_2/MWh]); c^v denote the variable cost ([USD/MWh]) calculated using the eq. (6.1).

Name	**Type**	P^{min}	P^{max}	ρ^{up}	ρ^{down}	τ^{on}	τ^{off}	c^{on}	c^{off}	c^{nf}	hr	c^{rp}	ef	c^v
Ang_i	Coal	121.68	246.1	121	300	48	48	35232.0	35232.0	2.0	0.35	2.02	1.27	25.48
Ang_ii	Coal	121.68	250.5	141	300	48	48	0.0	0.0	2.0	0.35	2.02	1.27	25.48
Bocamina_01	Coal	65.8	121.0	120	120	72	48	19533.0	0.0	7.35	0.38	2.02	1.27	32.85
Bocamina_02	Coal	211.9	319.3	211	211	72	48	145747.0	145747.0	4.3	0.38	2.02	1.27	29.8
Campiche	Coal	98.7	241.4	300	300	24	168	0.0	0.0	5.55	0.38	2.02	1.27	31.05
Cochrane_1	Coal	75.94	233.6	159	159	48	48	0.0	0.0	2.0	0.35	2.02	1.27	25.48

Cochrane_2	Coal	75.94	233.6	159	159	48	48	0.0	0.0	2.0	0.35	2.02	1.27	25.48
Cta	Coal	83.8	159.2	83	83	72	48	21874.0	21874.0	2.0	0.35	2.02	1.27	25.48
Cth	Coal	83.8	159.7	83	83	48	48	20845.0	20845.0	2.0	0.35	2.02	1.27	25.48
Ctm1	Coal	79.0	147.1	180	180	48	120	0.0	0.0	2.0	0.35	2.02	1.27	25.48
Ctm2	Coal	79.0	152.5	180	180	48	120	0.0	0.0	2.0	0.35	2.02	1.27	25.48
Cttar	Coal	90.52	147.0	90	180	48	48	19186.0	19186.0	2.0	0.35	2.02	1.27	25.48
Curico	Coal	0.0	2.0	999	999	0	0	0.0	0.0	2.0	0.35	2.02	1.27	25.48
Guacolda_01	Coal	55.22	141.5	120	120	4	8	0.0	0.0	1.0	0.4	2.02	1.27	27.84
Guacolda_02	Coal	55.22	141.5	120	120	4	8	29177.0	29177.0	1.0	0.4	2.02	1.27	27.84
Guacolda_03	Coal	52.98	135.7	120	120	4	4	0.0	0.0	2.1	0.38	2.02	1.27	27.6
Guacolda_04	Coal	53.75	137.6	120	120	4	4	0.0	0.0	2.0	0.38	2.02	1.27	27.5
Guacolda_05	Coal	53.72	130.4	120	120	4	4	0.0	0.0	2.0	0.38	2.02	1.27	27.5
Iem	Coal	170.0	371.3	816	816	48	48	0.0	0.0	2.0	0.35	2.02	1.27	25.48
Nto1	Coal	56.14	120.5	180	180	48	48	0.0	0.0	2.0	0.35	2.02	1.27	25.48
Nto2	Coal	55.83	124.7	180	180	48	48	0.0	0.0	2.0	0.35	2.02	1.27	25.48
Nueva_ventanas	Coal	97.8	246.5	300	300	24	168	0.0	0.0	5.55	0.38	2.02	1.27	31.05
Santa_maria	Coal	221.8	338.6	221	221	120	48	257646.0	257646.0	3.0	0.35	2.02	1.27	26.48
U12	Coal	44.28	80.4	240	240	24	48	0.0	0.0	2.0	0.35	2.02	1.27	25.48
U13	Coal	44.28	79.1	240	240	24	48	0.0	0.0	2.0	0.35	2.02	1.27	25.48
U14	Coal	66.27	126.4	300	300	24	48	0.0	0.0	2.0	0.35	2.02	1.27	25.48
U15	Coal	66.66	122.8	120	120	24	48	0.0	0.0	2.0	0.35	2.02	1.27	25.48
Ventanas_01	Coal	56.2	112.3	180	180	24	168	0.0	0.0	2.18	0.42	2.02	1.27	30.36
Ventanas_02	Coal	111.8	206.5	180	180	24	168	0.0	0.0	1.38	0.4	2.02	1.27	28.22

Table C.6: Parameters of coal generation units in scenario D.

C.1.7 Scenario D: Diesel generation units

In the following table, hr denote the heart rate value, which is expressed in $[m^3/MWh]$ for all diesel generation units; ef denote the emission factor ([tonCO_2/MWh]); c^v denote the variable cost ([USD/MWh]) calculated using the eq. (6.1).

Name	**Type**	P^{min}	P^{max}	ρ^{up}	ρ^{down}	τ^{on}	τ^{off}	c^{on}	c^{off}	c^{nf}	hr	c^{rp}	ef	c^{v}
Candelaria_ca_01_diesel	59.7	124.0	600	600	0	0	5000.0	5000.0	2.8	0.4	0.56	0.88	237.69	
Candelaria_ca_02_diesel	59.7	127.3	600	600	0	0	5000.0	5000.0	2.8	0.4	0.56	0.88	237.69	
Colmito	24.9	57.4	999	612	0	0	1500.0	1500.0	3.5	0.27	0.56	0.88	162.05	
Ctm3	0.0	248.3	480	480	2	2	0.0	0.0	3.5	0.27	0.56	0.88	163.73	
Die_equiv_1	0.0	988.7	999	999	0	0	0.0	0.0	0.0	0.0	0.56	0.88	163.41	
Die_equiv_2	0.0	533.7	999	999	0	0	0.0	0.0	0.0	0.0	0.56	0.88	192.29	
Die_equiv_3	0.0	14.1	999	999	0	0	0.0	0.0	0.0	0.0	0.56	0.88	208.49	
Die_equiv_4	0.0	133.7	999	999	0	0	0.0	0.0	0.0	0.0	0.56	0.88	246.53	
Los_pinos	29.6	103.1	999	999	0	1	1000.0	1000.0	4.5	0.29	0.56	0.88	173.32	
Mimb	0.0	27.6	180	6	0	0	0.0	0.0	3.5	0.27	0.56	0.88	163.73	
U10	13.5	35.6	360	360	8	24	1733.0	1733.0	3.5	0.27	0.56	0.88	163.73	
U11	13.5	35.6	360	360	8	24	1733.0	1733.0	3.5	0.27	0.56	0.88	163.73	

Table C.7: Parameters of diesel generation units in scenario D.

C.2 Generation Units for Scenario E

C.2.1 Scenario E: Grouped solar generation units

Name	**Type**	**Zone**	P^{max}
Fv_sing	PV	FV_SING	7978.1
Fv_sic_norte	PV	FV_SIC_NORTE	5260.9
Fv_sic_centro	PV	FV_SIC_CENTRO	192.4
Fv_sic_sur	PV	FV_SIC_SUR	172.8

Table C.8: Parameters of grouped solar generation units in scenario E.

C.2.2 Scenario E: Grouped wind generation untis

Name	**Type**	**Zone**	P^{max}
Eol_sing	Wind	EOL_SING	691.9
Eol_sic_norte	Wind	EOL_SIC_NORTE	3700.45
Eol_sic_centro	Wind	EOL_SIC_CENTRO	1112.99
Eol_sic_sur	Wind	EOL_SIC_SUR	2424.49

Table C.9: Parameters of grouped wind generation units in scenario E.

C.2.3 Scenario E: Grouped run-of-the-river generation units

Name	**Type**	**Zone**	P^{max}	η
Pas1	RoR	ROR_1_PAN_DE_AZUCAR	81.29	3.8
Pas2	RoR	ROR_2_ALTO_JAHUEL	1334.73	7.6
Pas3	RoR	ROR_3_ANCOA	777.61	17.1
Pas4	RoR	ROR_4_ITAHUE	431.0	13.3
Pas5	RoR	ROR_5_CHARRUA	1109.29	16.8
Pas6	RoR	ROR_6_CARILAFQUEN	354.8	7.6
Pas7	RoR	ROR_7_PUERTO_MONTT	133.98	3.8
Pas8	RoR	ROR_8_COLBUN	115.0	1.31

Table C.10: Parameters of grouped run-of-the-river generation units in scenario E.

C.2.4 Scenario E: Hydro reservoirs

Name	**Type**	**Zone**	P^{max}	η	V_0	V^{min}
Rapel	Dam	RAPEL	350.0	0.61	358.57	272.3
Pehuenche	Dam	PEHUENCHE	457.46	1.74	116.91	106.6
Cipreses	Dam	CIPRESES	105.0	2.6	68.62	4.7
Eltoro	Dam	ELTORO	367.61	4.54	1149.05	431.0
Ralco	Dam	RALCO	539.15	1.44	417.88	409.4
Pangue	Dam	PANGUE	472.0	0.81	65.07	30.8
Canutillar	Dam	CANUTILLAR	169.0	1.9	108.39	89.9
Colbun	Dam	COLBUN	375.77	1.23	1039.51	381.6

Table C.11: Parameters of hydro reservoirs in scenario E.

C.2.5 Scenario E: Gas generation units

In the following table, hr denote the heart rate value, which is expressed in [MMBtu/MWh] for all gas generation units; ef denote the emission factor ([tonCO_2/MWh]); c^v denote the variable cost ([USE/MWh]) calculated using the eq. (6.1).

Name	**Type**	P^{min}	P^{max}	ρ^{up}	ρ^{down}	τ^{on}	τ^{off}	c^{on}	c^{off}	c^{nf}	hr	c^{rp}	ef	c^v
Gas_atacama_cc1_gnl	CCGT	213.5	319.2	480	480	2	2	17903.0	17903.0	4.39	8.82	0.56	0.46	107.54
Gas_atacama_cc2_gnl	CCGT	213.5	318.8	480	480	2	2	17903.0	17903.0	4.39	8.82	0.56	0.46	107.54
Gnlca_equiv	OCGT	0.0	69.8	999	999	0	0	0.0	0.0	0.0	0.0	0.9	0.56	112.43
Kelar	CCGT	200.6	511.8	999	999	3	5	27582.0	27582.0	1.69	10.94	0.56	0.46	129.59
Nehuenco_01_gnl	CCGT	252.1	331.3	600	600	4	8	18000.0	18000.0	2.9	7.28	0.56	0.46	87.99
Nehuenco_02_gnl	CCGT	245.0	367.6	600	600	4	8	26300.0	26300.0	2.4	6.69	0.56	0.46	80.59
Nueva_renca_gnl	CCGT	234.2	358.0	600	600	40	2	12539.0	12539.0	5.55	7.06	0.56	0.46	88.07
San_isidro_01_cc	CCGT	259.4	322.0	600	600	2	2	61170.0	61170.0	9.21	7.06	0.56	0.46	91.73
San_isidro_02_cc	CCGT	259.4	373.9	600	600	2	2	39327.0	39327.0	9.21	7.06	0.56	0.46	91.73
U16_gnl	OCGT	117.0	339.6	870	870	4	4	18865.0	18865.0	3.5	9.32	0.9	0.56	112.43

Table C.12: Parameters of gas generation units in scenario E.

C.2.6 Scenario E: Coal generation units

In the following table, hr denote the heart rate value, which is expressed in [ton/MWh] for all coal generation units; ef denote the emission factor ([tonCO_2/MWh]); c^v denote the variable cost ([USE/MWh]) calculated using the eq. (6.1).

Name	**Type**	P^{min}	P^{max}	ρ^{up}	ρ^{down}	τ^{on}	τ^{off}	c^{on}	c^{off}	c^{nf}	hr	c^{rp}	ef	c^v
Ang_i	Coal	121.68	246.1	121	300	48	48	35232.0	35232.0	2.0	0.35	2.02	1.27	35.8
Ang_ii	Coal	121.68	250.5	141	300	48	48	0.0	0.0	2.0	0.35	2.02	1.27	35.8
Bocamina_01	Coal	65.8	121.0	120	120	72	48	19533.0	19533.0	7.35	0.38	2.02	1.27	44.04
Bocamina_02	Coal	211.9	319.3	211	211	72	48	145747.0	145747.0	4.3	0.38	2.02	1.27	40.99
Campiche	Coal	98.7	241.4	300	300	24	168	0.0	0.0	5.55	0.38	2.02	1.27	42.24
Cochrane_1	Coal	75.94	233.6	159	159	48	48	0.0	0.0	2.0	0.35	2.02	1.27	35.8

Cochrane_2	Coal	75.94	233.6	159	159	48	48	0.0	0.0	2.0	0.35	2.02	1.27	35.8
Cta	Coal	83.8	159.2	83	83	72	48	21874.0	21874.0	2.0	0.35	2.02	1.27	35.8
Cth	Coal	83.8	159.7	83	83	48	48	20845.0	20845.0	2.0	0.35	2.02	1.27	35.8
Ctm1	Coal	79.0	147.1	180	180	48	120	0.0	0.0	2.0	0.35	2.02	1.27	35.8
Ctm2	Coal	79.0	152.5	180	180	48	120	0.0	0.0	2.0	0.35	2.02	1.27	35.8
Cttar	Coal	90.52	147.0	90	180	48	48	19186.0	19186.0	2.0	0.35	2.02	1.27	35.8
Curico	Coal	0.0	2.0	999	999	0	0	0.0	0.0	2.0	0.35	2.02	1.27	35.8
Guacolda_01	Coal	55.22	141.5	120	120	4	8	0.0	0.0	1.0	0.4	2.02	1.27	39.62
Guacolda_02	Coal	55.22	141.5	120	120	4	8	29177.0	29177.0	1.0	0.4	2.02	1.27	39.62
Guacolda_03	Coal	52.98	135.7	120	120	4	4	0.0	0.0	2.1	0.38	2.02	1.27	38.79
Guacolda_04	Coal	53.75	137.6	120	120	4	4	0.0	0.0	2.0	0.38	2.02	1.27	38.69
Guacolda_05	Coal	53.72	130.4	120	120	4	4	0.0	0.0	2.0	0.38	2.02	1.27	38.69
Iem	Coal	170.0	371.3	816	816	48	48	0.0	0.0	2.0	0.35	2.02	1.27	35.8
Nto1	Coal	56.14	120.5	180	180	48	48	0.0	0.0	2.0	0.35	2.02	1.27	35.8
Nto2	Coal	55.83	124.7	180	180	48	48	0.0	0.0	2.0	0.35	2.02	1.27	35.8
Nueva_ventanas	Coal	97.8	246.5	300	300	24	168	0.0	0.0	5.55	0.38	2.02	1.27	42.24
Santa_maria	Coal	221.8	338.6	221	221	120	48	257646.0	257646.0	3.0	0.35	2.02	1.27	36.8
U12	Coal	44.28	80.4	240	240	24	48	0.0	0.0	2.0	0.35	2.02	1.27	35.8
U13	Coal	44.28	79.1	240	240	24	48	0.0	0.0	2.0	0.35	2.02	1.27	35.8
U14	Coal	66.27	126.4	300	300	24	48	0.0	0.0	2.0	0.35	2.02	1.27	35.8
U15	Coal	66.66	122.8	120	120	24	48	0.0	0.0	2.0	0.35	2.02	1.27	35.8
Ventanas_01	Coal	56.2	112.3	180	180	24	168	0.0	0.0	2.18	0.42	2.02	1.27	42.74
Ventanas_02	Coal	111.8	206.5	180	180	24	168	0.0	0.0	1.38	0.4	2.02	1.27	40.0

Table C.13: Parameters of coal generation units in scenario E.

C.2.7 Scenario E: Diesel generation units

In the following table, hr denote the heart rate value, which is expressed in $[m^3/MWh]$ for all diesel generation units; ef denote the emission factor ([tonCO_2/MWh]); c^v denote the variable cost ([USE/MWh]) calculated using the eq. (6.1).

Name	**Type**	P^{min}	P^{max}	ρ^{up}	ρ^{down}	τ^{on}	τ^{off}	c^{on}	c^{off}	c^{nf}	hr	c^{rp}	ef	c^{v}
Candelaria_ca_01_diesel	59.7	124.0	600	600	0	0	5000.0	5000.0	2.8	0.4	0.56	0.88	387.33	
Candelaria_ca_02_diesel	59.7	127.3	600	600	0	0	5000.0	5000.0	2.8	0.4	0.56	0.88	387.33	
Cardones	69.7	151.5	660	660	0	8	15346.0	15346.0	24.41	0.3	0.56	0.88	312.81	
Colmito	24.9	57.4	999	612	0	0	1500.0	1500.0	3.5	0.27	0.56	0.88	263.06	
Ctm3	0.0	248.3	480	480	2	2	0.0	0.0	3.5	0.27	0.56	0.88	265.81	
Die_equiv_1	0.0	1561.7	999	999	0	0	0.0	0.0	0.0	0.0	0.56	0.88	274.24	
Die_equiv_2	0.0	364.9	999	999	0	0	0.0	0.0	0.0	0.0	0.56	0.88	337.66	
Die_equiv_3	0.0	342.0	999	999	0	0	0.0	0.0	0.0	0.0	0.56	0.88	408.5	
Die_equiv_4	0.0	166.9	999	999	0	0	0.0	0.0	0.0	0.0	0.56	0.88	465.14	
Los_guindos	64.7	136.6	600	600	4	1	3635.0	3635.0	3.25	0.3	0.56	0.88	291.65	
Los_pinos	29.6	103.1	999	999	0	1	1000.0	1000.0	4.5	0.29	0.56	0.88	280.88	
Los_vientos	59.7	130.7	600	600	2	1	11329.0	11329.0	2.95	0.34	0.56	0.88	327.4	
Mimb	0.0	27.6	180	6	0	0	0.0	0.0	3.5	0.27	0.56	0.88	265.81	
Santa_lidia	59.7	137.6	600	600	2	1	10698.0	10698.0	3.53	0.32	0.56	0.88	315.96	
Taltal_01_diesel	74.9	108.9	600	600	0	0	16770.0	16770.0	6.75	0.31	0.56	0.88	307.16	
Taltal_02_diesel	74.9	108.9	600	600	0	0	16770.0	16770.0	6.75	0.31	0.56	0.88	307.16	
U10	13.5	35.6	360	360	8	24	1733.0	1733.0	3.5	0.27	0.56	0.88	265.81	
U11	13.5	35.6	360	360	8	24	1733.0	1733.0	3.5	0.27	0.56	0.88	265.81	

Table C.14: Parameters of diesel generation units in scenario E.

C.3 Solutions of the simple example

C.3.1 Business as Usual (BAU)

Without any demand flexibility integration, the unit commitment optimisation example problem presented in Section 6.4.1 becomes

$$\min_{\{P_{g,t},\, u_{g,t}\}_{t\in\mathcal{T},g\in\mathcal{G}}} \sum_{g\in\mathcal{G}}\sum_{t\in\mathcal{T}} c_g^v \cdot P_{g,t} \tag{C.1}$$

subject to eqs. (5.11), (5.15), (5.16), (5.17), (5.18), (5.31), (5.32) and to the power balance constraint

$$\sum_{g\in\mathcal{G}} P_{g,t} = D_t, \quad \forall t \in \mathcal{T} \tag{C.2}$$

First let's assume that $D_2 > P_P^{max}$, hence in $t = t2$, both the base and the peak generation unit must be turned on in order to satisfy the demand. With this, $u_{B,t2} = u_{P,t2} = 1$ ($P_{P,t2} > 0$). This together with minimum uptime restrictions (5.17) and (5.18), yields that base generation unit should also be on in $t = t1$ with

$$P_{B,t1} \geq P_B^{min} \tag{C.3}$$

Eq. (C.3) together with eqs. (C.2), (5.16) (note that $P_P^{min} = 0$) and (5.31) imply that $P_{RE,t1} = P_{P,t1} = 0$ and $P_{B,t1} = D_{t1} = P_B^{min}$. Denoting $P_B = P_{B,t2}$ and $P_P = P_{P,t2}$, the problem is simplified to:

$$\min_{\{P_B,\, P_P\}} \; c_B^v \cdot (P_B^{min} + P_B) + c_P^v \cdot P_P \tag{C.4}$$

subject to

$$P_B + P_P - D_2 = 0 \tag{C.5}$$

$$P_B^{min} - P_B \leq 0 \tag{C.6}$$

$$P_B - P_B^{max} \leq 0 \tag{C.7}$$

$$P_P - P_P^{max} \leq 0 \tag{C.8}$$

Using λ for the equality constraint and μ for the inequality constraints, the Lagrangian function becomes:

$$\mathcal{L} = c_B^v \cdot (P_B^{min} + P_B) + c_P^v \cdot P_P + \lambda(P_B + P_P - D_2) + \mu_1(P_B^{min} - P_B) + \mu_2(P_B - P_B^{max}) + \mu_3(P_P - P_P^{max}) \tag{C.9}$$

Assuming that both $P_B > 0$ and $P_P > 0$ (arguments above), the resulting Karush-Kuhn-Tucker conditions are:

$$\frac{\partial \mathcal{L}}{\partial P_B} = c_B^v + \lambda - \mu_1 + \mu_2 = 0 \tag{C.10}$$

$$\frac{\partial \mathcal{L}}{\partial P_P} = c_P^v + \lambda + \mu_3 = 0 \tag{C.11}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = P_B + P_P - D_2 = 0 \tag{C.12}$$

$$\frac{\partial \mathcal{L}}{\partial \mu_1} = P_B^{min} - P_B \leq 0, \qquad \mu_1 \frac{\partial \mathcal{L}}{\partial \mu_1} = 0, \qquad \mu_1 \geq 0 \tag{C.13}$$

$$\frac{\partial \mathcal{L}}{\partial \mu_2} = P_B - P_B^{max} \leq 0, \qquad \mu_2 \frac{\partial \mathcal{L}}{\partial \mu_2} = 0, \qquad \mu_2 \geq 0 \tag{C.14}$$

$$\frac{\partial \mathcal{L}}{\partial \mu_3} = P_P - P_P^{max} \leq 0, \qquad \mu_3 \frac{\partial \mathcal{L}}{\partial \mu_3} = 0, \qquad \mu_3 \geq 0 \tag{C.15}$$

Let's assume that $\mu_1 > 0$. With this, the inequality in eq. C.13 becomes an equality and $P_B = P_B^{min}$. With this, $P_B - P_B^{max} > 0$ and hence, from eq. (C.14), $\mu_2 = 0$ in order to keep $\mu_2 \frac{\partial \mathcal{L}}{\partial \mu_2} = 0$. Similarly, from eq. (C.12), $P_P = D_2 - P_B^{min} < P_P^{max}$ (from the fact that $D_2 < P_B^{min} + P_P^{max}$), and hence from eq. (C.15), $\mu_3 = 0$.

However, from eq. (C.10), $\lambda = \mu_1 - \mu_2 - c_B^v$, and from eq. (C.11), $\lambda = -\mu_3 - c_P^v$. With this

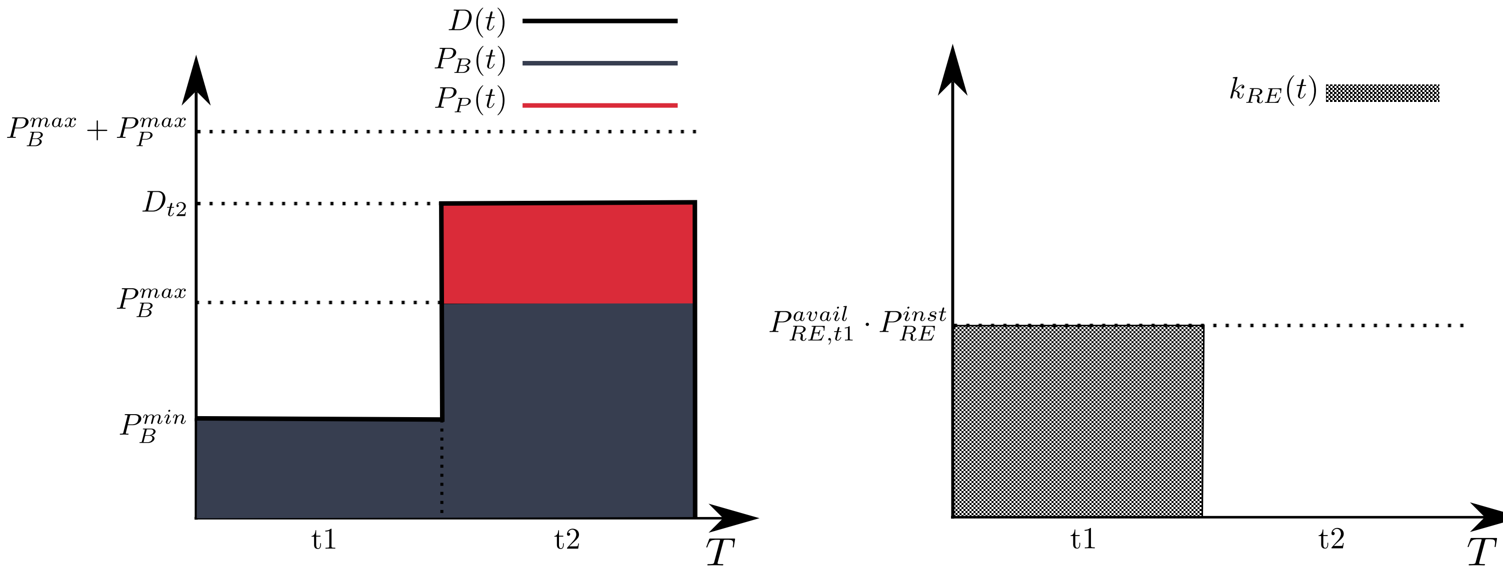
$$\mu_1 - \mu_2 - c_B^v = -\mu_3 - c_P^v \quad \Rightarrow \quad c_P^v - c_B^v = \mu_2 - \mu_3 - \mu_1 \tag{C.16}$$

As $\mu_2 = \mu_3 = 0$ and $\mu_1 > 0$ (assumption), this means that $c_P^v - c_B^v = -\mu_1 < 0$ which is inconsistent with the fact that $c_B^v < c_P^v$. This is a contradiction, and hence, $\mu_1 = 0$

Using $\mu_1 = 0$, from eq. (C.16) and $c_B^v < c_P^v$, $c_P^v - c_B^v = \mu_2 - \mu_3 > 0$. Here, if $\mu_3 > 0$, then $\mu_2 > \mu_3 > 0$ and hence $P_B = P_B^{max}$ and $P_P = P_P^{max}$, which it is possible if and ony if $P_B^{max} + P_P^{max} = D_2$. If this is not the case, then $\mu_3 = 0$, $\mu_2 > 0$, $P_B^{BAU} = P_B^{max}$ and $P_P^{BAU} = D_2 - P_B^{max}$ (note that this solution involves the previous solution in the case that $P_B^{max} + P_P^{max} = D_2$). With this solution, renewable energy curtailment is

$$k_{RE}^{BAU} = P_{t1}^{avail} \cdot P_{RE}^{inst} - P_{RE,t1} = P_{t1}^{avail} \cdot P_{RE}^{inst} \tag{C.17}$$

as shown in Fig. (C.1).



(a) Optimal dispatch in the case without DR. (b) Renewable energy curtailment without DR.

Figure C.1: Optimal dispatch and renewable energy curtailment in a case without DR.

C.3.2 Only Shiftable Demand (BAT)

The DR-UC optimisation problem in the case of DR provided by shiftable demand is

$$\min_{\{P_{g,t}, u_{g,t}, R_t\}_{t \in \mathcal{T}, g \in \mathcal{G}}} C_{DR}(\mathbf{R}) + \sum_{g \in \mathcal{G}} \sum_{t \in \mathcal{T}} c_g^v \cdot P_{g,t} \tag{C.18}$$

subject to eqs. (5.8) (5.9), (5.10), (5.11), (5.15), (5.16), (5.17), (5.18), (5.31), (5.32), ($\beta_c = +\infty$) and ($\beta_a \geq 0$). First note that the use of $\beta_c = +\infty$ is equivalent of using a cost function $C_{DR}(\mathbf{R}) = \sum_{t \in \mathcal{T}} (\alpha_a \cdot R_t^2 + \beta_a \cdot |R_t|)$ subject to $\sum_{t \in \mathcal{T}_{\mathrm{d}}} R_t = 0$ (see Section 5.2). As here $\mathcal{T} = \{t1, t2\}$, then $R = R_{t1} = -R_{t2}$ and hence $C_{DR} = 2 \cdot \alpha_a \cdot R^2 + 2 \cdot \beta \cdot R$. Also, and using the same argument than for the BAU case, we assume that $u_{B,t2} = 1$ and hence $u_{B,t1} = 1$. Also, given a demand reduction R and a renewable energy contribution P_{RE}, from eq. (5.8)

$$P_{B,t1} = P_B^{min} + R - P_{RE} \tag{C.19}$$

. Also, from solutions in the previous section, we can assume that $P_{B,t2} = P_B^{max}$ and

$$P_P = D_2 - P_B^{max} - R \tag{C.20}$$

. With eq. (C.19), constraint (5.16) becomes

$$R - P_{RE} \geq 0 \tag{C.21}$$

while constraint (5.15) becomes

$$P_B^{min} + R - P_{RE} \leq P_B^{max} \tag{C.22}$$

. Hence, the problem is simplified to

$$\min_{\{R, P_{RE}\}} \quad c_B^v \cdot (P_B^{min} - R - P_{RE} + P_B) + c_P^v \cdot (D_2 - P_B^{max} - R) + 2 \cdot \Delta \cdot \beta^2 + 2 \cdot \beta \cdot R \quad \text{(C.23)}$$

subject to

$$P_{RE} - R \leq 0 \quad \text{(C.24)}$$

$$P_B^{min} + R - P_{RE} - P_B^{max} \leq 0 \quad \text{(C.25)}$$

$$P_{RE} - P_{RE}^{inst} \cdot P_{RE}^{avail} \leq 0 \quad \text{(C.26)}$$

$$- P_{RE} \leq 0 \quad \text{(C.27)}$$

The Lagrangian function becomes:

$$\begin{aligned} \mathcal{L} \ = \ & c_B^v \cdot (P_B^{min} + R - P_{RE} + P_B) + c_P^v \cdot (D_2 - P_B^{max} - R) + 2 \cdot \Delta \cdot \beta^2 + 2 \cdot \beta \cdot R \\ & + \mu_1 (P_{RE} - R) + \mu_3 (P_{RE} - P_{RE}^{inst} \cdot P_{RE}^{avail}) + \mu_4 (-P_{RE}) \end{aligned} \quad \text{(C.28)}$$

With this, the resulting Karush-Kuhn-Tucker conditions are

$$\frac{\partial \mathcal{L}}{\partial R} = c_B^v - c_P^v + 4 \cdot \Delta \cdot \beta \cdot R + 2 \cdot \beta - \mu_1 = 0 \quad \text{(C.29)}$$

$$\frac{\partial \mathcal{L}}{\partial P_{RE}} = -c_B^v + \mu_1 + \mu_3 - \mu_4 = 0 \quad \text{(C.30)}$$

$$\frac{\partial \mathcal{L}}{\partial \mu_1} = P_{RE} - R \leq 0, \qquad \mu_1 \frac{\partial \mathcal{L}}{\partial \mu_1} = 0, \qquad \mu_1 \geq 0 \quad \text{(C.31)}$$

$$\frac{\partial \mathcal{L}}{\partial \mu_3} = P_{RE} - P_{RE\,RE}^{inst avail} \leq 0, \qquad \mu_3 \frac{\partial \mathcal{L}}{\partial \mu_3} = 0, \qquad \mu_3 \geq 0 \quad \text{(C.32)}$$

$$\frac{\partial \mathcal{L}}{\partial \mu_4} = -P_{RE} \leq 0, \qquad \mu_4 \frac{\partial \mathcal{L}}{\partial \mu_4} = 0, \qquad \mu_4 \geq 0 \quad \text{(C.33)}$$

C.3.2.1 When there is no Renewable energy available

If $P_R^{avail}E = 0$, then from eq. (C.32) and (C.33) $P_{RE} = 0$ and

$$R = \frac{c_P^v - c_B^v - 2\beta_a}{4 \cdot \Delta \cdot \beta_a} \quad \text{(C.34)}$$

hence, in order to be a positive demand response, it is then necessary that

$$R > 0 \Rightarrow \beta_a < \frac{c_P^v - c_B^v}{2} \quad \text{(C.35)}$$

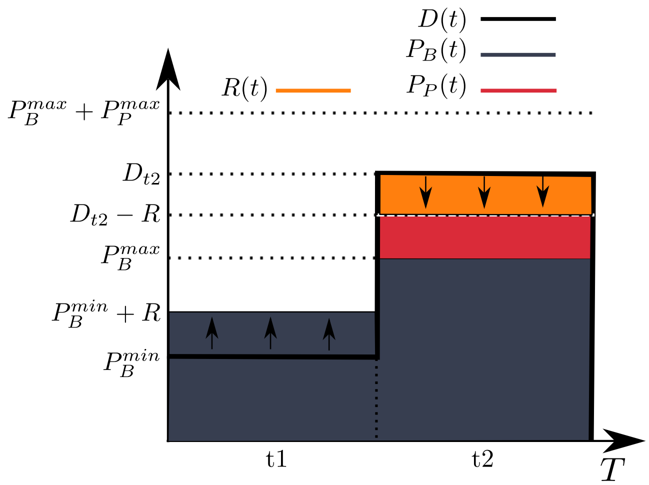


Figure C.2: Optimal dispatch in the BAT case in the case without renewable energy available.

C.3.2.2 When there is renewable energy available

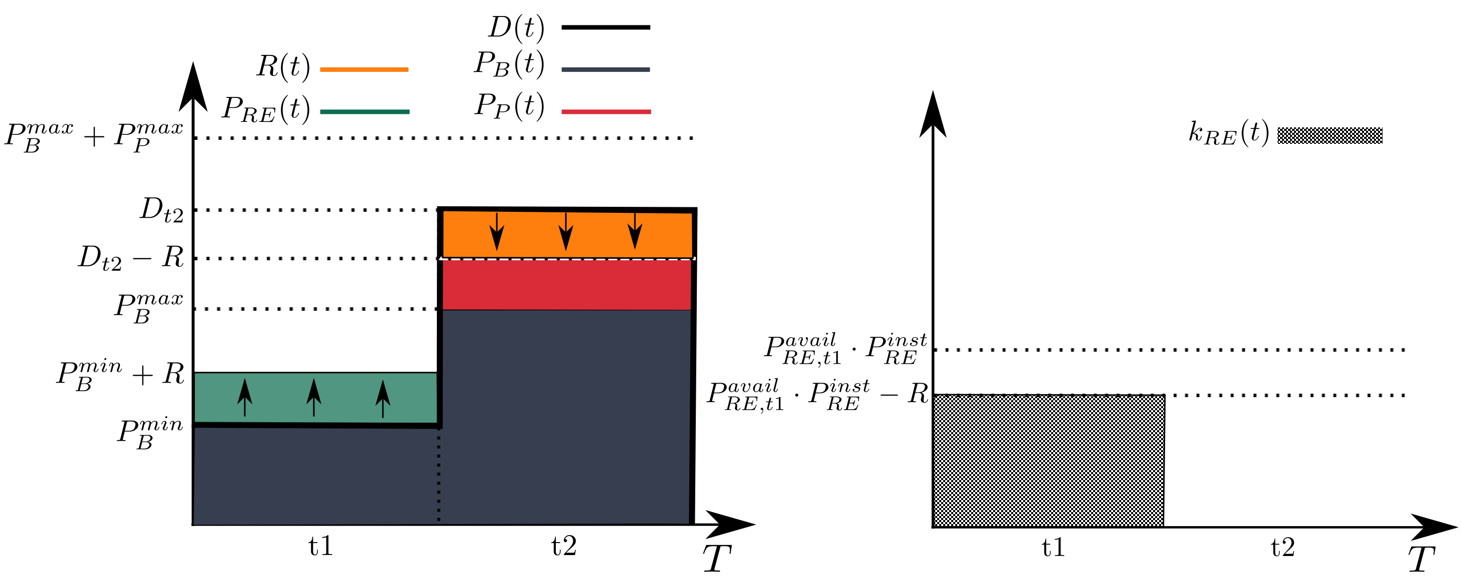
If $P_R^{avail} E > 0$, then $\mu_4 = 0$. Also, the interesting problem to analize here is when there is enough renewable energy available, and even thought demand response does not reduce totally the peak unit's generation. Then, we also assume that $P_{RE} < P_{RE}^{inst} \cdot P_{RE}^{avail}$ and hence $\mu_3 = 0$. With this, constraint (C.30) becomes $\mu_1 = c_B^v > 0$, and hence, $R = P_{RE}$,

$$R = \frac{c_P^v - 2\beta_a}{4 \cdot \Delta \cdot \beta_a} \tag{C.36}$$

and

$$R > 0 \Rightarrow \beta_a < \frac{c_P^v}{2} \tag{C.37}$$

In this case, Demand Response and renewable energy curtailment are as shown in Fig. (C.3)



(a) Optimal dispatch in the BAT case with RE. (b) RE curtailment in BAT case.

Figure C.3: Optimal dispatch and renewable energy curtailment in the BAT case in the case of renewable energy availability.

Appendix D

Main Code in Julia Language

The following shows the main code written in Julia language. This code is released as free software with a GNU GPLv3 licence[1]. For the rest of the codes written to solve the UC-DR problem, please visit the Git repository of the project in *https://github.com/estebaniglesias/DemandResponse-UnitCommitment*.

```julia
function UC_DR_Iglesias(Solver,Gens,Demanda,Avail,DR_Data,T,factorRE)
  #With Solver we allow Julia to solve the problem with Gurobi or CPLEX
  #Gens is the array of Generators' characteristics and restrictions:
  p_min=Gens[:p_min];
  p_max=Gens[:p_max];
  c_on=Gens[:c_on];
  c_off=Gens[:c_off];
  c_var=Gens[:c_var];
  c_ramp=Gens[:c_ramp];
  min_on=Gens[:min_on];
  min_off=Gens[:min_off];
  type_gen=Gens[:type];
  ramp_up=Gens[:ramp_up];
  ramp_down=Gens[:ramp_down];
  v_minimo=Gens[:v_minimo]; #Minimum stored water level (for hydro reservoirs)
  v_inicial=Gens[:v_inicial]; #Initial stored water level
  zone=Gens[:zone];
  eta=Gens[:eta];
  G=countnz(Gens[1]);#Quantity of Power Stations
```

[1]See more in *https://www.gnu.org/licenses/quick-guide-gplv3.html*

```
    #Demanda is the baseline demand array
    Tmax =countnz(Demanda[:demanda])
    if T>Tmax
        T=Tmax
    end
    Days=convert(Int,(T/24));

    #DR_Data carries the DR Characteristics (costs)
    #alpha_r is alpha_a (adjustment)
    theta=DR_Data[:theta][1];
    alpha_c=DR_Data[:alpha_c][1];
    alpha_r=DR_Data[:alpha_r][1];
    beta_c=DR_Data[:beta_c][1];
    beta_r=DR_Data[:beta_r][1];

    println("T: ",T," G: ",G)


    #Fixed and Flexible demand.
    #In our model we always use theta=1
    D_F=Demanda[:demanda]*(1-theta)
    D_R=Demanda[:demanda]*theta

    #Set the solver
    if Solver=="Gurobi"
        uc=Model(solver=GurobiSolver(Presolve=0))
    end
    if Solver=="Cplex"
        uc=Model(solver=CplexSolver(CPX_PARAM_MEMORYEMPHASIS=1,
   CPX_PARAM_WORKMEM=23000,CPX_PARAM_REDUCE=1))
    end

    #Demand Response restrictions:
        #Load reduction:
    @variable(uc, 0 <= Rdown[t=1:T] <= D_R[t])
        #Load Increment
    @variable(uc,0<= Rup[t=1:T]<=D_R[t])


    #Power Generation: P
    @variable(uc, P[g=1:G, t=1:T] >=0)
    #Renewable energy curtailment: C
    @variable(uc, C[g=1:G, t=1:T] >=0)
    #Daily demand curtailment Rc
    @variable(uc,Rc[day=1:Days] >=0)
    #Generators' state variables
    @variable(uc,u[g=1:G, t=1:T],Bin)
```

```
    @variable(uc,ON[g=1:G, t=1:T],Bin)
    @variable(uc,OFF[g=1:G, t=1:T],Bin)
    #Hydro reservoirs' volume levels
    @variable(uc,V[g=1:G, t=1:T]>=v_minimo[g])

    #Costs
    @variable(uc,ONOFFCost>=0)
    @variable(uc,VarCost>=0)
    @variable(uc,CurtCost>=0)
    @variable(uc,FlexCost>=0)
    #Ramping definition and costs
    @variable(uc,CRamp[g=1:G, t=1:T]>=0)
    @variable(uc,RampCost>=0)

    #OnOff costs definition
    @constraint(uc,ONOFFCost==sum(ON[g,t]*c_on[g]+OFF[g,t]*c_off[
   g] for g=1:G,t=1:T))
    #Variable costs
    @constraint(uc,VarCost==sum(c_var[g]*P[g,t] for g=1:G,t=1:T))
    #Ramping costs
    @constraint(uc,RampCost==sum(CRamp[g,t] for g=1:G,t=2:T))


    #Objective function

    @objective(uc,Min,ONOFFCost+
        sum(alpha_r*(Rdown[t]-Rup[t])^2+beta_r*Rdown[t]+beta_r*
   Rup[t] for t=1:T)+
        sum(alpha_c*(Rc[day])^2 + beta_c*Rc[day] for day=1:Days)+
        VarCost+RampCost)

    #Daily demand curtailment definition
    for day=1:Days
        @constraint(uc,Rc[day]==sum((Rdown[t]-Rup[t]) for t=((day
   -1)*24+1):(day*24)))
    end



    ### PROBLEM CONSTRAINTS
    # # Power Balance as spot price dual variable
    @constraintref spot[1:T]
    for t = 1:T
          spot[t] = @constraint(uc, sum(P[g,t] for g=1:G)==D_F[t
   ]+(D_R[t]-(Rdown[t]-Rup[t])))
    end

```

```
    # # Restrictions to Generators:
    for g in 1:G
        ## Thermal Generators
        if (type_gen[g]=="CAR")||(type_gen[g]=="DIE")||(type_gen[g]=="GNLCC")||(type_gen[g]=="GNLCA")

            #Ramping costs definition per unit
            for t in 2:T
                @constraint(uc,CRamp[g,t]>= c_ramp[g]*(P[g,t]-P[g,t-1]-ON[g,t]*p_max[g])) #rampeo subida
                @constraint(uc,CRamp[g,t]>= c_ramp[g]*(P[g,t-1]-P[g,t]-OFF[g,t]*p_max[g])) #rampeo bajada
            end

            #Minimum Operation Times:
            #Only if min_on or min_off >1... let's start with min_on
            if min_on[g]>1
                #for t in 1:min_on[g]#
                for t in 1:min(min_on[g],T)
                   @constraint(uc, sum(ON[g,tau] for tau=1:t)<=u[g,t]) #First Restriction MOT
                end
                for t in min_on[g]+1:T
                    @constraint(uc, sum(ON[g,tau] for tau=(t-min_on[g]):t)<=u[g,t])#Second Restriction MOT
                end
            end

            # # Minimum Downtimes:
            if min_off[g]>1
                for t in 1:min(min_off[g],T)
                #for t in 1:min_off[g]
                    @constraint(uc, sum(OFF[g,tau] for tau=1:t)<=(1-u[g,t]))#First Restriction MDT
                end
                for t in min_off[g]+1:T
                   @constraint(uc, sum(OFF[g,tau] for tau=(t-min_off[g]):t)<=(1-u[g,t]))#Second Restriction MDT
                end
            end
         # #Unit commitment restrictions:
            for t in 1:T
                @constraint(uc,P[g,t] <= p_max[g]*u[g,t]) # maximum
                @constraint(uc,P[g,t] >= p_min[g]*u[g,t]) # minimum
```

```
        end
     #  # On/Off definition
            @constraint(uc,u[g,1]==ON[g,1]-OFF[g,1])
        for t in 2:T
            #On/Off definition
            @constraint(uc,u[g,t]==(u[g,t-1]+ON[g,t]-OFF[g,t
]))
        end
        ## Ramping
        if ramp_up[g]<p_max[g]
            for t in 2:T
                @constraint(uc,P[g,t]-P[g,t-1]<=ramp_up[g])
            end
        end

        if ramp_down[g]<p_max[g]
            for t in 2:T
                @constraint(uc,P[g,t-1]-P[g,t]<=ramp_down[g])
            end
        end


    end
    #Solar (FV: Fotovoltaicos, in Spanish )or Wind (EOL,
E licos , in Spanish) Genrators
    if (type_gen[g]=="EOL")||(type_gen[g]=="FV")
        for t in 1:T
            @constraint(uc,P[g,t]<= (factorRE*p_max[g]*Avail[
Symbol(zone[g])][t]))
            @constraint(uc,C[g,t] == (factorRE*p_max[g]*Avail
[Symbol(zone[g])][t]-P[g,t]))
        end
    end

    #Run-of-the-river (PAS: Pasada, in Spanish)
    if (type_gen[g]=="PAS")
        for t in 1:T
          @constraint(uc,P[g,t] <= p_max[g])
            @constraint(uc,P[g,t] <= (eta[g]*Avail[Symbol(
zone[g])][t]))
            @constraint(uc,C[g,t] == (eta[g]*Avail[Symbol(
zone[g])][t]-P[g,t]))
        end
    end

    #Hydro reservoirs (EMB: Embalses, in Spanish)
    if (type_gen[g]=="EMB")
```

```
            @constraint(uc,V[g,1]==(v_inicial[g]+Avail[Symbol(
   zone[g])][1]-P[g,1]/eta[g]))
            @constraint(uc,V[g,1]>=v_minimo[g])
           for t in 2:T
                @constraint(uc,V[g,t]==(V[g,t-1]+Avail[Symbol(
   zone[g])][t]-P[g,t]/eta[g]))
                @constraint(uc,V[g,t]>=v_minimo[g])
            end
            @constraint(uc,V[g,T]>=v_inicial[g])
        end

    end

    solve(uc)
    return getvalue(P),
    getvalue(C),
    getvalue(u),
    getvalue(ON),
    getvalue(OFF),
    getvalue(ONOFFCost),
    getvalue(VarCost),
    getobjectivevalue(uc),#Total Cost
    getvalue(Rdown),
    getvalue(Rup),
    getvalue(spot),
    getvalue(Rc),
    getvalue(RampCost)
end
```