

THE ROLE OF ELECTRICAL ENERGY STORAGE IN A FUTURE SUSTAINABLE ELECTRICITY GRID

Rick van Staveren

THE ROLE OF ELECTRICAL ENERGY STORAGE IN A FUTURE SUSTAINABLE ELECTRICITY GRID

By

Rick van Staveren

in partial fulfilment of the requirements for the degree of

Master of Science
Engineering and Policy Analysis

at the Delft University of Technology,

to be defended publicly on Friday August 29, 2014 at 13:00

Graduation committee

Chair	Prof. Dr. Ir. P.M. Herder	Delft University of Technology
First supervisor	Dr. Ir. L.J. de Vries	Delft University of Technology
Second supervisor	Dr. S. W. Cunningham	Delft University of Technology
Third supervisor	Dr. Ir. R.A. Verzijlbergh	Delft University of Technology
External supervisor	Dr. R. Aalbers	Netherlands Bureau for Economic Policy Analysis

An electronic version of this thesis is available at <http://repository.tudelft.nl/>

SUMMARY

The call for lower CO₂ emissions has increased the penetration of renewable energy sources (RES) such as wind and solar energy in the electricity system. However, these intermittent sources do not follow the traditional daily cycles of electricity demand. Secondly, renewable energy sources are unpredictable in their nature; their output is dependent on meteorological conditions. As the electrical system needs to constantly balance supply and demand, these renewable sources pose problems to the secure operations of the electricity grid.

Currently the main focus of reducing the negative effects of RES integration has been on the increase of interconnectedness between regions. As renewable output is dependent on local weather conditions, interconnections between regions can be used to transport electricity from locations with favourable weather conditions to locations where RES output is low.

Next to transmission, electrical energy storage (EES) is proposed as a solution to deal with the issues that come with renewable energy sources. By storing energy when supply is high and discharging when supply is low, storage is able to reduce temporal discrepancies between supply and demand.

From the short analysis given above, the technologies seem to have the same stabilising kind of effects on the power system, making them substitute for one another. However, some studies suggest that the technologies are complementary, meaning that the value of one technology will rise if the capacity of the other increases and vice versa. As the transmission system is in the hands of the regulated transmission system operators, the interplay between storage and transmission might pose regulatory problems.

The objective of this thesis is to find out what role electricity storage can play in the transition to a sustainable electricity system and which policies can be adopted to ensure adequate development of storage.

This research focuses on bulk electricity storage, a storage type used to level out hour to hour, day to day or seasonal variations in electricity supply and demand. Four different technologies are currently available for this purpose: pumped hydro storage, flow battery storage, compressed air energy storage (CAES) and hydrogen storage. Because pumped hydro is an accepted technology that is already applied in most regions of the world, the latter three were used in the analysis.

Flow battery storage has low power specific and high energy specific investment cost, making it suitable for storage of multiple hours. Hydrogen (H₂) storage has high power specific and low energy specific cost. This makes H₂ suitable for storage durations of multiple weeks. CAES fits in between these technologies and is most suitable for storage of a few hours to multiple days. Interestingly, the efficiency of the technologies follows the same order as their optimal storage duration. Flow batteries, CAES and H₂ have a round trip efficiency of 75%, 70% and 40% respectively.

To research the effects of electrical energy storage on the operation of the electrical system, an optimization model, using an innovative modelling approach, is built. The optimization model conceptually represents the European grid. However, instead of using individual countries, the European electricity system has been divided in three nodes, a northern, a central and a southern node. As both the north (Scandinavia) and the south of Europe already have a lot of storage capacity in the form of pumped hydro storage, the research focuses on introducing storage in the central region. This central region, which includes the UK and Germany, is expected to have the highest RES penetration levels in the future and is therefore a suitable test subject.

For the analysis, predictions from ENTSO-E about future installed generation capacities were used. To test the value of storage for different levels of RES penetration, the installed capacities of wind and solar were multiplied from the base prediction. Secondly, the transmission capacity is based on expectations about future capacities and scaled to include a pessimistic (low transmission) an optimistic scenario (high transmission).

The value of storage in systems with relatively low RES penetration primarily lies in allowing cheaper base load generators to run at a more constant output level, avoiding start-up cost of these bulky generators and reducing the use of more expensive peak load generators. Introducing a CO₂ cap in this scenario reduces price variance between fuels and reduces the value of storage. Short storage durations are enough to prevent most cycling and therefore flow batteries are the technology of choice in this situation.

The variable cost savings achieved by storage increase under the increase of renewable energy sources (RES) in the system. In this case, the primary value of storage lies in the reduction of curtailment¹. During periods of oversupply from RES sources, energy is stored for later use. A CO₂ cap increases the value of storage in this scenario. The difference between curtailing energy and the cheapest dispatchable plant becomes larger, which benefits the storage. As more energy needs to be stored during periods of high RES output, storage duration becomes more important. The highest cost reduction is reached by CAES, a technology with a reasonably high efficiency in combination with storage durations of multiple days.

After increasing the RES penetration even further, the value of energy storage reduces. In theory more energy could be loaded as periods of RES over-supply start being more frequent. However, the periods in which energy can be discharged from the storage become more infrequent. As periods of over- and undersupply are now further away from each other, the highest value is generated by storage with long storage duration; the efficiency of the storage becomes less important.

Transmission has a negative influence on the value of storage. The fact that more energy is transmitted and stored when introducing more storage *or* transmission makes the technologies technically complementary. However, both solutions deliver the same functions: they reduce operating cost by levelling out discrepancies between supply and

¹ Turning off renewable energy sources

demand, either in a spatial or temporal matter. Storage and transmission are therefore economical substitutes.

The current analysis merely includes savings in variable costs, which are not high enough to justify investments in storage under current investment costs. However, work of others suggests that storage is able to deter investments in transmission, distribution and generation capacity. Secondly, the used model is deterministic and does not allow storage to benefit from prediction errors in RES output and demand. This value increase together with an expected investment cost decrease could make storage a viable option for the integration of renewables.

PREFACE

This thesis is the end product of the final research project of the two year Master program Engineering and Policy Analysis, lectured at the faculty of Technology Policy and Management of the Delft University of Technology.

The report is aimed at everyone who is interested in the future of power systems, the role electricity storage can play in the future power system and people that are generally interested in what I've been doing for the past half year.

Although the writing of a master thesis is primarily an individual job, I could not have done it without the help of the people around me. Therefore, I would like to take this opportunity to thank some of the people that helped substantiating this thesis. First of all I would like to thank everyone at the Netherlands Bureau for Economic Policy Analysis (in Dutch *het Centraal Planbureau* or CPB) which provided me with the assignment, a very pleasant working location and, not unimportant, an income. Secondly, I would like to thank Remco Verzijlbergh, my day to day supervisor from TU Delft. From the beginning on he has been enthusiastic about my project and has been a great help in finding the right research direction and problem setting. The fact that I could walk into his office for advice from time to time gave me a comfortable feeling. I would like to thank my first supervisor Laurens de Vries for lecturing the course Electricity and Gas markets, in which I learned a great deal about the inner workings of the electricity market even before starting this thesis. As my supervisor Laurens was also able to direct my research into the right direction, keeping a critical eye on quality, innovativeness and especially time constraints. Scott Cunningham helped me a great deal by not only giving feedback about the contents of the thesis, but also on the writing process and project management. Paulien Herder, chair of the graduation committee, was able to quickly pinpoint the most important shortcomings of the research plan and thesis itself, making meetings greatly more efficient. I would also like to take this opportunity to thank the people that devote their time and energy in creating the free and open source software packages that are used during the thesis process. Finally I would like to thank my direct family and girlfriend, who supported me mentally during the project.

Rick van Staveren, August 2014

TABLE OF CONTENTS

Summary	i
Preface	v
Table of contents	vii
List of figures	xi
List of tables	xv
Nomenclature	xvii
1. Introduction	1
1.1. Problem orientation.....	1
1.2. Solutions to introducing renewables - state of the art.....	3
1.2.1. The effect of transmission capacity on the future electricity system	3
1.2.2. The effect of storage capacity on the future electricity system.....	4
1.2.3. Combining the effects of transmission and storage.....	5
1.3. Problem statement	5
1.4. Research questions	6
1.5. Thesis outline	6
2. The electricity system and electricity storage – the basics	7
2.1. The electricity system	7
2.1.1. Generation, transmission and distribution.....	7
2.1.2. Consumption.....	9
2.1.3. The electricity system’s institutional layer	10
2.2. Current state of electricity storage	10
2.2.1. Pumped hydro energy storage	12
2.2.2. Compressed air energy storage	12
2.2.3. Battery storage	13
2.2.3.1. Lead acid batteries	14
2.2.3.2. Lithium ion batteries	14
2.2.3.3. Flow batteries.....	14
2.2.3.4. Other types of batteries	15
2.2.4. Hydrogen storage	15
2.2.5. Flywheels	16
2.2.6. Other storage technologies	16
3. Model description	19

3.1. Modelling approach	19
3.1.1. Energy sector modelling	19
3.1.2. Electricity system modelling	21
3.1.3. Clustered unit commitment.....	22
3.2. Mathematical formulation.....	23
The optimization problem.....	24
3.2.1. Objective function	25
3.2.2. Constraints.....	26
3.2.2.1. Load constraint.....	26
3.2.2.2. Transmission constraints.....	26
3.2.2.3. Unit states	26
3.2.2.4. Generator output limits.....	27
3.2.2.5. Ramping constraints.....	29
3.2.2.6. Storage level and maximum storage power.....	29
3.2.2.7. Maintenance constraints.....	30
3.2.2.8. CO ₂ constraint.....	30
3.2.2.9. Reserve constraints	31
3.3. Proposed speed up strategies.....	36
3.3.1. Sub models using economic dispatch pre-run.....	36
3.3.2. Relaxed mixed integer programming	36
3.3.3. Solving only a pre-selected part of the year	37
3.3.4. Derated maintenance	37
3.3.5. Combined reserves	37
3.4. Scenario selection and data usage.....	37
3.4.1. Scenario description	38
3.4.2. Transmission capacity.....	41
3.4.3. Installed generation capacity.....	42
3.4.4. Generator properties.....	46
3.4.5. Electrical energy storage properties.....	47
3.4.6. Model implementation of pumped hydro storage.....	50
3.4.7. Fuel cost and fuel CO ₂ emissions	50
3.4.8. Demand data	50
3.4.9. Profiles of renewable inflow.....	51
3.4.9.1. Wind power	51
3.4.9.2. Solar irradiation.....	53
3.4.9.3. Natural hydro inflow	53
4. Validation, verification and testing	55

4.1. Testing inter model differences and model selection	55
4.1.1.1. No CO ₂ policy	56
4.1.1.2. 10% CO ₂ reduction	63
4.1.1.3. Model selection	68
4.2. Verification and validation	68
4.3. Testing intra model differences	70
4.3.1. Reserve constraints.....	70
4.3.2. Maintenance constraints	73
5. Experimentation	81
5.1. Scenario setup.....	81
5.2. Reference scenario – ENTSO-E Vision 3	83
5.3. Future scenario - Highly renewable power system	91
5.4. Sensitivity analysis - Effect of renewable capacity on energy storage	101
6. Discussion	107
6.1. Discussion of model results.....	107
6.2. Implications for the power sector.....	109
6.3. Discussion of modelling technique	111
7. Conclusions & Recommendations	113
7.1. Conclusions	113
7.2. Recommendations for actors in power sector.....	114
7.3. Directions for future research.....	116
8. Reflection	119
References.....	123
Appendices.....	129
Appendix A Combined reserves equations.....	131
Appendix B Generator and storage parameters	132
Appendix C Fuel properties.....	133
Appendix D Detailed effects of different models on energy mix	135
Appendix E GAMS Model code	138

LIST OF FIGURES

Figure 2-1: Schematic representation of traditional power system	8
Figure 2-2: Schematic representation of changes in power system	9
Figure 2-3: Worldwide installed electrical energy storage (EPRI, 2010).....	11
Figure 3-1: Classification of different energy model types (Jägemann et al., 2013)	20
Figure 3-2: The concept of clustering, adapted from B. S. Palmintier (2013).....	22
Figure 3-3: Graphical representation of maximum units online within cluster (B. S. Palmintier, 2013)	27
Figure 3-4: Graphical presentation of distinction between regions and sub-regions	28
Figure 3-5: Overview of ENTSO-E control mechanisms (ENTSO-E).....	32
Figure 3-6: Solar irradiance in Europe (Green Rhino Energy, 2014)	38
Figure 3-7: Wind power potential in Europe (EEA, 2009).....	39
Figure 3-8: Solar and wind exchange (EEA, 2010).....	40
Figure 3-9: The division between Northern, Central and Southern Europe in the three node model, image adapted from (ENTSO-E, 2014).....	41
Figure 3-10: The capacity mix of individual countries in Northern and central Europe combined with the capacity mix of the EU-North node, the total installed capacity is given above the bars	43
Figure 3-11: The capacity mix of individual countries in Southern Europe combined with the capacity mix of the corresponding node, the total installed capacity is given above the bars	44
Figure 3-12: Capacity mix and residual load curve for Germany, the Netherlands and Central Europe	45
Figure 3-13: Change in installed generation capacity 2012-2030.....	46
Figure 3-14: Cost range as found in literature (Chen et al., 2009; EPRI, 2010; Grünewald, Cockerill, Contestabile, & Pearson, 2011; Kaldellis & Zafirakis, 2007; Kloess & Zach, 2014; S. M. Schoenung & Eyer, 2008; S. Schoenung, 2011)	48
Figure 3-15: comparison of storage technology cost and selected cost figure	49
Figure 3-16: Energy specific storage cost dependent on storage duration	49
Figure 3-17: representation of stage in the model	50
Figure 3-18: Maximum demand in 2012 of individual countries sorted by node	52
Figure 4-1: The dispatch profile of the clustered unit commitment and economic dispatch model	57

Figure 4-2: Effect of different models on solving time	59
Figure 4-3: The differences in the energy mix between model types compared to the benchmark.....	59
Figure 4-4: The difference in CO ₂ emissions between model types	60
Figure 4-5: Effect of different models on absolute variable cost	60
Figure 4-6: Effect of different models on relative variable cost	62
Figure 4-7: Effect of different models on storage behaviour	62
Figure 4-8: Effect of different models on solving time	63
Figure 4-9: The differences in the energy mix between model types compared to the benchmark.....	64
Figure 4-10: Effect of different models on absolute variable cost	65
Figure 4-11: Relative effect of different models on variable cost	65
Figure 4-12: Effect of model type on hydro storage levels.....	66
Figure 4-13: Difference in storage behaviour due to reduction of technical details.....	67
Figure 4-14: The energy mix within the modelled region. Left the actual data from 2012 (ENTSO-E, 2013c), right the model run with 2012 capacities.....	69
Figure 4-15: The effect of reserves on the energy mix in the 3 regions - full year.....	72
Figure 4-16: The effect of reserves on the energy mix in the 3 regions - only winter and summer month	73
Figure 4-17: The effect of planning maintenance on the energy mix.....	74
Figure 4-18: Amount of capacity under maintenance over the year.....	75
Figure 4-19: Power balance dependent on maintenance - winter week (top) and summer week (bottom).....	76
Figure 4-20: Correlation between average demand and maintenance.....	77
Figure 4-21: Planned maintenance in scenario with more renewables	78
Figure 4-22: Correlation between maintenance and residual load in the 2x 2030 capacity scenario.....	79
Figure 5-1: The load, installed dispatchable capacity and residual load with 1x and 2x ENTSO-E Vision 3 renewable capacities.....	82
Figure 5-2: Variable cost difference based on amount of storage	84
Figure 5-3: Source of variable cost savings due to storage (for flow battery storage).....	85
Figure 5-4: The marginal value of storage	86
Figure 5-5: Energy mix without storage.....	87
Figure 5-6: Effect of storage on total energy mix (transmission used is 100% 2030).....	88

Figure 5-7: Regional effects of storage for two storage capacities, using flow battery storage and 100% 2030 transmission.....	89
Figure 5-8: The cumulative effect of storage on the energy mix over the course of the year (50 GW flow battery compared to no additional storage, situation with no CO ₂ cap and 100% 2030).....	90
Figure 5-9: variation in marginal cost dependent on transmission and storage	91
Figure 5-10: The energy mix without adding storage for different transmission capacities and CO ₂ constraints	92
Figure 5-11: Variable cost savings dependent on storage technology	94
Figure 5-12: Source of variable cost savings for CAES	94
Figure 5-13: Marginal value of storage technologies	95
Figure 5-14: Effect of storage on total energy mix (transmission 100% 2030).....	96
Figure 5-15: Utilization of generation capacity in the central region, situation with a CO ₂ cap.....	97
Figure 5-16: Utilization of storage technologies	98
Figure 5-17: Regional effects of storage for two storage capacities, using CAES and 100% 2030 transmission capacities.....	99
Figure 5-18: The cumulative effect of storage on the energy mix (50 GW CAES compared to no additional storage, situation with CO ₂ cap and 100% 2030 transmission) ...	99
Figure 5-19: The effect of storage on CO ₂ emissions.....	100
Figure 5-20: Variation in marginal cost of production in the central node	101
Figure 5-21: Installed capacities as a ratio to maximum demand, the black lines are the regions maximum and minimum demand.....	102
Figure 5-22: Residual load curves after introducing more renewables. The black line is the initial load.	103
Figure 5-23: Effect of renewable capacity on storage value.....	104
Figure 5-24: Changing CO ₂ cap with increasing renewables.....	105

LIST OF TABLES

Table 3.1: Net transfer capacities between nodes	41
Table 3.2: The amounts of controllable and non-controllable generation capacity in the nodes	46
Table 3.3: Characteristics of storage.....	49
Table 3.4: demand characteristics of nodes	51
Table 4.1: Overview of model runs used in test	56
Table 4.2: Effect of different reserve settings on KPIs - full year.....	71
Table 4.3: Effect of different reserve settings on KPIs - only winter and summer month	72
Table 4.4: Effect of different maintenance settings on KPIs.....	73
Table 5.1: Considered scenarios	81
Table 5.2: Storage technology characteristics	82
Table 5.3: Transmission capacities considered	83

NOMENCLATURE

Sets

$g \in G$	Clusters of generating units
$g \in G_{UC}$	Clusters of generating units under unit commitment constraints
$g \in G_{Qstart}$	Clusters of generating units that can deliver quick start reserves
$r \in R$	Regions/nodes
$s \in S$	Clusters of storage units
$sub - r \in SR$	Sub regions belonging to main regions R
$t \in T$	Time periods

Parameters

c_g^{fuel}	Cost of fuel for generator g (m€/GWh)
$c_g^{varO\&M}$	Variable operation and maintenance cost for generator g (m€/GWh)
c^{NSE}	Penalty of not meeting demand (m€/GWh)
$c_g^{CO_2}$	Cost of CO ₂ for generator g (m€/GWh)
c_g^{start}	Start-up cost for generator g (m€/start)
$CO_2^{intensity}_g$	CO ₂ intensity for generator g (Mt/GWh)
CO_2^{max}	CO ₂ cap (Mt/year)
m_g^{yearly}	Required maintenance (weeks/year)
$n_{g,r,t}$	Amount of units in a cluster of generators g in region r at time t (#)
$p_{g,r}^{avail}$	Available power for cluster g in region r (GW)
$p_{s,r}^{avail}$	Available power for cluster s in region r (GW)
$p^{contingency}$	Largest contingency considered (GW)
p_g^{max}	Maximum output of an individual generator in cluster g (GW)
p_g^{min}	Minimum output of an individual generator in cluster g (GW)
Δp_g^{max}	Maximum change of output of individual generator in cluster g (GW/h)
q_s^{max}	Maximum output of an individual storage unit in cluster s (GW)
q_r^{year}	Yearly energy demand in region r (GWh/year)

η_g	Output efficiency of generator g (%)
η_s	Charging efficiency of storage s (%)
$\varphi_{g,sub-r,t}$	Output profile for renewable energy sources dependent on weather (GW/GW)

Variables

C^{CO_2}	Total CO ₂ cost (m€)
C^{fuel}	Total fuel cost (m€)
C^{NSE}	Total non-served energy cost (m€)
$C^{O\&M}$	Total variable operation and maintenance cost (m€)
$C^{startup}$	Total start-up cost (m€)
C^{total}	Total variable cost (m€)
L_r^{max}	Maximum load in region r (GW)
$M_{g,r,t}$	Units on maintenance for generator g in region r at time t (#)
$NSE_{r,t}$	Non-served energy in region r at time t (GW)
$P_{g,r,t}$	Power output of generation cluster g in region r at time t (GW)
$Q_{s,r,t}$	Power stored in storage cluster s in region r at time t (GWh)
$R_{s,r,t}$	Available reserve power storage cluster s in region r at time t (GWh)
$R_{g,r,t}^{Qstart}$	Quick start reserves from generator g in region r at time t (GW)
$R_{r,t}^{prim}$	Primary reserve requirement in region r at time t (GW)
$R_{g,r,t}^{PrimUp/Down}$	Primary reserve supply from generator g in region r at time t (GW)
$R_{r,t}^{sec}$	Secondary reserve requirement in region r at time t (GW)
$R_{g,r,t}^{SecUp/Down}$	Secondary reserve supply from generator g in region r at time t (GW)
$SD_{g,r,t}$	Shut downs of generation cluster g in region r at time t (#)
$SU_{g,r,t}$	Start-ups of generation cluster g in region r at time t (#)
$T_{r,r',t}^{import}$	Power imported into region r from region r' at time t (GW)
$T_{r,r',t}^{export}$	Power exported from r to region r' at time t (GW)
$UC_{g,r,t}$	Amount of units turned on in generation cluster g in region r at time t (#)

Chapter 1

INTRODUCTION

Every decade since 1850 has had a higher global average temperature than its preceding decade. Higher temperatures cause sea levels to rise and increase the chance of extreme weather events like hot spells, droughts and storms (IPCC, 2013). The impacts that climate change will have on human societies are enormous and should be avoided, especially because the earth's poorest are likely to be most heavily affected (the World Bank, 2012).

It is now well accepted that climate change is the result of CO₂ emissions are the cause of the observed global warming. Since the industrial revolution, carbon hydrates that have been stored in fossil fuels over millions of years are being released into the atmosphere at an ever increasing pace. To keep global temperature rise under 2°C it is important that worldwide CO₂ emissions are cut drastically (IPCC, 2013).

1.1. Problem orientation

The current electricity system is almost entirely based on the combustion of fossil fuels and accounts for approximately 40% of global CO₂ emissions (Saber & Venayagamoorthy, 2010). In an effort to minimize the effects of climate change; the EU has set out policies to reduce CO₂ emissions. In 2030, the total European CO₂ emissions should be reduced with 40 to 44% compared to 1990 levels. As expectations about CO₂ reductions in the electricity sector are high, a reduction of 54 to 68% is required for 2030. By 2050 the European Commission wants to reduce greenhouse gas emissions by approximately 80% (compared to 1990), the expectation is that the power sector will need to reduce emissions with at least 93% to reach the overall 80% target (European Commission, 2011). These policies require us to move towards an almost CO₂-neutral electricity sector in less than 40 years.

The fact that other sectors will also be increasingly dependent on electricity for their energy supply makes the transition even more challenging. For instance, it is expected that the transport sector will be largely electrified within the coming decades (Verzijlbergh, Brancucci Martínez-Anido, Lukszo, & de Vries, 2014). At the same time,

heating of dwellings and offices will switch from gas fired boilers to electrical heat pumps.

Nonetheless, the expectations about CO₂ reduction in the electricity sector are not unfounded, several technologies, based on the current energy system, are available that are able to produce electricity without emitting greenhouse gasses. Nuclear energy has no CO₂ emissions and is already widely applied in the electricity sector. Traditional fossil fuel plants can be fuelled by bio fuels or can capture the CO₂ from their flume gasses and store this in underground cavities such as empty oil and gas fields, this storage process is called Carbon Capture and Storage (CCS).

However, nuclear energy and CCS come with their technical and societal downsides. After the nuclear meltdown in Fukushima, countries are critically reviewing their stock of nuclear plants and either choosing to close down existing plants or not permitting new ones. Besides, problems with long term storage of radioactive waste have not been solved to date. CCS is deemed too expensive at this moment, as can be seen from recent developments in Rotterdam (NOS, 2014). Furthermore, CCS is subject to public distrust which hampers large scale research projects (NOS, 2010).

Renewable Energy Sources (RES) such as wind and solar are clean, safe and have proven their technical feasibility. In an effort to comply with international agreements, country specific support packages have boosted the shares of renewable energy in the electricity mix in recent years. With these developments have also come great reductions in the cost of renewables, almost closing the gap between the cost of renewables and traditional technologies. Therefore, renewable energy sources are generally seen as the most promising solution to de-carbonise the electricity sector.

In spite of their benefits, technologies like wind and solar energy fluctuate with weather conditions and their output is uncontrollable. During periods of unfavourable weather conditions, the output of solar and wind can be zero. Besides, due to weather forecasting errors, the output of renewables is uncertain. When large shares of renewables are introduced into the system, the uncontrollability and uncertainty of the output poses new problems for the electrical system (Richardson, 2013). During periods of low wind and/or solar irradiation the gap between the supply and demand needs to be met using dispatchable back-up generators. During periods of high RES output and low demand not all electricity that is produced is used, possibly resulting in negative prices and high grid loads.

Several solutions have been proposed to solve the issues around renewable energy. First of all, consumers should be able to react to the amount of electricity that is supplied to the grid. This can be achieved through price incentives in combination with technical developments such as smart grids and electric vehicles. Secondly, a stronger interconnected network is able to benefit from differences in weather over a larger area, exporting electricity from windy or sunny regions to areas with less favourable conditions. Finally there are possibilities to store electric energy, in for instance hydro reservoirs or batteries, in order to use the produced energy at a later point in time.

1.2. Solutions to introducing renewables - state of the art

This paragraph shortly goes into the effects that the solutions presented above have on the integration of renewable energy into the power system. Subsection 1.2.1 looks into the effects of interconnection, section 1.2.2 looks at storage and demand response and section 1.2.3 concludes by combining the 2 solutions.

1.2.1. The effect of transmission capacity on the future electricity system

Transmission capacity can help in transporting electricity from locations with high RES output to areas with low output, enabling higher penetration levels. A recent 10 year network development plan by the European Network of Transmission System Operators for Electricity (ENTSO-E) identifies 100 bottlenecks in the transmission system, 80% due to integration of RES. The ENTSO-E plans to invest €104 billion in the coming ten years alone (ENTSO-E, 2012 pg. 12-17). Brancucci Martínez-Anido et al. (2013) conclude that no further investments in the electricity grid are needed before 2025 if the current plans for both grid expansion and RES penetration are executed; local network congestion is more important within that time frame.

Looking at the market side of grid expansion it seems that both RES and base load suppliers benefit from grid expansions, other generating technologies do not benefit (or even detriment), causing possible conflicts between suppliers and the transmission grid operators. In general the dispatch costs are reduced as more areas can benefit from high RES output at different locations and from other countries' base load generators during low output of RES (C. Brancucci Martínez-Anido et al., 2013; Schaber, Steinke, & Hamacher, 2012).

Heide et al. (2010) present an optimization model and minimize the required storage capacity under the assumption that 100% of energy is provided with wind and solar energy. They find a mix of 55% wind and 45% solar to be optimal. Rodríguez et al. (2014) use the same optimization technique to look into a future Europe where RES technologies generate an amount of energy equal to the yearly energy demand, energy that is not consumed goes to waste. They find that the average amount of energy produced by backup plants is 24% in a scenario without any cross border transmission, letting electricity flow unconstrained reduces this to 15% of total energy production and can be achieved by increasing transmission capacity by a factor 12. An intermediate transmission capacity is chosen at half of the unconstrained capacity resulting in a backup plant energy need of 18%. Schaber, Steinke, Mühlich, & Hamacher (2012) state that minimal storage requirement is achieved with a ratio of 80% wind and 20% solar generation. Heide et al. extrapolate installed capacities from 2020 plans of individual European countries while Schaber et al. use the available full load hours to determine the location of the renewable sources. Whether the difference in location is the only reason for the difference in optimal ratios is unclear from analysing the articles. However, both articles come to the conclusion that a 5 to 6 fold increase in transmission capacity is most opti-

mal for a fully renewable European grid (Rodríguez et al., 2014; Schaber, Steinke, Mühlich, et al., 2012).

Becker, Rodriguez, Andresen, Schramm, & Greiner (2014) use results from Rodríguez et al., (2014) to research the transitional path towards a future 100% renewable European electricity grid in 2050, meeting the European goals of 2020 on the way. Heavy investments in the grid need to start by 2025, continuing all the way up to 2050. Although the investments seem large, multiple studies suggest that they are feasible as their costs are low compared to investments in RES (Becker et al., 2014; Rodríguez et al., 2014; Schaber, Steinke, & Hamacher, 2012). A remaining problem is that in the beginning investment is attractive for early adopters of RES because of high export expectations. However, later, when all countries have high penetration levels, the value of these lines decrease with the lower export possibilities (Becker et al., 2014).

1.2.2. The effect of storage capacity on the future electricity system

The expected increase in Electric Vehicles (EV's) can be an opportunity for the electricity grid (Verzijlbergh, Brancucci Martínez-Anido, Lukszo, & de Vries, 2013). The batteries of plugged in EV's can be used as small distributed storage (Dallinger, Gerda, & Wietschel, 2013). A requisite is the presence of a system that manages these charging decisions, the smart grid, otherwise EV's only increase peak demands (Peterson, Whitacre, & Apt, 2010). As the process of charging and discharging causes increased degradation of the vehicles battery it is expected that EV's will only play a role by increasing demand during off-peak hours, also known as peak shaving (Richardson, 2013).

In addition to the use of electric vehicles, several independent storage technologies are available. The most well-known and most widely applied technology is pumped hydro storage. Multiple other storage technologies are currently available and under development. These technologies include batteries, compressed air, hydrogen fuel cells and flywheels (Ibrahim, Ilinca, & Perron, 2008; Kaldellis & Zafirakis, 2007; Steinke, Wolfrum, & Hoffmann, 2013). The applicability of different technologies is dependent on parameters such as cost, efficiency, storage capacities (MWh), output capacities (MW), and the ratio between these parameters. In order to solve the issues with the intermittency of RES only pumped hydro power qualifies as a suitable technology (Ibrahim et al., 2008). Kaldellis and Zafirakis (2007) also see benefits from the use of compressed air storage, although the cost of this technology is currently above that of pumped hydro storage. The optimization model used by Steinke, Wolfrum and Hoffmann (2013) suggests storage capable of delivering 90 days of average demand would be necessary to fully eradicate back-up plants. They conclude that pumped hydro and battery storage is sufficient for regional grids and see a role for hydrogen fuel cell combinations for larger grid applications.

1.2.3. Combining the effects of transmission and storage

Both transmission and storage of electricity serve the same goal, level out supply and demand, either in a spatial or temporal manner. Verzijlbergh et al. (2013) find that, in scenarios with low RES penetration (the expected scenario), transmission and storage (in this case in EV's) are substitute technologies. However, when RES penetration increases the technologies become more and more complementary. This is explained as follows: when the high output of RES has saturated all the EV batteries in one area, the transmission network offers access to storage capacity in other locations. Steinke et al. (2013) also find substitutability for the two technologies, but do not find the complementarity at high RES penetration. This can be explained by the fact that they model individual cells (without connections to surrounding cells) instead of the physical grid, therefore the electricity generated in one cell cannot be transported if its own storage is saturated.

1.3. Problem statement

It seems that both electricity transmission and electricity storage can help in increasing RES penetration in the European energy system. Although one study (Verzijlbergh et al., 2013) suggests that the technologies seem complementary in situations with high RES levels, it seems that the two technologies will be substitute for the coming years, especially during the transition into a more renewable electricity system. In opposition to the similar role that the technologies could play, the laws and regulations for the technologies are fundamentally different. The European transmission system is operated by natural monopolies, the Transmission System Operators (TSO's), and therefore heavily regulated (EY, 2013; Glachant, Saguan, Rious, & Douguet, 2013). Storage capacity however is a very different technology; it can be seen as a facility that produces energy, as any other power plant, with the only difference that its fuel needs to be ordered from the electricity market itself. Like any generator they are not natural monopolies and therefore not heavily regulated.

This contradiction poses issues, although the TSO's can clearly benefit from an increase in storage capacity due to the lower investment needs in transmission capacity, investments in storage are made by private parties. On the other hand, private investors are at risk when investing in storage as the need for storage might be reduced by an increase in transmission capacity. Some countries, such as Ireland, already have regulations in place that make some storage capacity fall under transmission assets, other countries like Germany and the U.K. regulate storage as any other grid connection (European Commission, 2013). This situation makes the development and future role of storage in the electricity system uncertain.

To address this uncertainty, this thesis describes a quantitative research into the possible future roles of different electricity storage techniques, looking especially at the interrelations between electricity storage and transmission.

1.4. Research questions

Based on the research problem above, the main research question can be formulated:

What roles can electricity storage play in the transition to a sustainable electricity system and which policies can be adopted to ensure adequate development of this storage?

Based upon the main research question, several sub questions arise:

- Which electricity storage types are available, what are their characteristics and which functions can they perform in the power system?
- Which modelling technique is best able to capture the effects of storage on the daily and seasonal cycles of consumption and production?
- How can the effects of storage on the electricity grid be captured into a quantitative model, both conceptually and formally?
- What is the effect of the storage technology and the technologies characteristics on the value it has for the power system?
- To what extent do storage and transmission influence each other?
- What are the effects of storage on the operation of the electricity system?
- In what kind of power system is storage able to generate value?
- How can storage be beneficial for the integration of renewables into the power system?
- What is the effect of electricity storage on the actors within the power sector and which strategies can they use to optimally benefit from electricity storage?

1.5. Thesis outline

Chapter 2 explains general power sector concepts and goes into the current state of electricity storage technologies. Chapter 3 uses this knowledge to present a mathematical formulation of an optimization model; a discussion about modelling approaches in the power sector precedes the model formulation. Chapter 4 shortly describes how the model performs under 'reference' conditions in order to validate the models. In Chapter 5 the model is used for analysing the role of storage in a highly renewable electricity system. Chapter 6 discusses model results and explains the implications for the electricity sector. Chapter 7 concludes, and does suggestions for future research. Finally, Chapter 8 takes a few steps back and gives a personal reflection upon the process of writing this thesis.

Chapter 2

THE ELECTRICITY SYSTEM AND ELECTRICITY STORAGE – THE BASICS

Before presenting the mathematical model formulation (Chapter 3), a short introduction about the functioning of the electricity sector will be given. Secondly the current economic and technical developments in the field of electrical energy storage are presented.

2.1. The electricity system

Electricity is a highly important commodity in our modern society. During a black out, the entire economy comes to a grinding halt. However, many people only know that if they plug an electrical appliance in a power socket, electricity magically flows out and powers the device. The complex system of generation, transmission and distribution that exists behind a power socket is largely unknown. To better understand the rest of this thesis, a very (very) brief introduction to the functioning of the power sector is given. The model described in Chapter 3 is based upon the description given in this chapter. For more information, textbooks like Pérez-Arriaga (2013) give an extensive overview of both the technical and institutional functioning of the power sector.

2.1.1. Generation, transmission and distribution

Traditionally, electricity is produced in large dispatchable power plants like nuclear and fossil fuel plants. The produced electricity is then fed to the high voltage transmission network. The transmission network's function is to transport large bulks of electricity from the location where the electricity is produced to locations where electricity is consumed. Small consumers are not directly connected to the transmission network but to smaller and lower voltage distribution networks. This system is illustrated in Figure 2-1.

Recently, more and more renewable energy sources (RES) and distributed energy sources are added to the network. This changes the hierarchical structure of the electricity system, where power used to flow from generators to the consumers via the trans-

mission and distribution network it is now also possible that the flows are reversed. A schematic representation of the changing power system is shown in Figure 2-2.

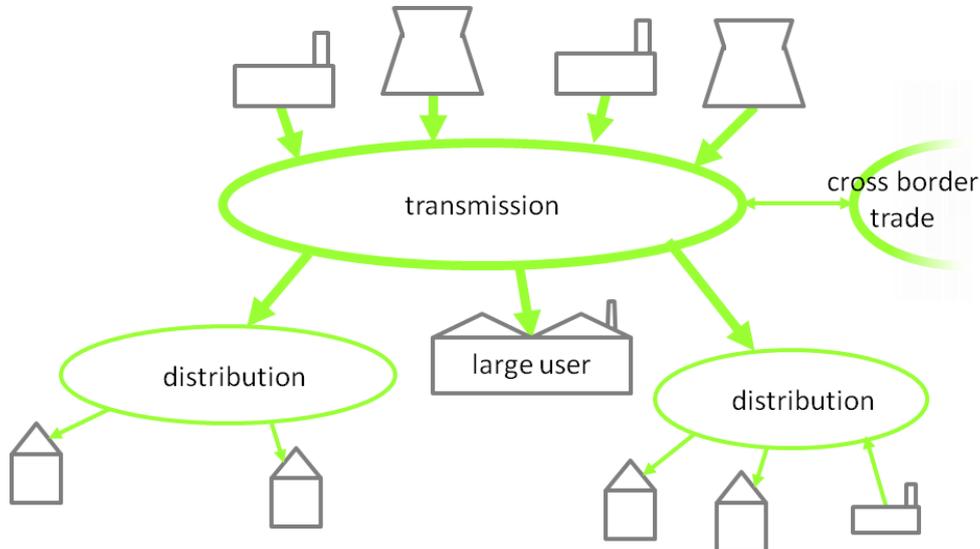


Figure 2-1: Schematic representation of traditional power system

Although large renewable energy sources like groups of wind turbines are connected to the transmission network, smaller energy sources like individual wind turbines, solar panels or combined heat and power (CHP) plants are connected to the distribution network. If there is an oversupply of electricity within a distribution area, this electricity flows back onto the transmission network into other distribution grids.

In Europe, individual countries' transmission networks are interconnected. Historically these interconnections were used for security reasons. Due to the political goal of integrating the European electricity market and the increase in renewable energy capacity, the interconnectedness has increased and will continue to do so (ENTSO-E, 2012a).

The combined development of increased renewable energy sources and better interconnection opens up the possibilities for electrical energy storage (EES). As the output of renewables is dependent on meteorological conditions, demand and supply of energy will increasingly mismatch. Although the interconnectedness of grids makes it possible to exchange power with regions that have less renewable energy available, neighbouring countries show high correlation in weather patterns and therefore international exchange is not always possible (Nagl, Fürsch, & Lindenberger, 2012). EES can store oversupply for times where supply is low.

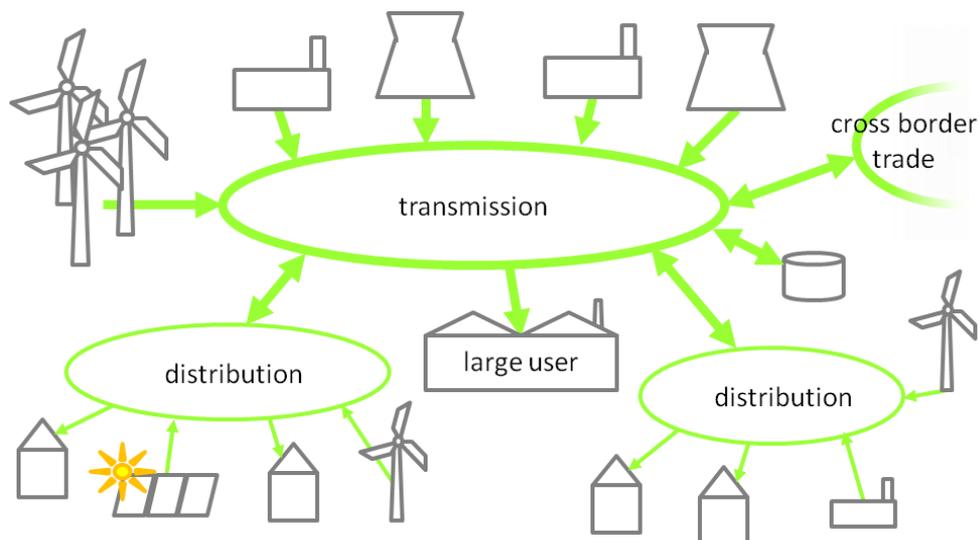


Figure 2-2: Schematic representation of changes in power system

2.1.2. Consumption

The demand for electricity varies depending on the hour of the day, the day of the week and the seasons. The daily pattern follows a day night pattern with low demand during the nights and high demand during the day. On weekdays the demand is generally higher than in weekends. Finally, most countries have their peak demand in winter; however, some warmer regions have their highest peaks during the summer due to the use of air-conditioning.

Because demand and supply have to balance at each and every moment, predictions have to be made about the future demand. In a traditional power system, large generators are dispatched in such a way that they are able to meet the expected demand. Because of the repetitive patterns, this was relatively easy. Small variations from the prediction still occur but these can easily be managed by adjusting the output of already running generators which keep a margin, called a reserve, available to change output on a second to second basis.

In future power systems it will be increasingly difficult to match supply and demand. The introduction of renewables has introduced a new term in the power sector: residual load. The residual load is the load that remains after the power output of non-controllable sources such as wind and solar has been deducted from the demand. Weather patterns don't follow the demand patterns; therefore the residual load does not follow the daily patterns as described above and makes it more difficult to plan the dispatch strategy. Besides, due to the weather prediction errors the residual demand is growing more uncertain. This increases the difference between expected and actual load, making it necessary to increase the reserves that generators have to keep in order to follow prediction errors.

2.1.3. The electricity system's institutional layer

Next to the physical layer of generators and electricity cables, there is an entire institutional layer that ensures reliable operation of the power system. Several actors can be identified and will be discussed shortly.

As discussed above, there are electricity consumers and producers. The consumers and producers come together on the market and the combination of demand and supply results into a market price. In a well-functioning market, the cheapest generators supply the demanded electricity. The market price corresponds to the production cost of the most expensive generator running at that moment².

Only large consumers directly bid for electricity on the market. Small consumers are represented by retail companies; these companies buy electricity from the market and sell this to their consumers for fixed prices. Small consumers are therefore not exposed to market prices. This causes a large part of the demand to be inflexible to the market price; therefore the supply curve determines most of the market price. After supply, demand and price have been set, the consumers and producers provide their agreements to the transmission system operator (TSO).

The TSO is responsible for the balance in the transmission system. Using the received production and consumption information, the TSO determines the expected flows through the transmission network. If the flows cause a system overload, the market based production and consumption schedule needs to be changed by the TSO in order to come to a technically feasible schedule. If system overload becomes frequent, investments in the network are necessary. Secondly, the TSO makes sure enough reserve capacity is available in order to quickly respond to mismatches in predicted and actual demand.

2.2. Current state of electricity storage

Currently, electricity storage is not used on a large commercial scale. Only 4 technologies have a global installed capacity greater than 100 MW, these technologies include pumped hydro storage (PHS), compressed air energy storage (CAES), sodium-sulphur batteries and thermal storage (Denholm, Ela, Kirby, & Milligan, 2010). Global capacity of storage technologies is approximately 141 GW, of which more than 99% is pumped hydro storage, see Figure 2-3.

Many reasons exist for the fact that electricity storage is not deployed on a large scale. First of all, electricity is not easily stored by itself. Most EES technologies first transfer the electrical energy into a different form of energy, such as potential energy for hydro storage, and have to convert it back to electrical energy later. These conversion processes come with energy losses. Secondly utilities have not yet fully understood the wide range of benefits that storage can have, they are often put off by perceptions of risk and technical feasibility (EPRI, 2003, pp. 2–25).

² Actually, it's the cost that would be incurred if the demand would increase with one unit of energy, but let's keep it simple here

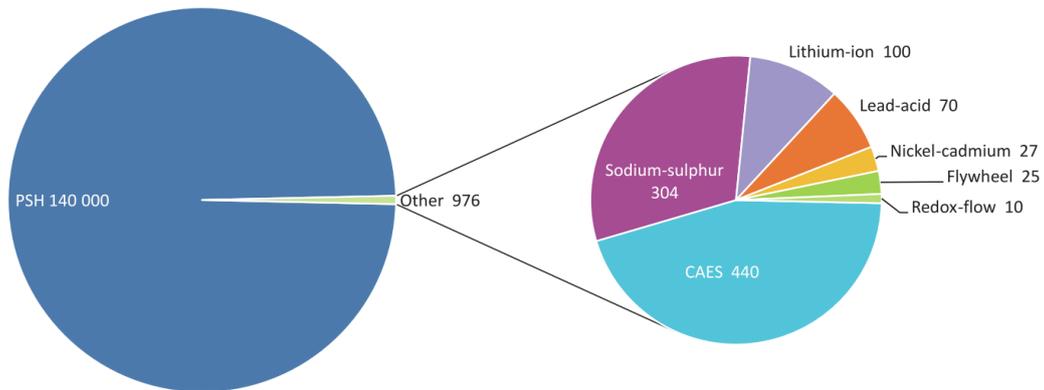


Figure 2-3: Worldwide installed electrical energy storage³ (EPRI, 2010)

The wide range of uses of EES can be roughly divided into three categories. Firstly, EES technologies can be used to provide power quality support. As the grid electrical grid needs to be in constant balance, small variation in demand and supply cause voltage and frequency to vary on a second to minute basis. The fast response time of some EES techniques can be used effectively to level out small and fast variations. Secondly storage can be used to level out hour to hour, day to day or seasonal variations in electricity demand. These variations are caused by day-night rhythms or the difference of electricity need in summer and winter. Delivering energy over period of multiple hours or more is called energy management or bulk energy storage (International Energy Agency [IEA], 2009). Finally, bridging power fits in between power quality and energy management. Bridging power, delivering from minutes to one hour, can be seen as what is previously described as a reserve. These reserves are used to let fast responding dispatchable generators come online to meet weather or demand forecast errors.

Although many sources provide information about the technical and economic parameters of EES, uncertainty around the efficiency and cost of storage technologies remains. The reported efficiencies sometimes exclude the cost of converting alternating current (AC) to direct current (DC). Sometimes they also do not include parasitic loads that are for instance used to regulate the temperature of the storage; these parasitic loads vary greatly between locations based on local conditions. Besides, cost estimations are based on individual (pilot) projects, of which the costs are influenced by both locational factors and global economic trends (Denholm et al., 2010).

In the rest of this section, more details will be given about various EES technologies.

³ This figure excludes thermal energy storage as thermal energy is usually not converted back to electricity

2.2.1. Pumped hydro energy storage

Pumped hydro energy storage (PHS) is the most applied type of energy storage. It is based on pumping water from a low to a high reservoir and stores energy as potential energy. During periods of higher demand, water is released through a turbine and the potential energy is converted back into electricity. The storage capacity is a function of the height difference between the reservoirs and the stored water volume (Evans, Strezov, & Evans, 2012).

Many of the European large scale hydro dams were constructed in the middle of the 20th century. Later, small pumping capacities were added to these dams in order to also be able to store electricity. The business case for PHS in Europe existed when networks still had little interconnection and hydro storage was used to balance day night differences. As the European grid becomes more and more interconnected, PHS plants are increasingly cycled multiple times a day to reduce fluctuation caused by renewables (European Commission, 2013).

The advantages of pumped hydro are the large volumes of stored energy, small storage losses and relatively low cost per unit of energy. This makes it a technology that is suitable for energy management and bridging power. However, the response time of PHS is fast enough to also provide power quality services (Chen et al., 2009).

Although pumped hydro is the most mature and cost efficient technology to store electricity, there are some clear downsides. The need for two reservoirs at different altitudes makes PHS location dependent. These locations are often far from load centres, which adds to the cost by having to develop transmission lines (Evans et al., 2012). Besides, the reservoirs of PHS cause environmental damage and often have long lead times.

In the future, existing conventional hydro power plants will be increasingly equipped with pumping capacity, in this way these hydroelectric dams can also store energy. Besides, hydro and pumped hydro storage will be equipped with more generators that can change output quicker, adding even more operational flexibility (European Commission, 2013).

Other developments are being made in the use of underground cavities from empty mines for the lower reservoir. In this way the upper reservoir can be at ground level. Using this technique reduces the environmental impacts of PHS plants considerably (Mahlia, Saktisahdan, Jannifar, Hasan, & Matseelar, 2014).

2.2.2. Compressed air energy storage

Compressed air energy storage (CAES) has the second largest global installed capacity. To store energy, the technology compresses air and pumps this into empty gas, oil or salt caverns. To release energy, the air is released from the cavern and used to improve the efficiency of a conventional gas turbine. This implies that CAES combusts fossil fuels and emits CO₂.

However, developments are being made with adiabatic compressed air energy storage (A-CAES). A-CAES also stores the heat that is released during compression and re-uses the heat when the compressed air is released. This removes the necessity for a gas turbine. With A-CAES, round trip efficiencies of 60 to 80% can be reached. However, the technology is still in its planning and demonstration phase (Kloess & Zach, 2014).

Currently, two conventional CAES plants are operational: 1 in Huntorf, Germany (290 MW, 3 hr) and 1 in McIntosh, Alabama, USA (110 MW, 26 hr). Several other projects in the US, Japan and South-Africa are under consideration or construction (Chen et al., 2009).

Like pumped hydro storage, CAES is highly dependent on locational factors for the possibilities to store compressed air in underground caverns. However, there are more suitable locations than one would expect; 80% of the US territory has formations that are suitable for CAES (EPRI, 2003, pp. 15–9). Besides, CAES provides a good alternative to PHS in regions that lack mountains like the Netherlands and the north of Germany (European Commission, 2013).

The large storage potential of underground cavities combined with relatively low capital cost requirements and the operational flexibility of conventional gas turbines, CAES is suitable to provide both power quality management and bulk storage (Chen et al., 2009; Mahlia et al., 2014).

2.2.3. Battery storage

Battery storage is the oldest and most well-known form of electricity storage. Batteries are built up from one or more electrochemical cells. During discharge, chemical reactions occur in the cells creating a flow of electrons through an external circuit. To reverse the reaction, the battery needs to be fed with an external electricity flow (Chen et al., 2009).

Many different types of batteries and chemical compositions exist. The common advantages of most batteries are the extremely fast response times, short lead times and modularity of the technology. Making it a flexible storage solution especially useful for power quality regulation (Kondoh et al., 2000). However, some battery types could also offer energy management services (Denholm et al., 2010).

Nonetheless, batteries also have some clear disadvantages. First of all, they have problems in meeting the extreme demands of the electricity sector which include high power demand, long service life and low cost (European Commission, 2013). Besides, they suffer from high maintenance cost and often contain heavy metals, so the ecological impact of battery systems need to be taken in consideration (Chen et al., 2009; Mahlia et al., 2014).

The most promising role for batteries probably lies in the application of energy storage for transport purposes, i.e. in cars. For more information about the possible benefits of using car batteries for energy storage see Saber and Venayagamoorthy (2010),

Dallinger et al. (2013), Verzijlbergh, Brancucci Martínez-Anido, Lukszo, and de Vries (2014) and Peterson et al. (2010).

2.2.3.1. Lead acid batteries

Lead acid batteries are the most used and well known batteries. They are the batteries that are used for the starter motor in conventional cars.

Due to the low cost (\$300-600/kWh), high efficiency (70-90%) and high reliability lead acid batteries have been applied for power quality regulation. However, short cycle lifetime (500-1000 cycles) hinders its further development (Chen et al., 2009).

Nonetheless, several lead acid energy management systems are operational, the largest of which is in California in the United States. This system has a rated power of 10 MW and can store up to 40 MWh (Chen et al., 2009).

2.2.3.2. Lithium ion batteries

Lithium ion (li-ion) batteries have two clear advantages. First of all, their efficiency is almost 100%; secondly, they have a cycle life of up to 10,000 cycles. This makes them the preferred choice in many consumer electronics (Chen et al., 2009). Recent developments in storage capabilities also increased their attractiveness for use in electric vehicles (Mahlia et al., 2014).

Currently, li-ion storage is expensive (more than \$600/kWh) due to safety measures that protect the battery from overcharging and, with lithium resources depleting, these prices are expected to rise in the future (Evans et al., 2012).

2.2.3.3. Flow batteries

Flow batteries are different from other types of batteries as they separate the storage of electrolytes from the actual cell where the reaction takes place. Flow batteries use 2 reactants that are stored in tanks, reactants flow through the cells to generate electricity, and reverse flow to store electricity.

The biggest advantage of this different design is the decoupling of energy and power. The power (kW) capacity is determined by the number of cells, the energy capacity (kWh) by the size of the storage tanks. This allows application specific design (Chen et al., 2009). Another advantage is the fact that the reactants are stable and don't undergo chemical changes during operation, making them safer and more easily maintainable (Mahlia et al., 2014).

A 15MW, 120 MWh flow battery using sodium bromide and sodium polysulfide electrolytes, has been built at Innogy's Little Barford power station in the UK. However, the storage system has never been commissioned due to engineering issues (EA Technology, 2004). This further adds to the discussion about flow batteries being an immature technology with too high cost (Evans et al., 2012).

However, the IEA (2014) still sees flow batteries as a promising solution for especially bridging power applications. Besides, their deep discharge capabilities and 'plug and

play' characteristics make them suitable for distributed storage (Beaudin, Zareipour, Schellenberglobe, & Rosehart, 2010).

2.2.3.4. Other types of batteries

Other batteries include sodium-sulphur (Na-S) batteries which have an efficiency of up to 90% and have a life time of approximately 2500 cycles. A large advantage for power quality services is that the battery is able to shortly output burst of power of six times their power rating. Besides, the Na-S battery has proven its value in daily load levelling in Japan, where more than 30 plants are operational (Chen et al., 2009). However, the batteries operate at temperatures around 300°C, this makes them suffer from high discharge rates (Evans et al., 2012).

Nickel-cadmium (Ni-Cd) and nickel metal hydride (Ni-MH) batteries are, due to their high energy density, low maintenance cost, high tolerance for over-discharge and better cycle-life, technically superior to lead acid batteries. Therefore the Ni-MH battery is used the Toyota Prius (Mahlia et al., 2014). Their high costs (\$1000/kWh) prevent the technology from being used for grid operation (Evans et al., 2012).

2.2.4. Hydrogen storage

Hydrogen fuel cells generate electricity by using hydrogen and oxygen to produce water. Electricity is needed when producing hydrogen and oxygen from water. As all the reactants (hydrogen, oxygen and water) can be stored, the process can be reversed. As long as new reactant is added to the cell, it will keep operational continuously (Chen et al., 2009).

The big advantage of this technology is that the generated hydrogen can contribute to a new part of the energy economy. Hydrogen can be stored and used as a fuel for fuel cell vehicles, can be added to the existing gas infrastructure or can be used by the energy intensive chemical industry (Korpås & Greiner, 2008).

The current low round trip efficiency of approximately 35% (70% electrolysis, 50% fuel cell) in combination with its high cost prevent current large scale adoption (Chen et al., 2009). However, market penetration is expected in 15 to 40 years (European Commission, 2013). These positive prospects are largely driven by expectations about future reductions in cost of fuel cells, some studies suggesting investment cost as low as 40 \$/kW by 2020, caused by mass production for the automotive industry (Tsuchiya, 2004).

Despite of current difficulties, hydrogen storage is already operational in several off-grid locations. In Norway, a small electrolyser (48 kW) is coupled with a 600 kW wind turbine and a 10 kW fuel cell. This system is able to reliably deliver necessary power to a small independent grid for up to three windless days (Nakken, Strand, Frantzen, Rohden, & Eide, 2006).

2.2.5. Flywheels

Flywheels use kinetic energy to store electricity. Electricity is fed to an electrical motor which spins a wheel. Energy is extracted back from the wheel using the same electrical motor as a generator. The amount of energy stored dependent on mass and speed of the wheel, the power capacity is determined by the motor. Typical units have a power rating of 100-250 kW and have storage durations up to a few minutes (Chen et al., 2009).

The largest advantage of a flywheel is its extremely fast response time in combination with very high short term efficiency (95%), which can be used to provide power quality services. Due to the fact that a flywheel has almost unlimited cycle life it is better suitable than batteries in providing fast charge and discharge cycles that are necessary for power quality control (Evans et al., 2012).

The disadvantage of flywheels lies with its high self-discharge of up to 45% a day (Ibrahim et al., 2008). Although the use of a vacuum environment and magnetic bearings reduces the self-discharge, flywheels are not expected to be used for energy management (Mahlia et al., 2014).

2.2.6. Other storage technologies

Several other technologies for electrical energy storage are under development. However, these technologies are still in the development phase and therefore only shortly discussed in this report.

Super capacitors store electricity in electrostatic fields between two conductive plates. The technology suffers, like flywheels, from high self-discharge but is able to provide short burst of energy (Chen et al., 2009). Therefore it will mainly be used for power quality regulation. However, progress is being made in the development of super capacitors and there are developers that claim technical supremacy over traditional batteries (Mahlia et al., 2014).

Superconducting magnetic energy storage (SMES) provides the only way to store electricity directly. Electrical current runs indefinitely through a superconducting coil with almost no direct energy losses. To be able to stay in superconducting state, low temperatures (just above 0 K) are required, causing high parasitic losses. SMES can only provide storage for a few seconds of power but research is done into storage of several minutes. Chen et al. (2009) expect SMES to primarily provide power quality service. However, as SMES has the same properties as super capacitors but is more expensive than super capacitor storage, Beaudin et al. (2010) do not expect SMES is to play a role in grid electricity storage.

Finally electricity can be stored in the form of heat (or cold). Thermal storage has multiple options: sensible heat energy storage simply heats or cools a material without making its phase change. The stored energy can be used for heating or cooling buildings. Latent heat energy storage makes material undergo a phase change, thermochemical energy storage breaks uses heat to break molecules, joining them back together will free

the heat again (Mahlia et al., 2014). Although the heat stored can be used by reverse heat pumps to generate electricity again; expectations about this application are low and therefore not further discussed.

Chapter 3

MODEL DESCRIPTION

This chapter presents the model that has been created for the purpose of this thesis. The first subsection discusses the currently used modelling techniques and optimization methods in the power sector and justifies the chosen modelling approach. Subsection 3.2 presents the complete mathematical formulation of the operational part of the model. Due to the complexity and size of the optimization model, various speed-up strategies are proposed in subsection 3.3. Finally, subsection 3.4 describes the usage of data within the model.

3.1. Modelling approach

The expectation is that electrical energy storage (EES) has an impact on the variable generation cost and capital cost of both generation and transmission capacity. To estimate these effects, a model of the electricity system is to be developed. Many different modelling approaches are described within the literature. This subsection elaborates on those approaches and picks an approach that is capable of capturing the effects of storage on the electrical grid.

3.1.1. Energy sector modelling

Looking from the larger energy system perspective Herbst, Toro, Reitze and Jochem, (2012) identify two general model types (see Figure 3-1): top-down and bottom-up models. Top-down models picture the energy system as part of a national or regional system. They are used to test energy policies with regards to the effect on the economic system and society as a whole and therefore mostly used by economists. An example of a top down energy model used at the CPB is the MERGE-CPB model (Aalbers & Bollen, 2013). On the other hand, bottom-up models look at a specific part of the energy system, contain more technical detail and are usually created and used by engineers (Götz, Blesl, Fahl, & Voß, 2012).

Another explanation of bottom-up modelling used at TU Delft is the act of modelling separate entities as individual decision makers; giving them input, output and ways to

interact with other entities in the model. This boils down to agent based simulation as discussed later as a separate group of bottom up models. In the further analysis, the definitions as used in Figure 3-1 are used.

As described in Chapter 2, the electricity system consists of many individual generators that produce electricity which is divided over end consumers through a complicated transport and distribution system. To capture the effects of EES on the hourly and daily operation of the electricity system, the bottom up approach is most suitable (Jägemann, Fürsch, Hagspiel, & Nagl, 2013).

The bottom-up model type can be further divided into two different model types: simulation and optimization models. Simulation models are used to research the development of a system based on the effects of many individual choices, modelling approaches include agent-based modelling and system dynamics. Optimization models try to find a system wide optimal solution within pre-defined boundary conditions. Although simulation models are better able to capture the market imperfections that are present in the power sector, an optimization model is able to determine an optimal solution from a central decision maker perspective (Herbst et al., 2012). The interest of this thesis lies in the capability of EES to reduce total system cost of introducing large amounts of renewables into the electricity system and the effects of storage and transmission can have on these integration cost; hence an optimization model is best suitable.

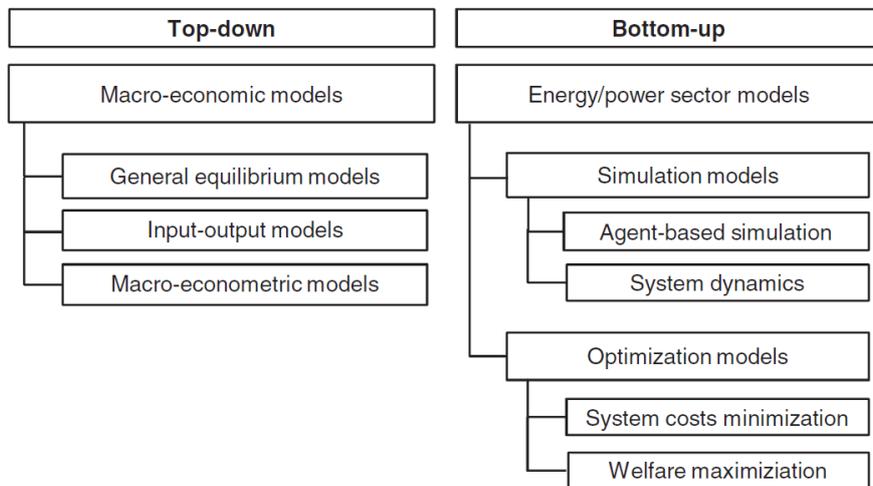


Figure 3-1: Classification of different energy model types (Jägemann et al., 2013)

In principle, the goal of an optimization model in the power sector is the maximization of social welfare. Within power systems, social welfare is defined as the utility that electricity consumers get from using electricity minus the cost of generating that electricity (M. Ilic, Xie, & Liu, 2013, p. 24). However, it is not easy to quantify the utility that is derived from using electricity. Therefore it is assumed that electricity demand is inelastic. This assumption reduces the welfare maximization problem into a cost minimization problem. Within the model, the demand can be based on historical time series (Jägemann et al., 2013).

Within the group of cost minimization models different types of models co-exist. The differences between the model types primarily lie in the considered time frame. Due to computational limits, the time frame considered negatively correlates with the amount of technical detail that can be included in the model. Models with the longest time frame determine optimal investment, which usually covers multiple decades but include small portions of the years simulated or make technical simplifications. Models with the shortest time frame are used to determine system operational stability on the frequency level but only include a few minutes of simulation time (B. S. Palmintier, 2013). Two types of electricity system optimization methods used for medium to long term problems will be further discussed.

3.1.2. Electricity system modelling

Economic dispatch (ED) models allocate the system demand over the available generating units in such a way that production costs are minimized (Galiana & Conejo, 2009). The demand is allocated considering the maximum output limits of all generators, and if transmission is included, the technical limits of the power lines. When modelling power flows, the assumption is made that the dispatch does not affect system voltage and frequency. This assumption leads to modelling direct current (DC) power flows, which are easier to model than alternating currents (M. Ilic et al., 2013, p. 18). Unit dispatch models are, depending on the cost function of the generators, linear or non-linear programming models and can be solved analytically for simple models (Galiana & Conejo, 2009).

Although economic dispatch models have been used historically by system operators to optimally dispatch generators they lack important details about the operation of the electricity grid. Due to the fact that thermal power plants need to heat their boiler and piping system before they can effectively deliver power to the grid, these units have considerable start-up costs. Besides, thermal power plants have a minimal output level, under which they cannot operate. Lannoye, Flynn and O'Malley (2012) show that simplifications of these technical details can lead to a misjudgment in the need for flexibility in the system by a factor three. Therefore a type of model that includes these technical characteristics is increasingly used for power sector modelling (M. D. Ilic, Xie, & Joo, 2011).

Unit commitment (UC) models add a binary variable to every generator to indicate whether the generator is on or off, making it a mixed-integer linear programming model (MILP). The binary operator can be used to include start-up cost and minimal output levels of generators. Including start-up cost might result in solutions where small generators with high variable and low start-up cost are favoured over large generators with low production cost if the power is demanded for a short amount of time. This is an improvement from the economic dispatch model described earlier but also makes solving the model more complex. The large combination of discrete decisions and other operational details make solving UC models with a scope of more than one week computationally challenging (B. Palmintier & Webster, 2011).

One of the advantages of electricity storage is the fact that many of the technologies have very fast response time and often no start-up cost and no minimum output levels. Due to the integration of renewables, the net demand pattern will show more unpredictable variation. Electrical energy storage technologies have a clear advantage over thermal generators in the quickly changing conditions that will be caused by the integration of renewables. Using an economic dispatch model does not capture these benefits, possibly under-valuing storage. On the other hand, unit commitment models are so complex to solve that modelling multiple weeks or even a year on an hourly basis is computationally impossible. However, optimizing over a short time period, for instance one week, results in a loss of the possibilities for seasonal storage.

3.1.3. Clustered unit commitment

Palmintier (2013) presents an innovative formulation of the unit commitment problem, solving the computational issues that arise when optimizing large UC models. This new method clusters generators of the same type into groups. Instead of having an individual binary variable for each generator, a cluster of similar generators has one integer variable.

The concept of clustering is explained using a simple example, graphically shown in Figure 3-2. Imagine a system with five identical power plants. In a traditional unit commitment model, each of these power plants has its own commitment variable that can either be zero or one. These identical plants are now grouped and the five individual binary commitment variables are replaced by one integer variable. This reduction in binary variables makes the optimization problem a lot easier. Besides, having to determine the output of 1 group of generators is easier than determining individual output of five generators, reducing the number of equations at the same time.

Generators can be clustered based on unit capacities, age, efficiency and other characteristics in order to not lose technical differences between generators. However, tests show that clustering units by generator type alone gives sufficiently accurate results compared to a full unit commitment problem. Differences between the full unit commitment and clustered commitment on key performance indicators such as cost and CO₂ emissions remain under 1.5%. Using full clustering shortens the solution time dramatically (2000x) compared to making more complex clusters.

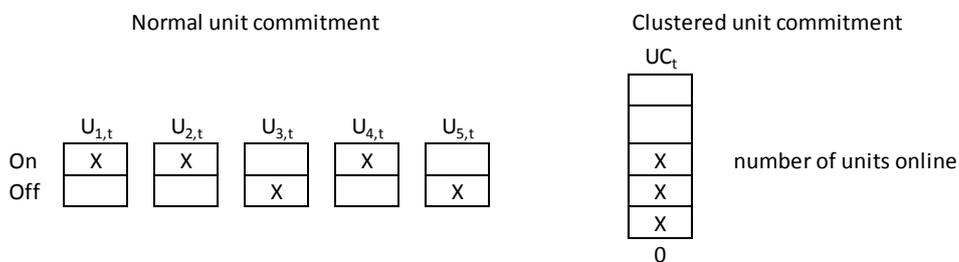


Figure 3-2: The concept of clustering, adapted from B. S. Palmintier (2013)

Next to showing the effectiveness of the clustering method for solving unit commitment problems, Palmintier (2013) also shows that flexibility becomes a key parameter of future renewable electricity systems. Solving economic dispatch models containing high shares of renewable energy sources results in dispatch schemes that are technically infeasible. The fact that storage is one of the technologies capable of supplying flexible services justifies the choice of making a complex unit commitment clustering model over an economic dispatch model.

Although the clustering approach seems promising, it has only been tested on ERCOT, the electricity network of Texas. This is an electricity system that, in 2007, had a peak load of 62 GW and a total installed generation capacity of 92.5 GW. For comparison, Germany alone has a maximum demand of 80 GW and an installed generation capacity of 190 GW. Besides, the ERCOT system is known for the fact that it has little interconnection to other power systems. Due to the fact that internal transmission constraints are also not considered, the system has not been tested using load flow optimization. Finally, the existing renewable hydro storage plants in ERCOT are not included in the model.

Despite of the shortcomings, the results achieved with the clustered unit commitment method are promising enough to develop a model for the European electricity system and use it to test the role of electrical energy storage in the grid. A further explanation and mathematical formulation is presented in the next section.

3.2. Mathematical formulation

An energy optimization model minimizes or maximizes a certain objective function by changing the energy system's variables. These variables are bound to a set of constraints including technical limitations, meteorological data, demand profiles and other details about the functioning of the power market (Götz et al., 2012).

For a computer to solve an optimization problem, the objective function and constraints need to be described mathematically. The following sub sections consecutively present the mathematical formulation of the objective function and constraints. As the model description in the following subsections is highly technical, a short textual representation of the functioning of the optimization model is given in Text box 1.

The equations and implementation of unit clustering are partly adapted from Palmintier (2013), however, to be able to include transmission, an extra set of regions is added to variables and parameters. Which is partly based on the economic dispatch model by Lion Hirth called EMMA (2013) and the unit commitment model EUPowerDispatch made by Carlo Brancucci Martínez-Anido (2013). To learn more about the general unit commitment model please refer to Baldick (1995).

For consistency purposes, upper case letters are variables and sets, lower case letters are parameters and set elements. When talking about a generator, g , what is actually meant is a cluster of generators of type g . Please refer back to the Nomenclature for the definition of used symbols. Nomenclature

The model is programmed using the General Algebraic Modelling System (GAMS, 2014) and solved using the powerful Linear Programming and Mixed Integer Programming solver CPLEX (IBM, 2014). The full model code can be found in Appendix E.

The model has been interfaced with R (R Core Team, 2014) using RStudio (RStudio Team, 2012) and gdxrrw (Jain & Dirkse, 2014). Several R-packages were used in to perform the analysis and generate figures (Wickham, 2007, 2009, 2011).

Text box 1

The optimization problem

Minimize

- Total cost of supplying yearly electricity demand
 - Fuel cost
 - Variable operation & maintenance (O&M) cost
 - Start-up cost
 - Penalty for not meeting specified demand
 - CO₂ cost (optional)

Subject to

- Grid stability requirements
 - The amount of energy produced + imported - exported - stored has to equal the energy demand in every region, at all times
 - Transport between regions stays below maximum line capacities
 - A certain amount of reserve capacity is kept available to respond quickly to unexpected changes that endanger grid stability
- Generator constraints
 - Generator output remains below maximum capacity
 - If a generator is turned on, its output remains above minimum output
 - A generator's change in output remains lower than its maximum ramping capabilities
 - The output of renewables is determined by meteorological conditions but can be reduced (curtailment)
 - Generators need to be offline for a certain period of time to allow maintenance
- Storage constraints
 - The energy stored cannot exceed a storage's maximum capacity
 - The storage needs to end with the same amount of energy as it started with
- CO₂ constraint (optional)
 - Yearly CO₂ emissions cannot exceed a given maximum

3.2.1. Objective function

The objective of this optimization model is the minimization of variable generation cost, the total cost are comprised out of fuel cost C^{fuel} , operation and maintenance cost $C^{O\&M}$, start up costs $C^{startup}$, non served energy (NSE) cost C^{NSE} and, if applicable, the cost of CO₂ emissions C^{CO_2} (see Eq. 3.1).

$$\min C^{total} = C^{fuel} + C^{O\&M} + C^{startup} + C^{NSE} + C^{CO_2} \quad 3.1$$

Fuel cost are the sum over all generators, g , regions, r and time periods, t of the power output, $P_{g,r,t}$, divided by the efficiency, η_g , and multiplied by the cost of fuel, c_g^{fuel} (see Eq. 3.2).

$$C^{fuel} = \sum_{g \in G} \sum_{r \in R} \sum_{t \in T} \frac{P_{g,r,t}}{\eta_g} \cdot c_g^{fuel} \quad 3.2$$

The cost of operation and maintenance are calculated using the variable operation and maintenance cost. Variable operation and maintenance cost are calculated by summing the power output multiplied by the variable operation and maintenance cost, $c_g^{varO\&M}$, over every generator, region and time period (see Eq. 3.3).

$$C^{O\&M} = \sum_{g \in G} \sum_{r \in R} \sum_{t \in T} P_{g,r,t} \cdot c_g^{varO\&M} \quad 3.3$$

The start-up costs, $C^{startup}$, are calculated as depicted in equation 3.4:

$$C^{startup} = \sum_{g \in G} \sum_{r \in R} \sum_{t \in T} SU_{g,r,t} \cdot c_g^{start} \quad 3.4$$

Where $SU_{g,r,t}$ is a generator start-up, and c_g^{start} are the start-up costs of that generator.

The non-served energy costs are calculated by the amount of non-served energy, $NSE_{r,t}$, multiplied by the cost of NSE, c^{NSE} summed over all region and all time periods, see equation 3.5.

$$C^{NSE} = \sum_{r \in R} \sum_{t \in T} NSE_{r,t} \cdot c^{NSE} \quad 3.5$$

Finally, an optional tax on CO₂ emissions is included in the total cost by determining the fuel use of a generator, $\frac{P_{g,r,t}}{\eta_g}$, and multiplying this with the cost of CO₂ emissions, $c_g^{CO_2}$ for that generator (dependent on fuel type).

$$C^{CO_2} = \sum_{g \in G} \sum_{r \in R} \sum_{t \in T} \frac{P_{g,r,t}}{\eta_g} \cdot c_g^{CO_2} \quad 3.6$$

3.2.2. Constraints

The objective function is subject to numerous operational constraints. The following subsections elaborate and these constraints.

3.2.2.1. Load constraint

The load constraint balances supply and demand in every region and during every time step. The equation proposed by Palmintier (2013) is adapted to include both the possibility of electricity storage and transport. Equation 3.7 shows the load equation.

$$\sum_{g \in G} P_{g,r,t} - \sum_{s \in S} P_{s,r,t} + \sum_{r' \in R} T_{r,r',t}^{import} - \sum_{r' \in R} T_{r,r',t}^{export} + NSE_{r,t} - P_{r,t}^{curtail} = l_{r,t} \quad \forall r, t \quad 3.7$$

The produced power, $P_{g,r,t}$, of all generators, g , the stored power, $P_{s,r,t}$, of all storages, s , the imported and exported power, $T_{r,r',t}^{import}$ and $T_{r,r',t}^{export}$, from region, r , to another region, r' , the non served energy, $NSE_{r,t}$, and the curtailed power, $P_{r,t}^{curtail}$, needs to be equal to the load, $l_{r,t}$. Non-served energy is the power that is not delivered to the end consumer, curtailment is the renewable energy that cannot be used and therefore needs to be curtailed. This equation has to hold for all regions and all time periods, t .

3.2.2.2. Transmission constraints

Transmission is the flow of power between two regions or power nodes. The import in a region, $T_{r,r',t}^{import}$, equals the export from another region, $T_{r',r,t}^{export}$, multiplied by the transport losses which account for 5% per 1000 km (Eq. 3.8). The exported power (which is higher than the imported power) needs to stay below the installed net transfer capacity, $NTC_{r,r'}$, of a line between two regions, r and r' (Eq. 3.9).

$$T_{r,r',t}^{import} = T_{r',r,t}^{export} \cdot \left(1 - \frac{0.05 \cdot km_{r,r'}}{1000}\right) \quad \forall r, r', t \quad 3.8$$

$$T_{r,r',t}^{export} \leq NTC_{r,r'} \quad \forall r, r', t \quad 3.9$$

3.2.2.3. Unit states

The state, $UC_{g,r,t}$, of a cluster is the integer number that represents the amount of units within the cluster that are turned on. It is calculated by taking the state of the

cluster during the previous time step, $UC_{g,r,t-1}$, adding the number of units that have started up, $SU_{g,r,t}$, and subtracting the number of units that shut down, $SD_{g,r,t}$, see equation 3.10. Notice that both the start-up and shut-down variables are also integer numbers.

To improve the speed of the optimization model, clustered unit commitment constraints are only applied to generators with considerable start-up costs or minimum output levels. Other generators, such as hydro power plants do not have an integer unit commitment number. This means that this equation only has to hold for all generators, g , that are under unit commitment, represented by the set, G_{uc} .

$$UC_{g,r,t} = UC_{g,r,t-1} + SU_{g,r,t} - SD_{g,r,t} \quad \forall g \in G_{uc}, r, t \quad 3.10$$

The number of committed units within a cluster needs to stay below the total amount of units that are in the cluster, $n_{g,r,t}$, minus the amount of units that are under maintenance, $M_{g,r,t}$. (integer number). This concept is shown mathematically in equation 3.11 and graphically in Figure 3-3.

$$UC_{g,r,t} \leq n_{g,r,t} - M_{g,r,t} \quad \forall g \in G_{uc}, r, t \quad 3.11$$

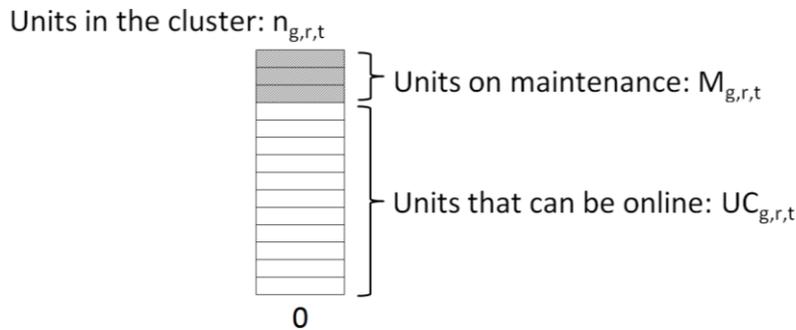


Figure 3-3: Graphical representation of maximum units online within cluster (B. S. Palmintier, 2013)

3.2.2.4. Generator output limits

The power output, $P_{g,r,t}$, of units that are under clustered unit commitment, $g \in G_{uc}$, needs to remain lower than the number of committed generators, $UC_{g,r,t}$, multiplied by the maximum output of individual generators within the cluster, p_g^{max} . Besides thermal generators also have a lower limit under which they cannot operate in a stable manner. Therefore, the power output of a unit commitment cluster needs to be higher than the number of committed units multiplied by the minimum output of an individual unit in the cluster, p_g^{min} . See equation 3.12.

$$UC_{g,r,t} \cdot p_g^{min} \leq P_{g,r,t} \leq UC_{g,r,t} \cdot p_g^{max} \quad \forall g \in G_{uc}, r, t \quad 3.12$$

Power output of generators that are not under unit commitment, $g \notin G_{UC}$, needs to stay below the total amount of available capacity, p_g^{avail} . The minimum output level needs to stay above zero (Eq. 3.13).

$$0 \leq P_{g,r,t} \leq p_{g,r}^{avail} \quad \forall g \notin G_{UC}, r, t \quad 3.13$$

Each region within the model can have multiple sub-regions for renewables; this can be useful when working with larger regions with different meteorological time series. The output of generators, g belonging to the set of renewable energy sources, G_{RES} , is dependent on meteorological time series data from the sub-region where the RES is located, $\varphi_{g,sub-r,t}$, which is fed into the model as a percentage of capacity (kW output / kW installed). The constraint is shown mathematically in equation 3.14; a graphical representation of regions and sub-regions is given in Figure 3-4. Although renewables can be switched off, equation 3.14 uses an equality sign. Switching off renewables is captured in the curtailment variable, $P_{r,t}^{curtail}$, in the load equation (Eq. 3.7).

$$P_{g,r,t} = \sum_{sub-r \in SR} p_{g,sub-r}^{avail} \cdot \varphi_{g,sub-r,t} \quad \forall g \in G_{RES}, r, t \quad 3.14$$

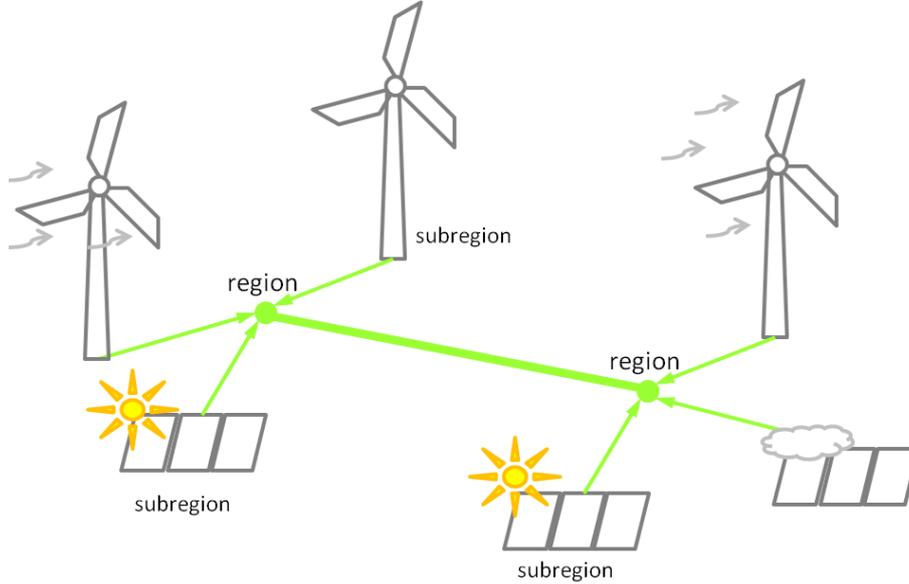


Figure 3-4: Graphical presentation of distinction between regions and sub-regions

3.2.2.5. Ramping constraints

Ramping constraints impose limits on the maximum change of the power output of a generator between 2 time steps. In principle, the maximum difference in power output, $P_{g,r,t} - P_{g,r,t-1}$, needs to be lower than the number of units committed within a cluster multiplied by the maximum change in power of a single unit within the cluster, Δp_g^{max} . However, some units have a minimum output level that is higher than their maximum change in output level, $p_g^{min} < \Delta p_g^{max}$. To allow these units to start up and shut down, two extra terms are added to the ramping constraints of clustered units. Equation 3.15 shows the ramping up constraint for clustered units, 3.16 the constraints for ramping down a cluster.

$$\begin{aligned} P_{g,r,t} - P_{g,r,t-1} &\leq (UC_{g,r,t} - SU_{g,r,t}) \cdot \Delta p_g^{max} \\ &\quad + SU_{g,r,t} \cdot \max(p_g^{min}, \Delta p_g^{max}) \\ &\quad - SD_{g,r,t} \cdot p_g^{min} \quad \forall g \in G_{UC}, r, t \end{aligned} \quad 3.15$$

$$\begin{aligned} P_{g,r,t-1} - P_{g,r,t} &\leq (UC_{g,r,t} - SU_{g,r,t}) \cdot \Delta p_g^{max} \\ &\quad + SD_{g,r,t} \cdot \max(p_g^{min}, \Delta p_g^{max}) \\ &\quad - SU_{g,r,t} \cdot p_g^{min} \quad \forall g \in G_{UC}, r, t \end{aligned} \quad 3.16$$

Ramping constraints for generators that are not under clustered unit commitment the ramping constraints are only dependent on the maximum change in power output, Δp_g^{max} (see Eq. 3.17 and 3.18).

$$P_{g,r,t} - P_{g,r,t-1} \leq \Delta p_g^{max} \quad \forall g \notin G_{UC}, r, t \quad 3.17$$

$$P_{g,r,t-1} - P_{g,r,t} \leq \Delta p_g^{max} \quad \forall g \notin G_{UC}, r, t \quad 3.18$$

3.2.2.6. Storage level and maximum storage power

The intertemporal relation of the storage level is determined by equation 3.19. The storage level, $Q_{s,r,t}$, of storage technology, s , is equal to the storage level of the previous time step minus the power delivered by storage multiplied by the production efficiency of the storage, $P_{g,r,t} \cdot \eta_p$, plus the power stored by the storage technology multiplied by the storage efficiency, $P_{s,r,t} \cdot \eta_s$. If the storage level for hydro power is calculated, an extra term for natural inflow, $\varphi_{s,r,t}$, is added.

$$Q_{s,r,t} = Q_{s,r,t-1} - P_{g,r,t} \cdot \eta_p + P_{s,r,t} \cdot \eta_s + \varphi_{s,r,t} \quad \forall s, r, t \quad 3.19$$

The energy stored (kWh) needs to remain lower than the storage capacity, q_s^{max} , and higher than zero, see equation 3.20. Secondly, the storage power (kW added to the storage),

$P_{s,r,t}$, plus the in section 3.2.2.8 described reserve capacity, $R_{s,r,t}$, needs to remain below the installed capacity, $p_{s,r}^{avail}$, see equation 3.21.

$$0 \leq Q_{s,r,t} \leq q_s^{max} \quad \forall s, r, t \quad 3.20$$

$$P_{s,r,t} + R_{s,r,t} \leq p_{s,r}^{avail} \quad \forall s, r, t \quad 3.21$$

It is assumed that every storage technology has 60% of its energy storage capacity available from the start of the simulation ($t = 1$), a constraint is added to make sure that the storage is filled for 60% at the end of the run ($t = T$), see equation 3.22. This assumption is based on the description of the storage levels as can be found in ENTSO-E's monthly statistic reports (ENTSO-E, 2013a).

$$Q_{s,r,t} \leq q_s^{max} \cdot 0.6 \quad \forall s, r, t = 1 \text{ or } t = T \quad 3.22$$

3.2.2.7. Maintenance constraints

As the clustered unit commitment model is deterministic unplanned shut-downs are not necessary, however all units do have a yearly maintenance requirement. The sum over the whole year of the amount of units within a cluster that are on maintenance, $M_{g,r,t}$, needs to be larger than the yearly maintenance, m_g^{yearly} , requirement (Eq. 3.23). The used time notation, t , suggests that units can be on maintenance one hour and be up and running the next hour, yet, within the model the maintenance decision is taken on a weekly basis, which makes the model more efficient to solve and makes it more realistic. A second constraint is added to ensure that not more than 15% of generator cluster in a region is under maintenance, this constraint represents the limit on regional maintenance personnel (Eq. 3.24).

$$\sum_{t \in T} M_{g,r,t} \geq m_g^{yearly} \cdot n_{g,r} \quad \forall g \in G_{UC}, r \quad 3.23$$

$$M_{g,r,t} \leq n_{g,r} \cdot 0.15 \quad \forall g \in G_{UC}, r, t \quad 3.24$$

Units that are not under clustered unit commitment are derated by their annual average availability factor, m_g^{avail} .

$$p_{g,r}^{avail} = p_{g,r}^{total} \cdot m_g^{avail} \quad \forall g \notin G_{UC}, r \quad 3.25$$

3.2.2.8. CO₂ constraint

A CO₂ cap limits the total amount of CO₂ emissions at a pre-defined value, CO_2^{max} (see Eq. 3.26). This constraint replicates a CO₂ cap and trade system that is applied in the European Union.

$$\sum_{g \in G} \sum_{r \in R} \sum_{t \in T} \frac{P_{g,r,t}}{\eta_g} \cdot CO_2^{intensity}_g \leq CO_2^{max} \quad 3.26$$

3.2.2.9. Reserve constraints

For a power system to operate safely, produced and consumed power need to remain in a constant equilibrium. A deviation from this equilibrium results in variations in frequency (ENTSO-E operation handbook- Appendix). Many uncertainties surround the operation of an electricity system. These uncertainties include demand uncertainty, renewable output uncertainty and unplanned generator or transmission line outages (Palmintier, 2013).

Reserves are used to be able to adequately respond to deviations between the expected and observed situation. Reserves are provided by generators that keep a margin between their output level and their minimum or maximum output; this allows them some leeway to quickly change their power production. Different types of reserves exist, depending on the time horizon over which they have to respond to contingencies.

Reserve requirements

The European grid is largely interconnected and operates on a single frequency. If a contingency occurs, the frequency change will affect the entire synchronised area. Therefore, the reserves requirements of transmission grid operators (TSO's) within the grid are determined by the European Network of Transmission System Operators for Electricity (ENTSO-E). The ENTSO-E describes three types of reserves: primary, secondary and tertiary reserves. Figure 3-5 gives an overview of the three reserve mechanisms.

Primary reserves are used to automatically respond to deviations from the frequency set point. If the demand unexpectedly increases, the system frequency over the entire synchronous area will increase. Generators over the entire area will respond by increasing their output and re-establish the balance of supply and demand. Every TSO needs to provide primary reserves proportional to their yearly energy use, q_r^{year} , in the total energy used of the synchronised area. The maximum contingency, $p^{contingency}$, is determined to be 3000 MW (ENTSO-E). Equation 3.27 shows the calculation of the primary reserves for an individual region.

Secondary reserves restore the balance of individual control areas. After the automatic primary reserve response of the generators throughout the ENTSO-E area, the power exchange over the interconnections between the areas differs from agreed set points. Secondary reserves in the area which originally caused the deviation are used to return to the agreed set points. The amount of secondary reserves are dependent on the maximum load within a region, L_r^{max} , and empirically determined safety values, see equation 3.28 (ENTSO-E).

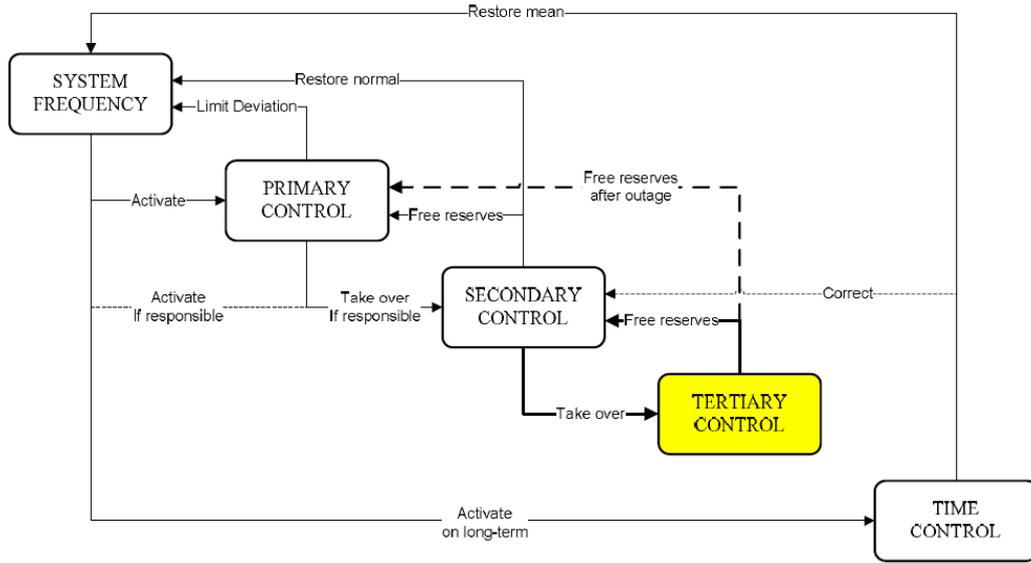


Figure 3-5: Overview of ENTSO-E control mechanisms (ENTSO-E)

Tertiary reserves are the reserves that are used to free the secondary reserves if a contingency isn't solved. In a sense tertiary reserves are both part of the scheduling domain and the reserves (ENTSO-E). Therefore, the tertiary reserves are combined with the secondary reserves in this thesis.

$$R_{r,t}^{prim} = \frac{q_r^{year}}{\sum_{r \in R} q_r^{year}} \cdot p^{contingency} \quad \forall r, t \quad 3.27$$

$$R_{r,t}^{sec} = \sqrt{10 * L_r^{max} + 150^2} - 150 \quad \forall r, t \quad 3.28$$

The sum of primary reserves provided by all generators, $R_{g,r,t}^{PrimUp}$, in a certain region needs to be larger than the primary reserve requirement in that region, $R_{r,t}^{prim}$. This applies for both reserves capable of regulating up (Eq. 3.29) and reserves capable of regulating down (Eq. 3.30). The same holds for secondary reserves, presented in equation 3.31 and 3.32.

$$\sum_{g \in G} R_{g,r,t}^{PrimUp} \geq R_{r,t}^{prim} \quad \forall g, r, t \quad 3.29$$

$$\sum_{g \in G} R_{g,r,t}^{SecUp} \geq R_{r,t}^{sec} \quad \forall g, r, t \quad 3.30$$

$$\sum_{g \in G} R_{g,r,t}^{PrimDown} \geq R_{r,t}^{prim} \quad \forall g, r, t \quad 3.31$$

$$\sum_{g \in G} R_{g,r,t}^{SecDown} \geq R_{r,t}^{sec} \quad \forall g, r, t \quad 3.32$$

Part of the secondary reserves can be supplied by thermal generators that have very short start up times, even if they are off. The units capable of doing this are open cycle gas turbines. However, the amount of quick-start reserves, $R_{g,r,t}^{Qstart}$, can not exceed 50% of total secondary reserve requirements (Eq. 3.33). Equation 3.30 is replaced with equation 3.34.

$$\sum_{g \in G_{Qstart}} R_{g,r,t}^{Qstart} \leq 0.5 \cdot R_{r,t}^{sec} \quad \forall r, t \quad 3.33$$

$$\sum_{g \in G} R_{g,r,t}^{SecUp} + \sum_{g \in G_{Qstart}} R_{g,r,t}^{Qstart} \geq R_{r,t}^{sec} \quad \forall g, r, t \quad 3.34$$

Many recent studies suggest that the introduction of renewables increases the need for reserve capacity (Holttinen, 2009; Milligan 2010). Wind and solar output are dependent on local weather conditions that can be hard to predict. A larger installed capacity of wind power increases the absolute forecasting error, threatening grid stability. Various increases in reserve requirements have been suggested. Bertsch (2012) expects a reserve margin of 10% of the expected power output of both wind and solar. Ibrahim (2011) projects reserves of 3 to 5% of total installed wind capacity while Holttinen (2009) uses various studies to come to the conclusion that reserves need to increase 2 to 8% depending on the wind penetration level. Beaudin (2010) shows that the need for reserves increases with 2-6% in situation with 20% wind penetration and 3-8% with systems with 30% penetration. Strbac (2012) claims that forecasting accuracy for wind is approximately 10% for 4 hours in advance, this will reduce to 5 or 6% when weather models improve. The model therefore has an inbuilt option to increase the reserves with 10% of renewable output.

Generator output limits with reserves

Generators providing reserves need to keep their power output, $P_{g,r,t}$, including their reserve margin below their maximum rated capacity and above their minimum rated capacity. Equations 3.35 and 3.36 show the formulation for generators under clustered unit commitment constraints. These equations replace equation 3.12 which determines maximum power output without considering reserves. Equations 3.37 and 3.38 show the formulation for non-unit commitment generators, and replace equation 3.13.

$$P_{g,r,t} + R_{g,r,t}^{PrimUp} + R_{g,r,t}^{SecUp} \leq UC_{g,r,t} \cdot p_g^{max} \quad \forall g \in G_{UC}, r, t \quad 3.35$$

$$P_{g,r,t} - R_{g,r,t}^{PrimUp} - R_{g,r,t}^{SecUp} \geq UC_{g,r,t} \cdot p_g^{min} \quad \forall g \in G_{uc}, r, t \quad 3.36$$

$$P_{g,r,t} + R_{g,r,t}^{PrimUp} + R_{g,r,t}^{SecUp} \leq p_g^{max} \quad \forall g \notin G_{UC}, r, t \quad 3.37$$

$$P_{g,r,t} - R_{g,r,t}^{PrimUp} - R_{g,r,t}^{SecUp} \geq 0 \quad \forall g \notin G_{uc}, r, t \quad 3.38$$

Maximum reserve capabilities

The amount of reserves that a generator is able to provide is dependent on how fast it is able to change its output. Primary reserves need be fully deployed within 30 seconds after an incident. This means that the primary reserves delivered by cluster of generators, $R_{g,r,t}^{PrimUp}$, can not exceed its maximum ramping capacity, Δp_g^{max} , per 30 seconds (1/120 of an hour) multiplied by the number of units within the cluster that are turned on $UC_{g,r,t}$, see quation 3.39 and 3.40 for primary up and primary down reserves respectively.

$$R_{g,r,t}^{PrimUp} \leq \frac{\Delta p_g^{max}}{120} \cdot UC_{g,r,t} \quad \forall g \in G_{UC}, r, t \quad 3.39$$

$$R_{g,r,t}^{PrimDown} \leq \frac{\Delta p_g^{max}}{120} \cdot UC_{g,r,t} \quad \forall g \in G_{UC}, r, t \quad 3.40$$

Secondary reserves on the other hand need to come online within 15 minutes in order to replace the primary reserves. Their capabilities of providing these reserves are again based on their maximum ramping rates, this time per one fourth of an hour, and the number of units within the cluster that are online (Eq. 3.41 and 3.42).

$$R_{g,r,t}^{SecUp} \leq \frac{\Delta p_g^{max}}{4} \cdot UC_{g,r,t} \quad \forall g \in G_{UC}, r, t \quad 3.41$$

$$R_{g,r,t}^{SecDown} \leq \frac{\Delta p_g^{max}}{4} \cdot UC_{g,r,t} \quad \forall g \in G_{UC}, r, t \quad 3.42$$

For generators not under unit commitment the same technical constraints apply, however, they are not dependent on the states of the units in the cluster (Eq. 3.43 - 3.46). This automatically means that non unit commitment clusters are able to provide quick start reserves at all times, however, within the model these reserves are not seen as quick-start as they have a unlimited regulating range within their capacity.

$$R_{g,r,t}^{PrimUp} \leq \frac{\Delta p_g^{max}}{120} \quad \forall g \notin G_{UC}, r, t \quad 3.43$$

$$R_{g,r,t}^{SecUp} \leq \frac{\Delta p_g^{max}}{4} \quad \forall g \notin G_{UC}, r, t \quad 3.44$$

$$R_{g,r,t}^{PrimDown} \leq \frac{\Delta p_g^{max}}{120} \quad \forall g \notin G_{UC}, r, t \quad 3.45$$

$$R_{g,r,t}^{SecDown} \leq \frac{\Delta p_g^{max}}{4} \quad \forall g \notin G_{UC}, r, t \quad 3.46$$

As explained before, open cycle gas turbines are also capable of providing quick start reserves. The amount of quick start reserves, $R_{g,r,t}^{Qstart}$, can not exceed their ramping rate per quarter of an hour multiplied the number of units that are offline (number of units within cluster, $n_{g,r,t}$, minus the number of units in maintenance, $M_{g,r,t}$, minus the unit that are online, $UC_{g,r,t}$).

$$R_{g,r,t}^{Qstart} \leq \frac{\Delta p_g^{max}}{4} \cdot (n_{g,r,t} - M_{g,r,t} - UC_{g,r,t}) \quad \forall g \in G_{Qstart}, r, t \quad 3.47$$

Maximum reserve capabilities for storage

The reserve capabilities of storage plants are, just like other generators, dependent on their maximum ramping rates. However, storage plants are not only power constrained, but also energy constrained. In other words, they need to have enough energy stored to provide the reserves if needed. This works in two directions, an empty storage cannot provide up reserves (deliver power) and a completely filled storage is not able to provide down reserves (take more power).

Primary reserves need to be delivered for 15 minutes before secondary reserves take over. Therefore, the stored energy, $Q_{s,r,t}$, is divided by one fourth of an hour for primary up reserves (eq. 3.48). For downward reserves, the stored energy is subtracted from the maximum storage capacity, q_s^{max} , and divided by $\frac{1}{4}$ of an hour (eq. 3.49).

$$R_{s,r,t}^{PrimUp} \leq \frac{Q_{s,r,t}}{1/4} \quad \forall s, r, t \quad 3.48$$

$$R_{s,r,t}^{PrimDown} \leq \frac{(q_s^{max} - Q_{s,r,t})}{1/4} \quad \forall s, r, t \quad 3.49$$

No clear guidelines can be found on how long the secondary reserves need to operate for. But, as secondary and tertiary reserves have been combined, the assumption is made that these reserves need to be able to deliver for 24 hours, see equation 3.50 and 3.51.

$$R_{s,r,t}^{SecUp} \leq \frac{Q_{s,r,t}}{24} \quad \forall s, r, t \quad 3.50$$

$$R_{s,r,t}^{SecDown} \leq \frac{(q_s^{\max} - Q_{s,r,t})}{24} \quad \forall s, r, t \quad 3.51$$

3.3. Proposed speed up strategies

The in the previous subsection presented model formulation is highly complex and finding an optimal solution, even with the most advanced solvers takes a lot of computational power. This subsection proposes solutions to speed up the solution search. Chapter 4 tests whether these simplifications have an effect on the model results.

3.3.1. Sub models using economic dispatch pre-run

One procedure that can help reduce the time that it takes to find an optimal solution is to use a more simple economic dispatch model that optimizes the power system over a whole year. The complex clustered unit commitment model is then cut up in blocks (weeks or months) and each block is solved separately. The individual blocks use the solution from the economic dispatch model to set start and end conditions for the blocks, such as the storage levels. The cluster states in the first hour of a block are taken from the last hour of the previous block. This approach is adapted from Carlo Brancucci Martínez-Anido's (2013) EUPowerDispatch model.

3.3.2. Relaxed mixed integer programming

As explained in subsection 3.1.2, solving a unit commitment model is much harder than solving an economic dispatch model due to the addition of integer variables. These integer values need to be individually considered through methods that are more time consuming than the extremely efficient family of simplex optimization methods (IBM, 2014).

The fact that the presented model uses integer commitment states allows for the linearization of these states. This is called relaxed mixed integer programming. Relaxing the integer constraints means that all integers become linearized. This implies that for instance 3.2 or 5.8 generators can be committed instead of only 3 or 6. A large part of the start-up costs are still considered this way, however, minimum output of levels of thermal generators are lost.

3.3.3. Solving only a pre-selected part of the year

The time it takes to solve an optimization model increases exponentially with the amount of equations and variables that need to be optimized. Small reductions in model size can therefore have a large impact on the amount of time that is necessary to solve the model. To decrease the size of the problem two solutions are proposed. Firstly, the time step of the model can be increased. Currently, the model has been described as having a resolution of 1 hour. Increasing the time step to two hours reduces the model size with 50%. Secondly, it might not be necessary to consider every hour of the year. Making a selection of time blocks of for instance a day or a week throughout the year can reduce the model size.

3.3.4. Derated maintenance

Another speed up strategy simplifies the optimization of maintenance presented in equations 3.23 and 3.24 (page 30). These equations find the optimal time to do maintenance, however, an assumption that is made in the literature often takes a derate factor for maintenance (Palmintier, Hirth, Carlo), as is done with the units not under unit commitment. In the case of derated maintenance, equation 3.52 replaces 3.23 and 3.24.

$$p_{g,r}^{avail} = p_{g,r}^{total} \cdot m_g^{avail} \quad \forall g \in G_{UC}, r \quad 3.52$$

3.3.5. Combined reserves

Finally, one could consider using combined reserves. Although Palmintier (2013) show that this significantly decreases the accuracy it is a highly effective speed up strategy. The strategy is to combine the necessary primary and secondary reserves into one type of reserves, dramatically decreasing the necessary reserve equations that the model needs to solve. Appendix A contains the updated formulation for combined the combined reserve equations.

3.4. Scenario selection and data usage

The model presented in the previous subsections is highly complex and is not able to find an optimal solution if all countries in the Europe are included in the model. Therefore this subsection presents a scenario where all countries are combined into three regions: The north of Europe, the centre of Europe and the south of Europe. The division is based on meteorological conditions of the individual countries.

Secondly, many of the functions presented in subsection 3.2 and 3.3 contain fixed parameters. Parameters contain information about technical details such as generator efficiency but also patterns of demand. The parameters need to be fed to the model and are used to determine the optimal solution. This section therefore also describes the parameters that are used in the various model runs.

3.4.1. Scenario description

As mentioned earlier, the model does not solve for optimization problems that cover the entire year for large numbers of nodes. Therefore various speed up strategies have been proposed, however considering the optimal dispatch of generators for every individual country in Europe is still too computationally demanding. To overcome this issue, a conceptual scenario is used to combine all individual countries into a small amount of regions.

However, relevant conclusions can only be drawn if the conceptual model captures the important characteristics of the real system. Therefore a conceptual model that does not represent the European electricity system on a one-to-one basis still needs to behave in the same general manner. In this way, the value of electrical energy storage can still be determined.

In the future, the energy system will be largely dependent on renewable energy sources (RES). However, the sources for renewable energy, like wind and solar radiation, are not evenly distributed over Europe. As can be seen from Figure 3-6, solar power is abundant in the south of Europe. Countries like Spain and Italy have a far larger yearly irradiance than northern countries, which also means that investments in solar power are more economically efficient in southern countries. On the contrary, wind is more profitable in the countries surrounding the North Sea, shown in Figure 3-7. From an economic point of view, solar power should be installed in the south and wind power in the north, maximally using the available resources.

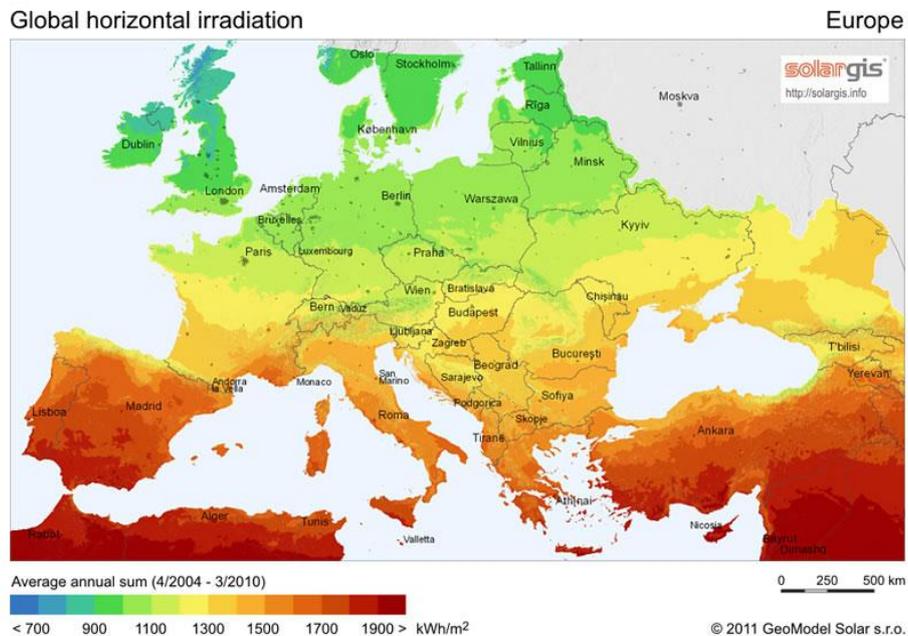


Figure 3-6: Solar irradiance in Europe (Green Rhino Energy, 2014)

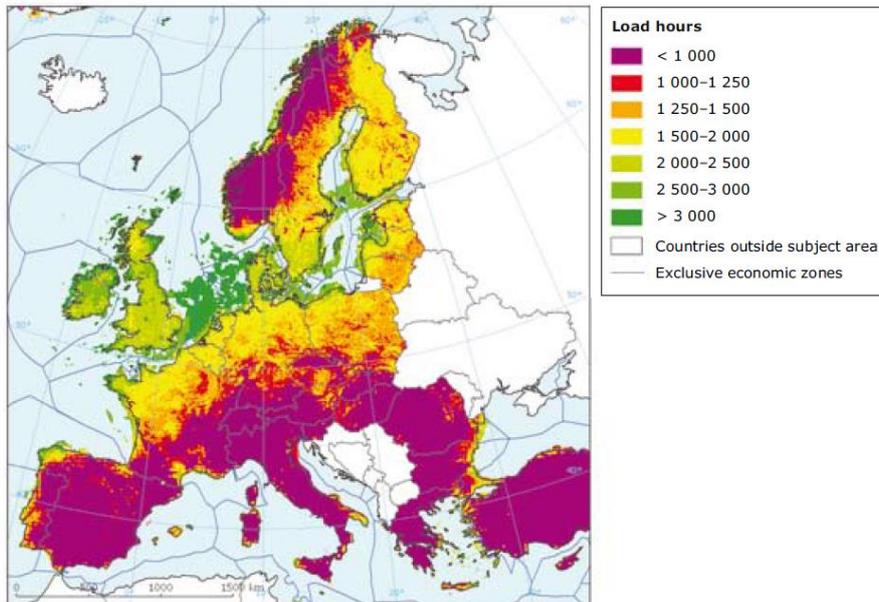


Figure 3-7: Wind power potential in Europe (EEA, 2009)

This skewed distribution of energy resources will have a large impact on the distribution of renewable output patterns across Europe. Solar power is only available during the day and has a higher output in summer than in winter. Wind power has more output in winter. This will result in a situation presented in Figure 3-8. In summer electricity produced by PV cells is transported from the south of Europe into the northern parts of Europe while wind generation is transported to the south during the winter.

A European electricity system with a limited number of regions would therefore best be represented by a two node system, one node for the north, and one for the south. However, both the north and the south of Europe already have large amounts of hydro storage capacity available. This already installed capacity reduces the value of additional storage. The purpose of this thesis is to determine the value that electricity storage can have when introducing more renewables into the grid and how this value interrelates with the value of additional transmission capacity.

The availability of storage in the northern part of Europe is mostly dependent on the hydro resources of Scandinavia. However, mainland Europe is not heavily connected to Scandinavia due to the North Sea and Baltic Sea. This results in the fact that wind energy produced in wind rich countries on the south side of the North Sea is not easily stored in the Scandinavian hydro reservoirs. Modelling Europe as a two node system would therefore result in a situation where energy can too easily be stored.

To overcome this issue, Scandinavia can be regarded as a separate node, resulting in a European system with three nodes: the hydro power and hence storage rich north, the wind rich center and the solar and hydro rich south. Figure 3-9 shows a map of the ENTSO-E members in which the countries are divided in 3 nodes.

The countries in central Europe have relatively low opportunities for creating hydro storage. Therefore the current division lends itself for an analysis regarding the value of installing additional storage capacity in the central European node and how the amount of transmission to both southern and northern Europe affects the value of storage.



Figure 3-8: Solar and wind exchange (EEA, 2010)

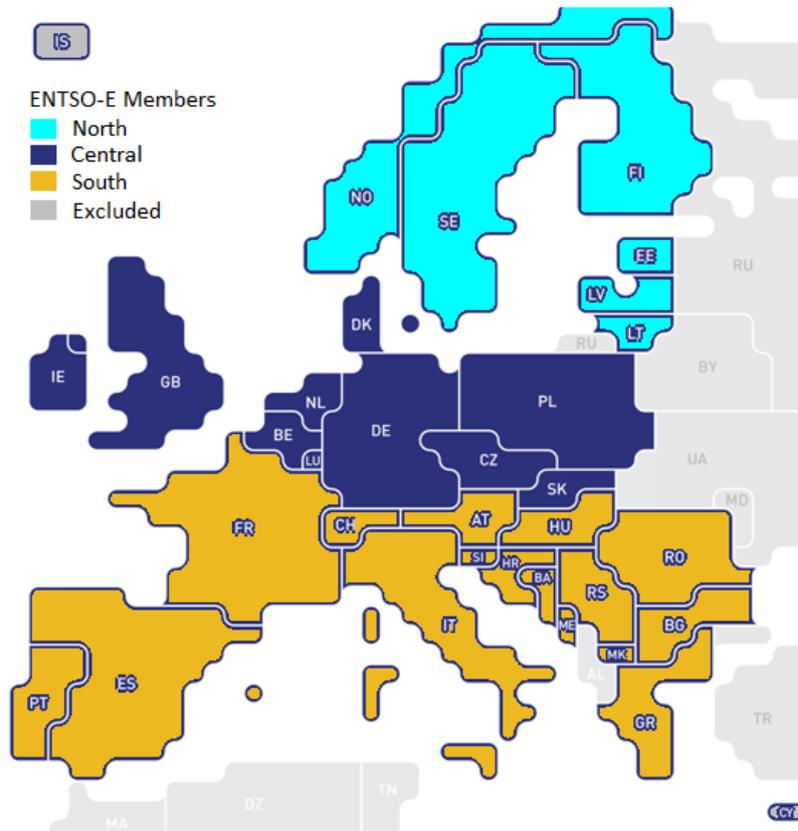


Figure 3-9: The division between Northern, Central and Southern Europe in the three node model, image adapted from (ENTSO-E, 2014)

3.4.2. Transmission capacity

The amount of transmission capacity between the nodes is the sum of individual capacities of every country that has a link with a country in another node. This for instance means that the capacity installed between the Netherlands and Belgium (both in the central node) is unlimited as they are in the same node. The installed capacity for 2012 is based on the net transfer capacities as published by in ENTSO-E's NTC matrix (2011).

The net transfer capacities for 2030 are based upon the 2025 transfer capacities presented by Carlo Brancucci Martínez-Anido (2013).

Table 3.1 presents the used transfer capacities between the nodes. Although some transmission links have different maximum capacities dependent on the direction of the power flow, the maximum transfer capacity has been used for all of these flows.

Table 3.1: Net transfer capacities between nodes

Scenario	North ↔ Central	South ↔ Central
2012	4 GW	15 GW
2030	11.5 GW	25.5 GW

3.4.3. Installed generation capacity

Every year, the ENTSO-E publishes expectations about the development of installed generation capacity of its member TSO's in the Scenario Outlook and Adequacy Forecast (SO&AF). Data about installed capacities used in this thesis comes from the 2012-2030 and 2013-2030 version of the SO&AF (ENTSO-E, 2012b, 2013b). Two different generation mixes are used in this thesis: a mix for the year 2012 and one for 2030.

The capacity values for 2012 are taken from the best estimate scenario B (ENTSO-E, 2012b). The generation capacity in a node (North, South or Central) is taken as the sum of the generation capacity of the individual countries within the nodes. Figure 3-10 and Figure 3-11 show the generation mix in the individual countries for the different nodes. The generation mix is given as a percentage of total demand in the country/node. Besides the generation mix the graphs also show the maximum demand (which is automatically 100%), and the average and minimum demand. These lines can be used to determine which generators supply what part of the load. The capacity stated on top of the bars is the total installed generation capacity; this includes renewable capacity that has availability dependent on weather patterns.

As can be seen from the capacity mix of northern Europe (Figure 3-10), a country like Finland uses gas to provide power during peak demand, however, when combining all the individual countries into one single node, the entire demand range falls within the hydro power range. Although the amount of energy hydro power can deliver is limited by the natural inflow of rivers, this still implies that gas plants are used less than they would be in individual countries.

The generation mix of the central and southern node shows the same effect. Although individual countries like the Netherlands, Ireland and Italy might use gas as their peaking plant, the amount of cheaper capacity over the entire region is so large that the more expensive gas plants are almost pushed out of the merit order. This trend is strengthened by the fact that a lot of renewable capacity is installed, which further reduces the use of the more expensive gas plants.

Figure 3-12 shows this by displaying the residual load, which is the demand minus the output of uncontrollable renewables, over the installed capacity. The installed capacity is adjusted for an average availability of generation capacity of 85%. The figure shows that in Germany, the hours with the lowest demand are covered by only nuclear and lignite plants, when the residual load increases, more expensive generators are added to the electricity mix. On the other hand, the capacity mix of the Netherlands shows that even in the hours of lowest demand, gas plants are part of the mix. Increasing demand will not cause a different fuel types to be used.

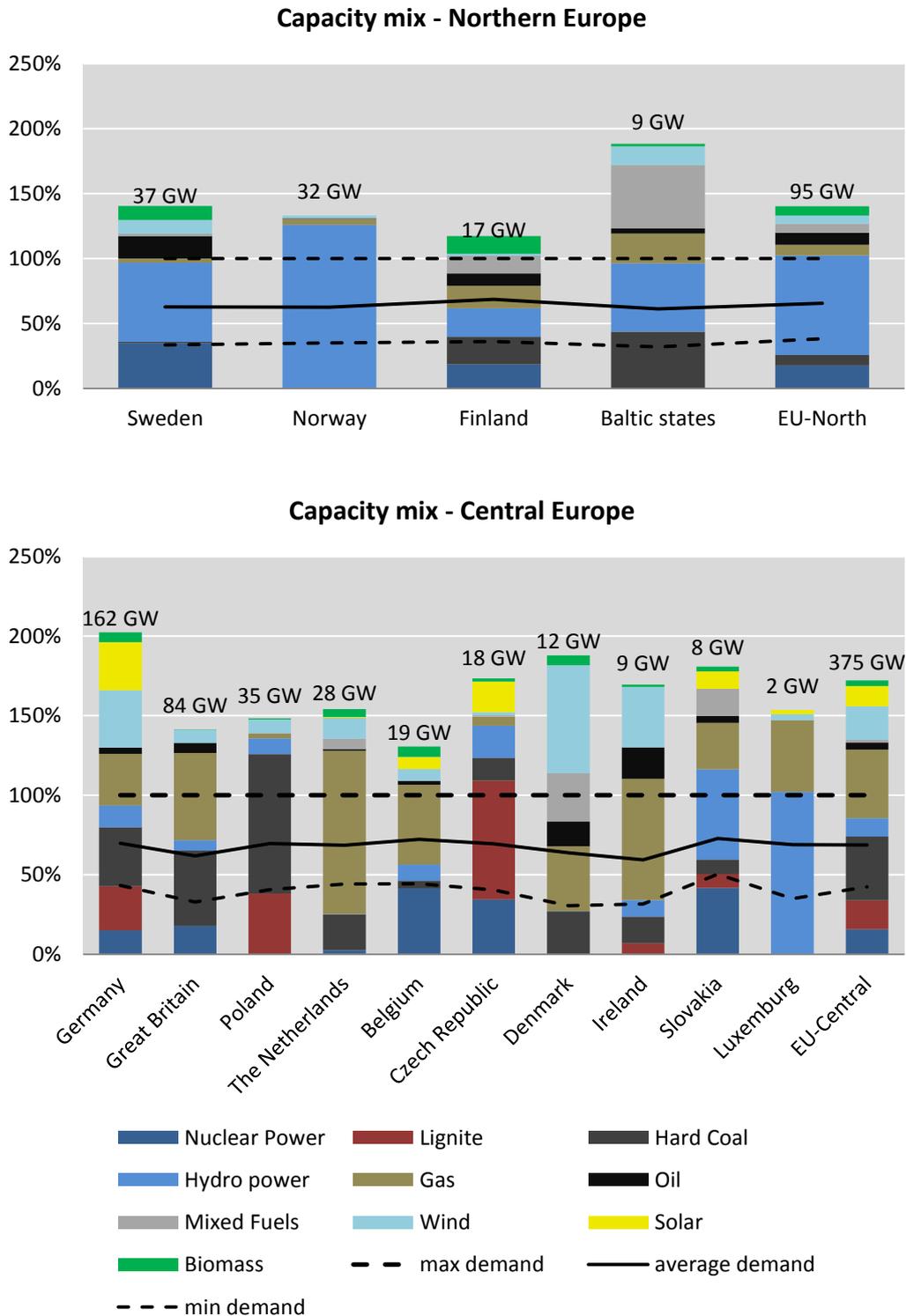


Figure 3-10: The capacity mix of individual countries in Northern and central Europe combined with the capacity mix of the EU-North node, the total installed capacity is given above the bars

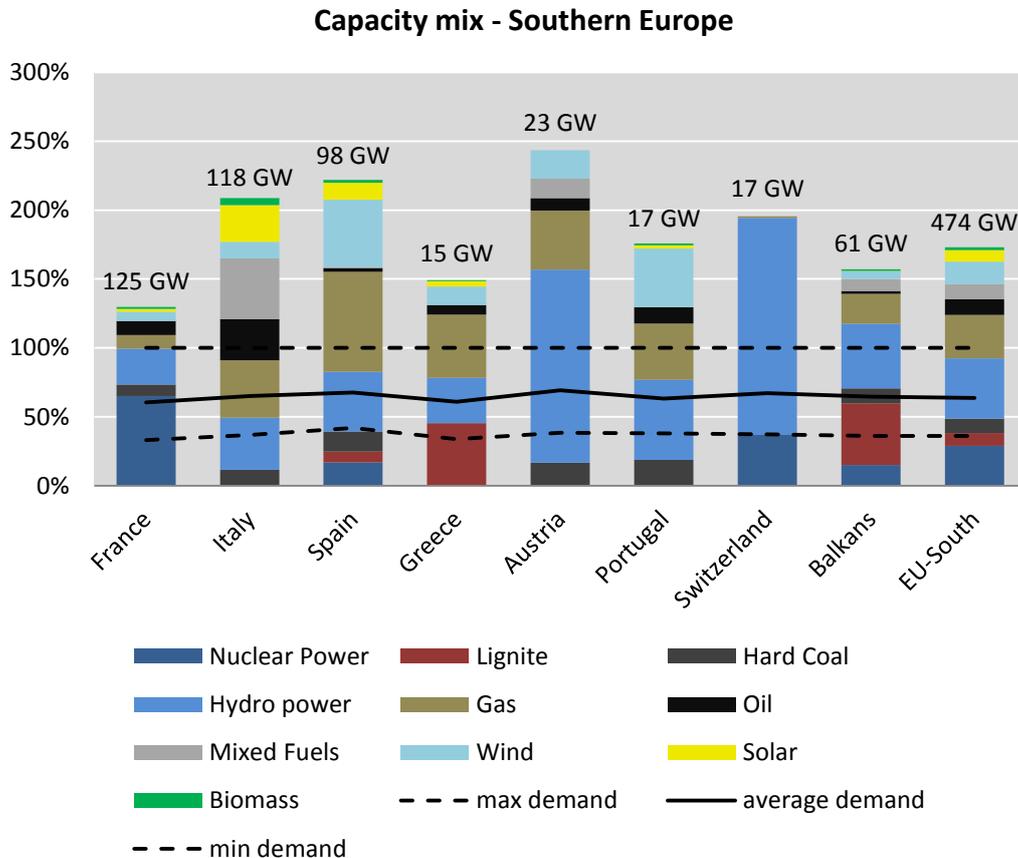


Figure 3-11: The capacity mix of individual countries in Southern Europe combined with the capacity mix of the corresponding node, the total installed capacity is given above the bars

The bottom graph in Figure 3-12 shows the residual demand curve of the Central European node and the generation mix of this node. This graph shows that combining all the individual countries results in a capacity mix that resembles that of Germany. The fact that gas is used during many hours of the year in the Netherlands is lost.

The capacity values for 2030 are taken from the in the SO&AF presented 2030 Vision 3. Vision 3 is based upon a scenario where the future generation mix is on track of reaching the 2050 decarbonization objectives. This vision also incorporates the growing public aversion to nuclear plants (ENTSO-E, 2013b). The capacities for 2012 and 2030 are shown in Figure 3-13. Table 3.2 shows the total controllable and non-controllable capacity and maximum demand in the three nodes for both 2012 and 2030.

Although the SO&AF gives detailed data about installed capacities for all ENTSO-E member countries, some data is still missing. This data is either taken from other sources or computed from the available data, as explained below.

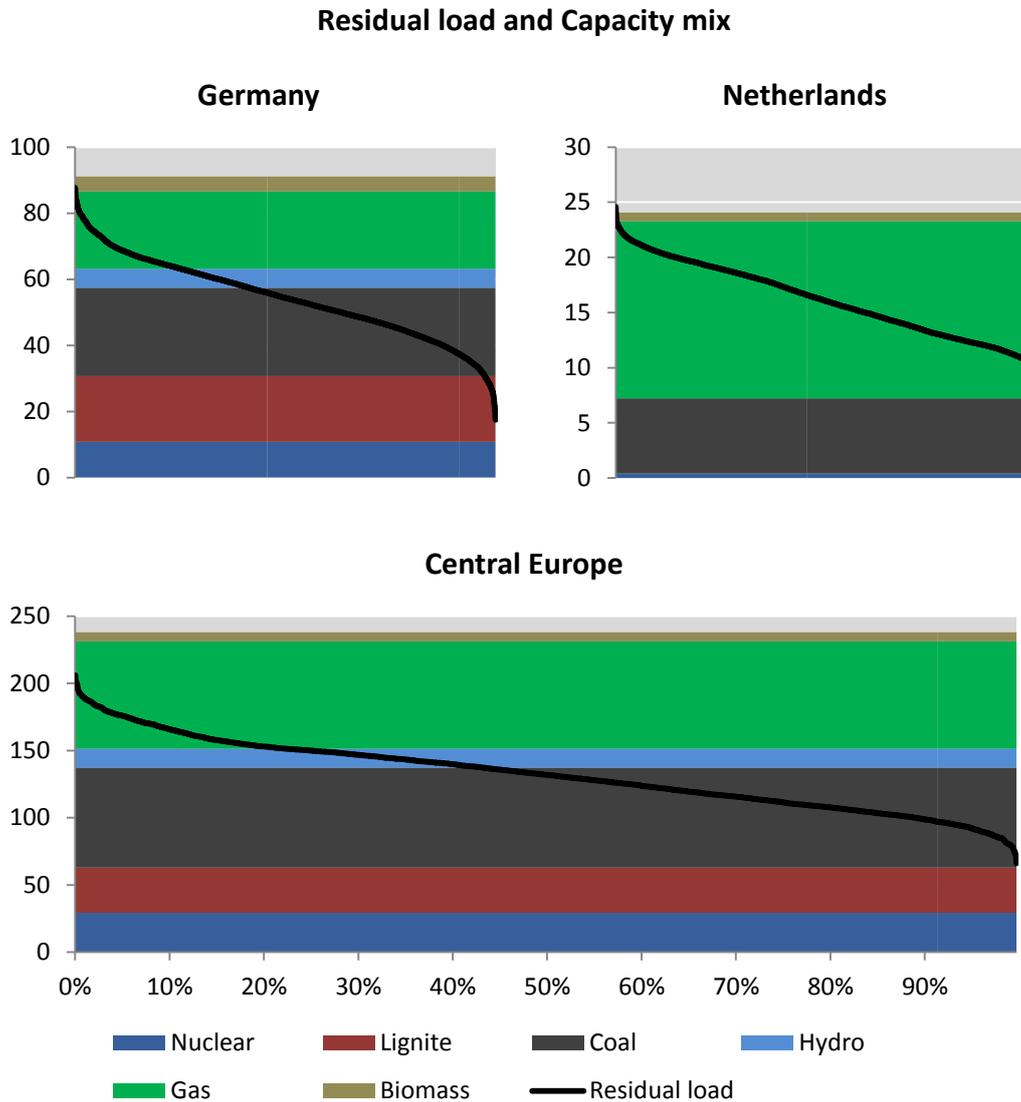


Figure 3-12: Capacity mix and residual load curve for Germany, the Netherlands and Central Europe

First of all, gas fired generation capacity is not further divided into closed cycle and open cycle gas or other types of gas engines. The assumption has been made that 10% of the reported gas capacity is open cycle; the other 90% is closed cycle.

Secondly, hydro power is not further divided into run-of-river hydro, pumped hydro storage and renewable hydro storage (using natural inflow and a dam to store water). This makes using the data in the model impossible. However, data about hydro subcategories was published with the SO&AF 2012-2030 (ENTSO-E, 2012b). The values for capacity of hydro plants were taken from this source and assumed to not have been changed.

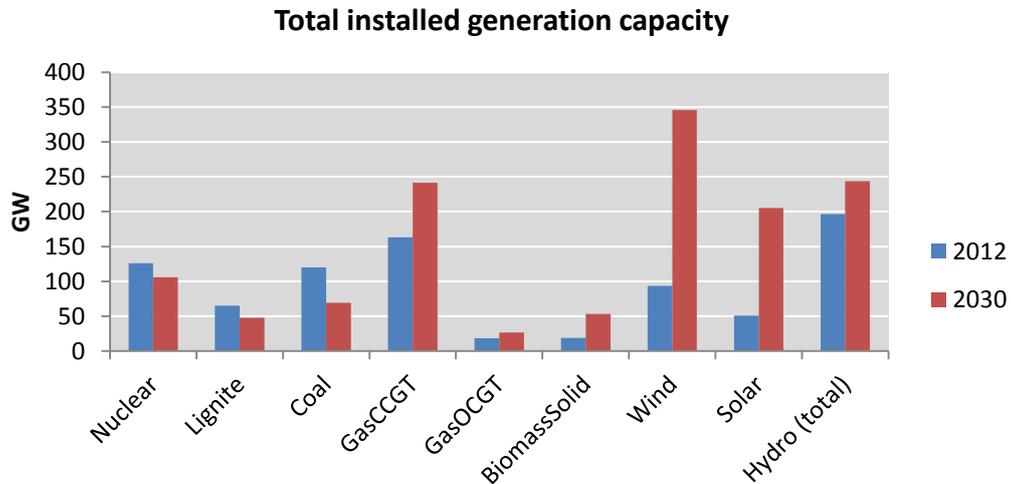


Figure 3-13: Change in installed generation capacity 2012-2030

Table 3.2: The amounts of controllable and non-controllable generation capacity in the nodes

Year	Node	Generation capacity		Maximum demand (GW)
		Controllable (GW)	Uncontrollable (GW)	
2012	North	91	4	68
	Central	302	74	218
	South	406	67	274
2030	North	102	25	77
	Central	304	272	262
	South	439	253	322

Thirdly, data about the energy storage capacity of pumped and renewable hydro capacity is not provided in the SO&AF. This data is taken from the PhD thesis of Carlo Brancucci Martínez-Anido (2013, pp. 142–147) and assumed not to have changed.

Finally, the data from the SO&AF includes capacities for oil and mixed fuel generation. In some countries these expensive technologies will occasionally be used to respond to peak energy demand. However, due to the aggregation of countries into three nodes, enough gas and hydro peaking capacity is available and these plants will never be used and hence not included in the model.

3.4.4. Generator properties

In the literature a large range of generator properties can be found. The technical and financial properties are based on various sources (Bertsch, Growitsch, Lorenczik, & Nagl, 2012; Fürsch et al., 2013; Hirth, 2013; International Energy Agency [IEA], 2010;

Northwest Power and Conservation Council, 2010a; B. S. Palmintier, 2013) and can be found in Appendix B. The combination of sources was used to get a complete picture on the used technical parameters in the literature, in almost all cases the median or an average was used as final data.

3.4.5. Electrical energy storage properties

As can be seen from the presentation of different energy storage solutions above, different kinds of EES technologies can serve different purposes. However, most EES techniques that are able to provide energy management services are, due to their fast response times, also capable of delivering bridging and sometimes even power quality services. This makes them superior to technologies that are only able to provide one type of service.

The optimization model described in this chapter has a resolution of one or two hours, which makes modelling fluctuations in voltage and frequency impossible. Besides, as the model is deterministic, it does not include forecasting uncertainty in both demand for electricity and supply of renewable output. So although both primary and secondary reserves can be included and kept available, these quality and bridging services will never be called upon during a model run. Therefore valuing power quality and bridging services is not possible with the created model.

The purpose of this research is determining the behaviour of different storage technologies in different renewable energy scenarios and determining possible substitution effects between electricity storage and transmission. Energy management EES technologies, capable of storing energy for several hours, are most suitable for these research objectives (Denholm et al., 2010; Kloess & Zach, 2014).

Based upon the analysis in subsection 2.2, four types of storage are selected to be further analysed. These technologies include pumped hydro storage, adiabatic compressed energy storage (CAES), flow battery and hydrogen fuel cell storage. This selection is made because all three technologies can be used for bulk energy storage.

Traditional CAES is a storage technology that has already proven its value in practice but requires a gas turbine to release the stored energy. Adiabatic storage is expected to be able to store energy without the gas turbine and its associated CO₂ emissions. In regions without possibilities for hydro storage, CAES is a promising alternative.

The reported economic characteristics of energy storage technologies show large variability. To illustrate this, Figure 3-14 shows the cost of the four selected technologies and their cost in terms of power (€/kW) and energy (€/kWh) capabilities, notice the different scales. Most technologies are still under development and therefore the capital costs are uncertain, besides, the capital costs of for instance pumped hydro storage and compressed air energy storage are highly location dependent. Authors therefore give estimations of the cost range of a technology, however large differences between the reported costs of authors still exist.

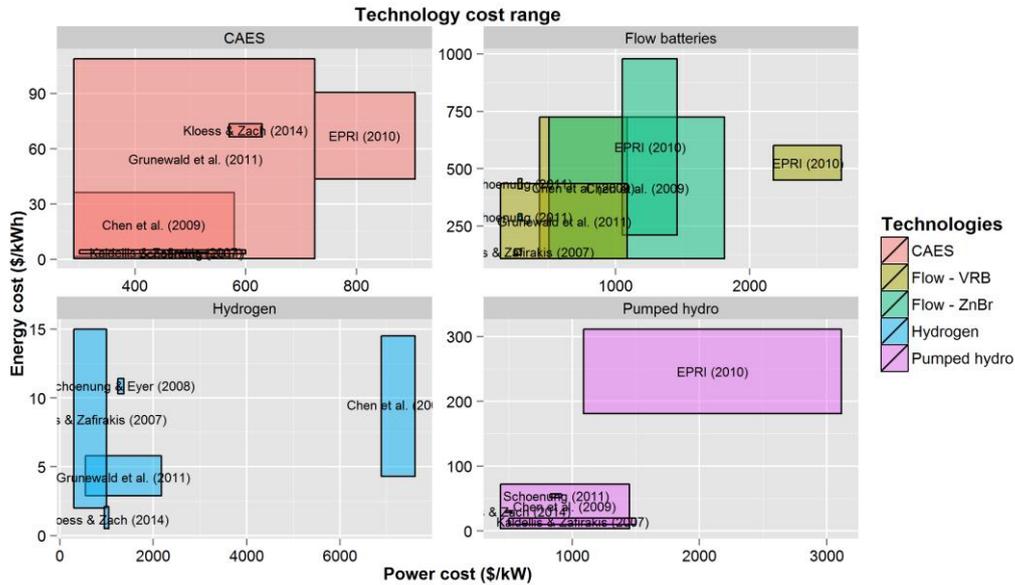


Figure 3-14: Cost range as found in literature⁴ (Chen et al., 2009; EPRI, 2010; Grunewald, Cockerill, Contestabile, & Pearson, 2011; Kaldellis & Zafirakis, 2007; Kloess & Zach, 2014; S. M. Schoenung & Eyer, 2008; S. Schoenung, 2011)

Figure 3-15 shows the full cost range as found in the literature. The markers indicate which costs are used within this thesis. The used costs are often chosen in the lower range of costs estimations, as the expectation is that the cost of the technologies will fall due to learning.

Flow batteries have relatively high energy related cost combined with low power related cost; this makes flow batteries more suitable for short storage durations. Hydrogen storage has the highest power related costs; however, the storage costs of hydrogen are relatively low. Therefore, hydrogen storage is a promising solution to use for longer term solution. Both pumped hydro and CAES are in between flow batteries and hydrogen storage.

Following Grunewald et al. (2011), the ratio between the power and energy costs can be used to derive the energy specific technology cost. These are the costs of a 1 kW storage plant, for a given storage duration. Figure 3-16 shows these costs. This figure shows that flow battery technology is cheapest for storage duration under approximately 5 hours, pumped hydro and CAES are economically most attractive between 5 and 100 hours, higher storage duration results in a preference for hydrogen storage systems.

⁴ This figure should be red as follows: EPRI (2010) estimates the costs of CAES (top left graph) between 700 and 900 €/kW and between 50 and 90 €/kWh

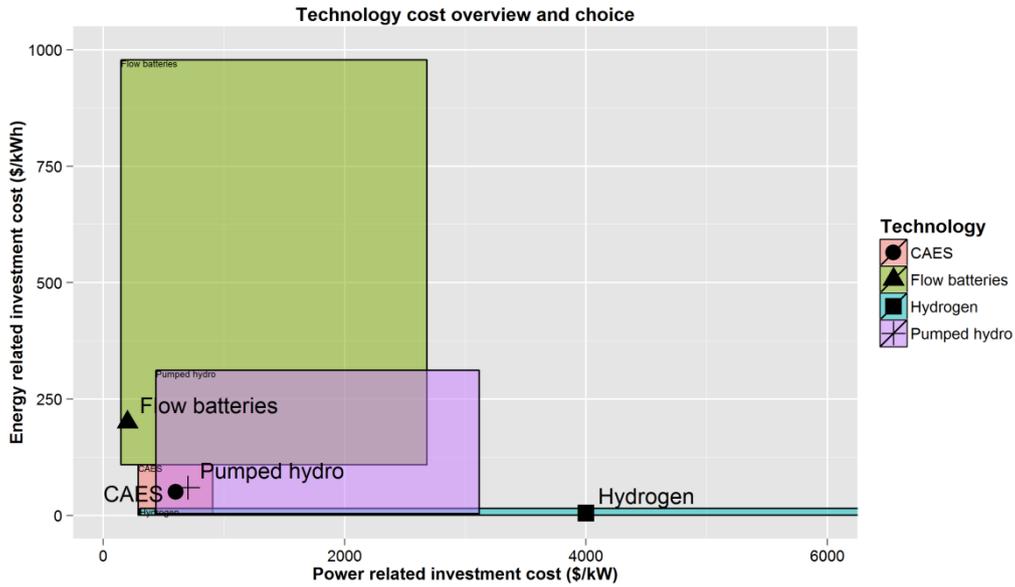


Figure 3-15: comparison of storage technology cost and selected cost figure

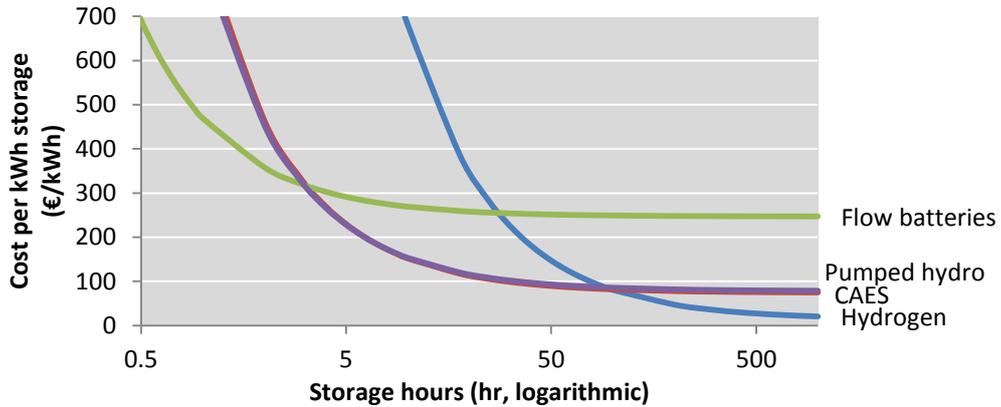


Figure 3-16: Energy specific storage cost dependent on storage duration

Table 3.3: Characteristics of storage

Technology	Power specific costs (€/kW)	Energy specific costs (€/kWh)	Round trip efficiency	Charge efficiency	Discharge efficiency
Flow batteries	200	200	75%	84%	90%
CAES	600	50	70%	84%	84%
Pumped hydro	700	60	81%	90%	90%
Hydrogen storage	4000	5	40%	60%	67%

To conclude, Table 3.3 shows the economic and technical characteristics of electrical energy storage used in this thesis. The characteristics are based on (Chen et al., 2009; EPRI, 2010; Grünewald, Cockerill, Contestabile, & Pearson, 2011; Kaldellis & Zafirakis, 2007; Kloess & Zach, 2014; S. M. Schoenung & Eyer, 2008; S. Schoenung, 2011). The technologies are ranked by power specific increasing cost. Interestingly, the efficiency of the storage technologies almost follows the same order. Although pumped hydro storage is most efficient, the technology is followed by flow batteries, CAES and hydrogen storage respectively.

3.4.6. Model implementation of pumped hydro storage

Hydro storage is implemented in a way that differs from reality. In essence, three different hydro storage configurations can be made. Hydroelectric plants with only natural inflow, hydroelectric dams with natural inflow and pumping capabilities and pure pumped hydro storage plants (no natural inflow). In the model, a simplification of the three possible hydro configurations is made by combining them into the type which has both natural inflow and pumping. Every node has a hydro storage capacity (GWh), a natural inflow (GW/h), a rated capacity of releasing energy (GW) and a rated pumping capacity (GW). This concept is illustrated in Figure 3-17.

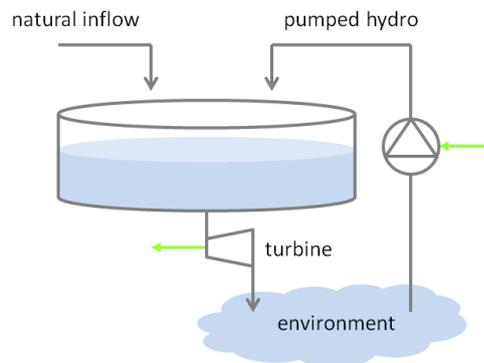


Figure 3-17: representation of stage in the model

3.4.7. Fuel cost and fuel CO₂ emissions

Fuel prices are based on the World Energy Outlook 2010 (IEA, 2010) and considered to remain constant over the considered years and within the year, Appendix C show the used fuel prices.

3.4.8. Demand data

The electricity demand for each country for every hour of the year is published by ENTSO-E (2014b). The time series from the year 2010 were chosen to be used because

weather pattern data was also available for that year. Data for Great Britain in the year 2010 is not provided in the ENTSO-E 2010 dataset, this has been downloaded from the National Grid website (2014). Although small irregularities between countries exist within the ENTSO-E data (ENTSO-E, 2014c), the aggregation of demand of the considered countries over only 3 nodes makes this less harmful for the end results.

The demand patterns for 2030 are based upon the demand patterns for 2010. The values for 2010 are scaled using the 2030 Vision 3 peak demand as published by ENTSO-E (2013b). This automatically means that changes between the ratio of peak and off-peak demand are not captured.

To determine the demand of the three nodes, the demand of individual countries is simply added up. This gives 3 nodes with the characteristics shown in Table 3.4. Figure 3-18 shows the maximum demand of individual countries within the nodes.

Table 3.4: demand characteristics of nodes

	Peak demand (GW)		Yearly demand (TWh)	
	2012	2030	2012	2030
North	68	77	390	444
Central	218	262	1,313	1,582
South	263	322	1,531	1,887

3.4.9. Profiles of renewable inflow

Output of renewable energy sources like wind and solar are driven by weather patterns. Within the model, power output is determined using hourly values for weather patterns of individual countries. The source of the wind, solar and hydro data is discussed below.

3.4.9.1. Wind power

The output of wind turbines is dependent on wind speed, wind variability and the roughness of the surroundings. Wind data is provided by the MERGE-CPB project (Aalbers & Bollen, 2013). This dataset contains 6 hourly wind turbine output values for all countries in Europe. Based on the yearly wind availability (full load hours) every country is split up into three sub categories: high, medium and low wind availability. The high and low categories contain the 10% best and 10% worst wind power nodes respectively, the rest of the nodes fall into the medium category. The same is done with off-shore wind areas.

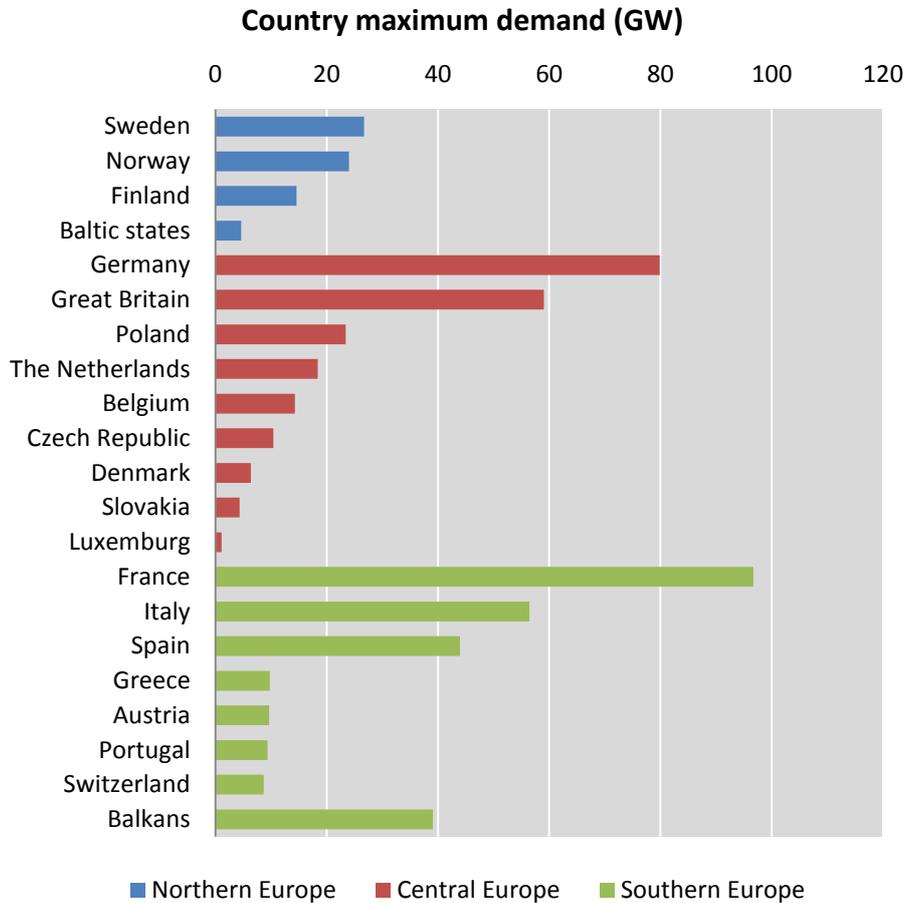


Figure 3-18: Maximum demand in 2012 of individual countries sorted by node

Each country has its own specific goals of wind power development, which might not always correspond to the optimal distribution of wind over Europe (Heide, 2010). However, the expectation is that in practice, project developers select sites dependent on favourable wind conditions. Therefore, the wind power profiles of the countries high output regions are used in the model.

Some issues were encountered using the data that was provided by the MERGE-CPB project. Wind profiles for Luxemburg were missing. Luxemburg is closest to the centre of Belgium, therefore Belgian wind profiles are used for Luxemburg's wind power output. However, as Belgium's high wind speed areas are probably towards the coast, the medium wind profile was used. For Belgium, no offshore wind profiles were available and therefore the offshore wind profile of the Netherlands was used. Finally, for Great Britain the data of England and Wales was used as the full load hours of Northern Ireland and Scotland are only marginally different than those from England and Wales.

3.4.9.2. Solar irradiation

Output of photovoltaic cells is determined by solar irradiation and ambient temperature. For the MERGE-CPB project (Aalbers & Bollen, 2013) solar irradiation and ambient temperature were used to determine PV output at every measurement node. Just like with the wind data, individual measurements are divided into three categories, low (10%), medium (80%) and high (10%). As PV is mainly installed on the rooftops of private housing or businesses, there is less opportunity for developers to select favourable solar regions. For this reason country's medium profiles are used to determine hour to hour output for PV capacity.

3.4.9.3. Natural hydro inflow

To quarterly model the power available hydro power plants, data about water inflow is necessary. As mentioned earlier, there are three types of hydro power plants: run-of-river, renewable hydro storage and pumped hydro storage. Run-of-river plants are directly fed by flowing river water and output cannot be controlled. Renewable hydro storage is also fed by natural inflow from a river; however, by using a dam the water can be stored and released when deemed necessary.

A comprehensive search into hourly river discharge did not have any results. However, ENTSO-E provides data about the monthly energy production grouped by generation type for every country (ENTSO-E, 2014a). This data provides a very rough function of yearly energy inflow. Using the total installed hydro power capacity these monthly values can be calculated back into an hourly inflow. The fact that river discharge is mainly determined by seasonal factors seems to make this a correct approach to modelling the water discharge.

Chapter 4

VALIDATION, VERIFICATION AND TESTING

Before using the model described in Chapter 3, tests need to show that the model is suitable for the purpose it has been designed for. Because the model can take a long time to solve, various speed up strategies have been proposed in subsection 3.3. Two separate models have been created, one optimizes over the entire time frame, while the second model uses results from an economic dispatch pre-run (which is in principle a third model) to solve individual weeks. Secondly, four different speeds up strategies are proposed: relaxed mixed integer programming, solving only parts of the year, simplifying maintenance and combining reserves. The effects of these speed up strategies on the model results need to be known before being able to benefit from the speed ups.

4.1. Testing inter model differences and model selection

Three different models have been created, the clustered unit commitment (CUC) model, the split CUC model which uses results from the economic dispatch pre-run (CUC & pre-run) and the economic dispatch (ED) model itself that functions as a pre-run for the split CUC model. This subsection compares the performance and results of these 3 models. The clustered unit commitment model is used as the benchmark as this model most directly and accurately solves the entire year in one consecutive optimization.

The standalone clustered unit commitment model for the full year including the detailed technical constraints did not find an optimum using the selected three node scenario. Therefore, the previously described speed up strategies, using derated maintenance and combining reserves, are used during the tests described in this subsection. The effects of individual speed up strategies will be tested in subsection 4.3.

Table 4.1 shows an overview of runs that are used for testing the models. The full clustered unit commitment model is solved in six different varieties. Next to the full problem, the first strategy contains the linearization of the integer unit states. The other four contain the speed up strategy of using a selected part of the year only, through this we can test whether the part of the year considered has an influence on the final results. Increasing the time resolution to two hours results in the choice of using even or

odd hours, using only one out of two weeks results in the choice of using even or odd weeks.

Table 4.1: Overview of model runs used in test

Run name	Model	Time frame
CUC (benchmark)	CUC model	Full year
CUC & PreRun	CUC model with pre-run	Full year in separate weeks
PreSolve	Economic dispatch	Full year
RMIP (Relaxed Mixed Integer)	CUC model	Full year
AWEH	CUC model	All weeks, even hours
AWOH	CUC model	All weeks, odd hours
EWAH	CUC model	Even weeks, all hours
OWAH	CUC model	Odd weeks, all hours

All the runs described are tested in two scenarios: no CO₂ policy or a 10% CO₂ reduction compared to the no CO₂ policy run⁵.

4.1.1.1. No CO₂ policy

In order to provide better understanding of the functioning of the different models, a two day dispatch profile of two different models is shown in Figure 4-1. The models used are the clustered unit commitment (CUC) benchmark model and the Economic Dispatch PreSolve model. The basic function of the model is to meet the demand (the black line) as inexpensively as possible. Transport between regions and storage are shown as negative loads.

The difference between the two models is most clearly visible in the central region. While the CUC models shows relatively stable output profiles, the PreSolve model shows fluctuating behaviour of gas plants. As the PreSolve model does not include start-up costs, there is no economic disadvantage to this fluctuation. However, the CUC model includes start-up cost and therefore tries to keep a stable output profile.

Secondly, the CUC model needs to keep reserves available for when contingencies occur. The practical implication can be seen during night-time, some gas plants are kept running to provide these reserves, the overproduced power is partly exported to the other regions and partly stored in hydro reservoirs. The PreSolve model does not include these constraints and turns all expensive gas plants off during the night.

The dispatch profile can also be used to gain insight in the energy mix of the different regions. Although these are two winter days and the demand is relatively high, a general understanding can still be gained. The northern region has some base load power available, which is topped up by a large portion of hydro power, which does not only provide peaking power, but is delivering day and night. The central region (EU-M) has a large proportion of base load plants in the form of nuclear, coal and lignite. During off-peak hours, if it wasn't for the reserve requirements, the amount of base load is enough to be

⁵ Other CO₂ settings have also been tested, however, the effect of introducing a CO₂ cap is well presented by the 10% case and therefore used in the analysis

able to turn of gas plants. The peaks are provided by gas and hydro plants. The southern region also has a lot of base load power, however, even during the nights, either gas or hydro power is necessary to provide the demand.

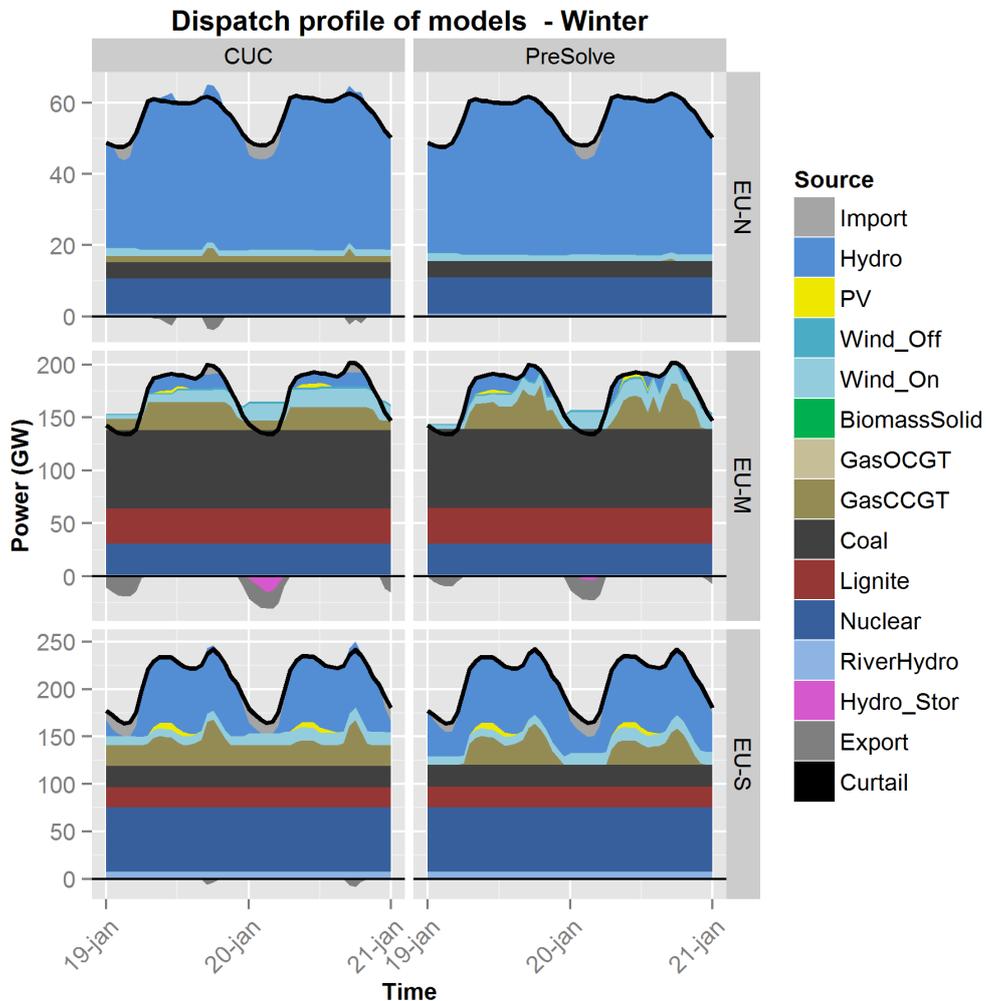


Figure 4-1: The dispatch profile of the clustered unit commitment and economic dispatch model

The differences between the model runs are now compared on different key performance indicators (KPI's). Firstly, the run time of the different models is compared. Thereafter, operational indicators such as the effect on the energy mix, CO₂ emissions, dispatch cost and behaviour of the storage levels is analysed. The solution time and other KPI's are important factors in selecting a model for further experimentation.

The time it takes to solve the models are shown in Figure 4-2. As can be seen, the economic dispatch "PreSolve" model took least time to solve, taking less than 1 minute. The second fastest performers are the models that limit optimization to only half of the weeks. The models that only consider half of the hours (AWEH and AWOH) and the

model that uses the results from the pre-run to optimize dispatch in individual weeks (CUC PreRun) follow; approximately seven and a half minutes are needed to find and optimum in these cases. However, this excludes the time of executing the pre-run, something that needs to be done before the CUC PreRun is able to optimize individual weeks. Looking at the other runs we can see that the relaxed mixed integer model "RMIP" performed worse than the benchmark. This is especially interesting because the RMIP model optimizes dispatch over the entire year in an hourly resolution but can optimize without the demanding integer constraints. To analyse operational results, the full clustered unit commitment model (CUC) is used as a benchmark for the other models.

Figure 4-3 shows the difference in the yearly energy balance of the different model runs. The first thing that catches the eye is that the both the economic dispatch "Pre-Solve" run and the RMIP run have the largest differences with the benchmark. The differences primarily lie in the increased use of large conventional power plants such as nuclear, lignite and coal while more flexible gas units are used less. Both the PreSolve and the RMIP model do not have integer commitment constraints, which means that large generators don't have minimum output levels, allowing them to provide a larger part of the energy mix. The PreSolve model shows the largest differences because an economic dispatch model does not consider start-up costs. A detailed overview of differences in energy mix can be found in Appendix D.

The models AWEH (all weeks, even hours) and AWOH (all weeks, odd hours) use a little bit more gas than the benchmark, while the models EWAH (even weeks, all hours) and OWAH (odd weeks, all hours) show a large difference in wind output. The pre selection of specific weeks of the year can have large impacts on the production from renewables.

The CO₂ emissions of the runs are shown in Figure 4-4. All differences are lower than half a percent; the higher emissions in the economic dispatch PreSolve model can be explained through the increased use in coal and lignite, while the differences in the models that only optimize even or odd weeks are caused by the difference in wind output in the considered periods.

Finally, the cost of an entire year of dispatch is compared between the models. We only look at variable cost as the fixed cost such as capital cost and fixed operation and maintenance cost are equal, they depend on the installed generation capacity. To come to the costs of one year, the costs of runs that only consider a specific part of the year are scaled.

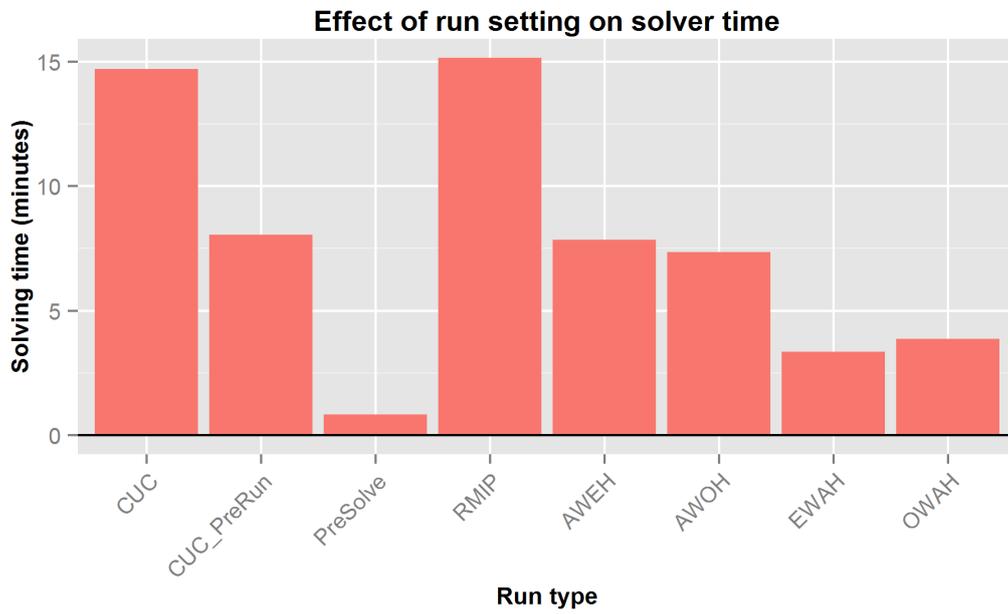


Figure 4-2: Effect of different models on solving time

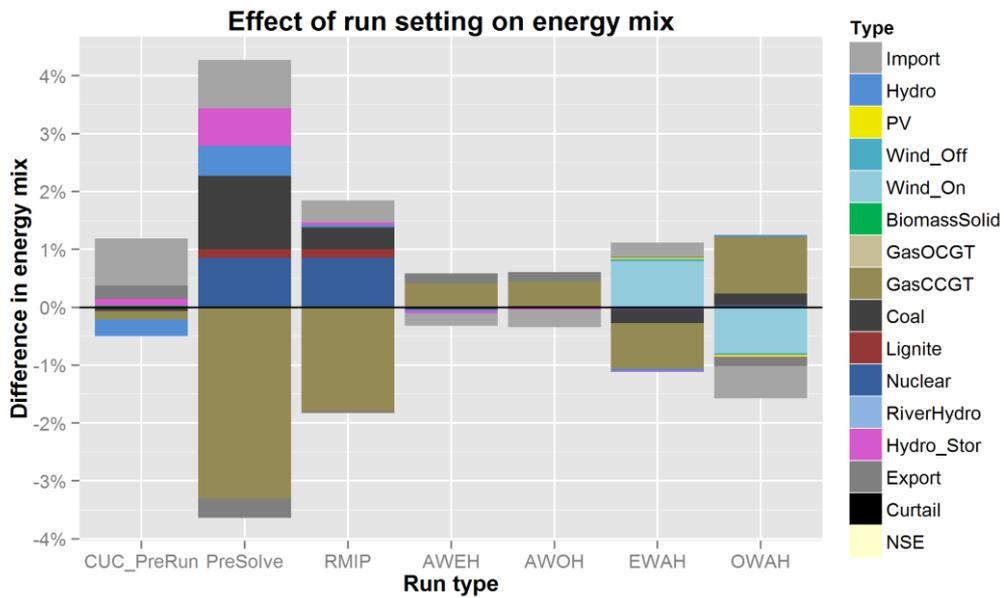


Figure 4-3: The differences in the energy mix between model types compared to the benchmark

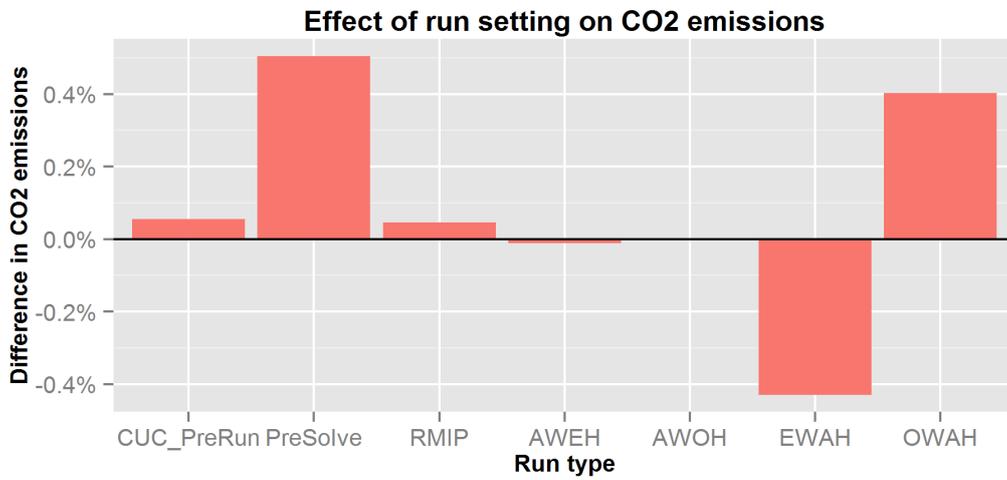


Figure 4-4: The difference in CO₂ emissions between model types

The cost difference in absolute numbers is shown in Figure 4-5. The differences in the PreSolve and RMIP model are caused by the increased use of cheaper fuels such as nuclear, lignite and coal. The EWAH run is less expensive due to higher wind output. Although a difference of almost 1 billion euros seems large, the relative differences displayed in Figure 4-6 show that the effect on the total cost is small.

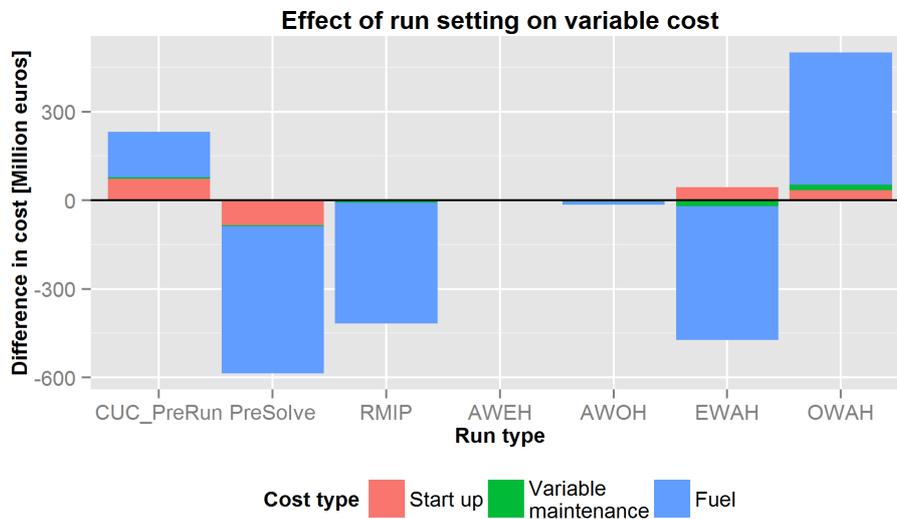


Figure 4-5: Effect of different models on absolute variable cost

Finally, Figure 4-7 shows the behaviour of the hydro storages in the separate regions. The storage levels are normalised to their maximum capacity and therefore range from 0 to 100%. It can be seen that all model runs show the same type of behaviour. Only the models that optimize even or odd weeks (EWAH, OWAH) show different behaviour. First

off all, the levels remain stable once every two weeks, which is expected and can be most easily seen for the storage levels of central Europe (EU-M). Secondly, the storage level off Southern Europe shows less variation due to less inflow and outflow (only one out of two weeks).

The behaviour in the different regions can be described as follows: In Northern and Southern Europe, the hydro levels decrease until March/April and rise from April to October, from October to December they go down again. This means that hydro generation is primarily used in winter months, when demand is generally higher than in summer months. The storage level in central Europe shows far more variation, this is because the storage level is smaller and, as can be seen from the fast fluctuations, is used to level out daily and weekly demand patterns.

The conclusion that can be drawn from these comparisons is that all models show about the same behaviour, nonetheless, differences still occur:

- The models that do not consider integer commitment states (PreSolve and RMIP) might overestimate the use of large thermal generators such as nuclear, lignite and coal plants.
- When looking at the comparison of runs that increase the time resolution to two hours and the runs that only consider one out of two weeks, the models that use a two hour time resolution seem relatively accurate. These models show little difference with the full scale model.



Figure 4-6: Effect of different models on relative variable cost



Figure 4-7: Effect of different models on storage behaviour

4.1.1.2. 10% CO₂ reduction

To test the effect of a CO₂ policy on the behaviour of the different models, a CO₂ cap is imposed. The CO₂ cap is set at a level that is 10% lower than the CO₂ emissions in the benchmark run in the case of no CO₂ policy (CUC of subsection 0). Except for the difference in CO₂ emissions, the same metrics are compared.

Looking at the time it takes to solve the different models (Figure 4-8) we observe that the economic dispatch PreSolve model (less than 1 minute) and the clustered unit commitment model that uses the pre-run (10 minutes) have by far the shortest solving times. The models that only consider a selection of hours or weeks have solving times of between 20 and 30 minutes. However, the models that consider the entire year in one go (CUC and RMIP) take more than one hour to find an optimum. Comparing the solve time to the situation without a CO₂ cap, we see an overall increase in the time it takes to find an optimal solution, except for the economic dispatch and clustered unit commitment model that uses the economic dispatch.

Figure 4-9 shows the difference in energy mix compared to the base run (full year clustered unit commitment). Again, the linear optimization models (PreSolve and RMIP) show a preference for large thermal generators while less gas is used. The models that use a two hour time resolution show very similar results to the model that optimizes the full year. The difference in wind output between weeks cause the difference in energy mix in the EWAH and OWAH models.

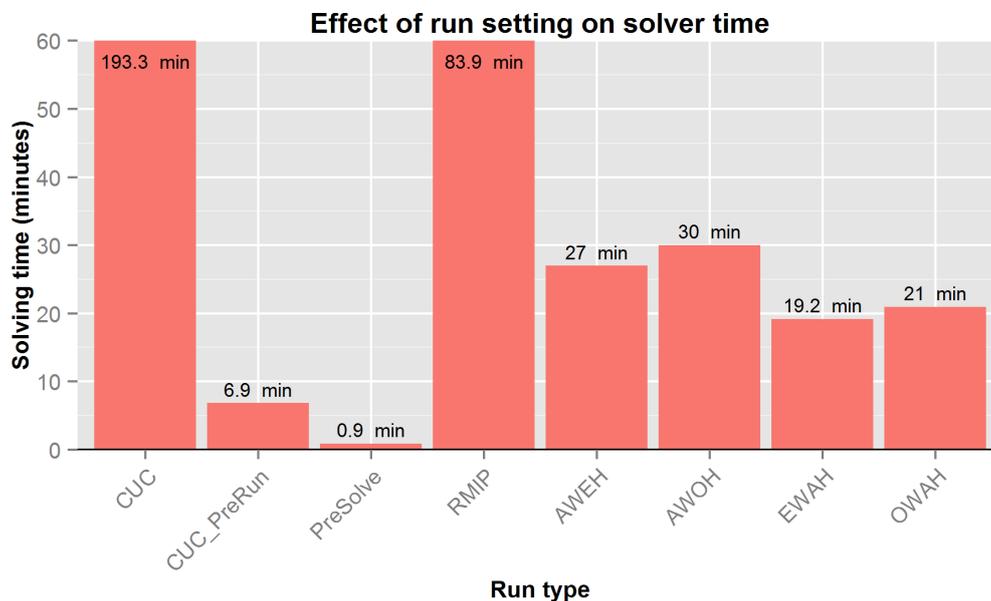


Figure 4-8: Effect of different models on solving time

The explanation for the increase in import and export of the CUC & PreRun lies in the implementation of the CO₂ cap in this model. The yearly CO₂ cap is first imposed over the economic dispatch model. This model then feeds its weekly CO₂ emissions to the clustered unit commitment model with pre-run, which uses these weekly CO₂ emissions

as weekly CO₂ caps. However, the cost of saving CO₂ in different regions may contrast due to the differences in technical detail between the models. This makes it necessary to transport energy across the regions.

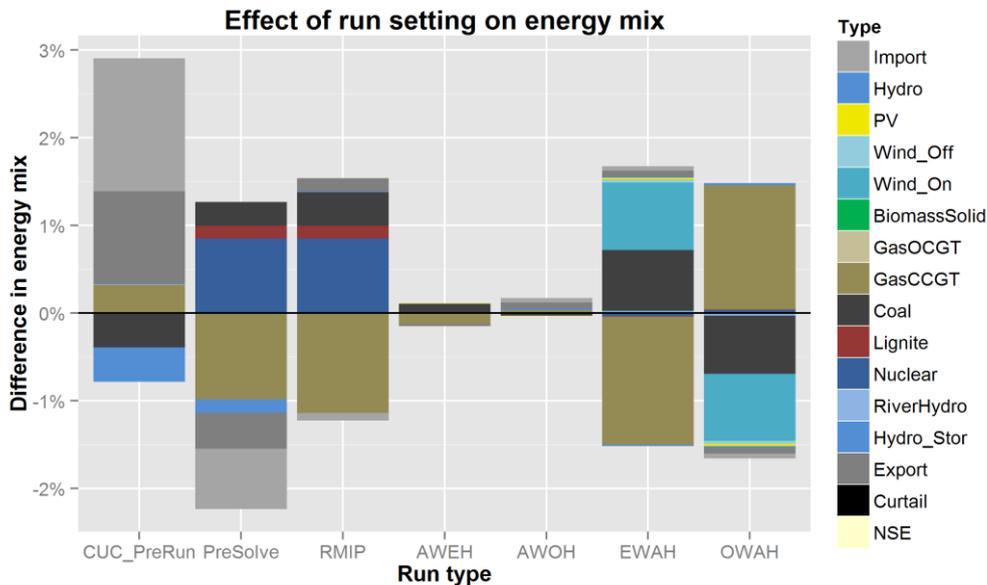


Figure 4-9: The differences in the energy mix between model types compared to the benchmark

The model differences with regards to variable costs are shown in Figure 4-10 and Figure 4-11. The same conclusions can be drawn as in the runs without CO₂ cap. The absolute costs vary significantly between runs, especially in the runs with low wind power output such as EWAH. However, relative effects are rather small with no more than 1.2% difference in variable cost for a run with low wind output.

So far, most results have been fairly similar with the results of the runs without a CO₂ cap. However, something interesting happens with the behaviour of the hydro storage levels, as shown in Figure 4-12. The economic dispatch model empties the storages in both central and southern Europe, only to fill them again at the end of the run. This filling seems to be an artificial effect of the constraint that requires the storage to be filled up to 60% at the end of the run. In other words: it seems that storage loses its value. The hydro storage modules of the clustered unit commitment model that uses the pre-run shows the same behaviour, this is caused by the fact that the CUC model uses values from the pre-run to determine the storage levels in the beginning and the end of the week. However, the CUC & PreRun model does try to use the storage in between the fixed beginning and ends of the weeks, visible from the saw-tooth effect in the central Europe hydro storage. Apparently, introducing a CO₂ cap into an economic dispatch model without technical constraints makes hydro storage lose its value.

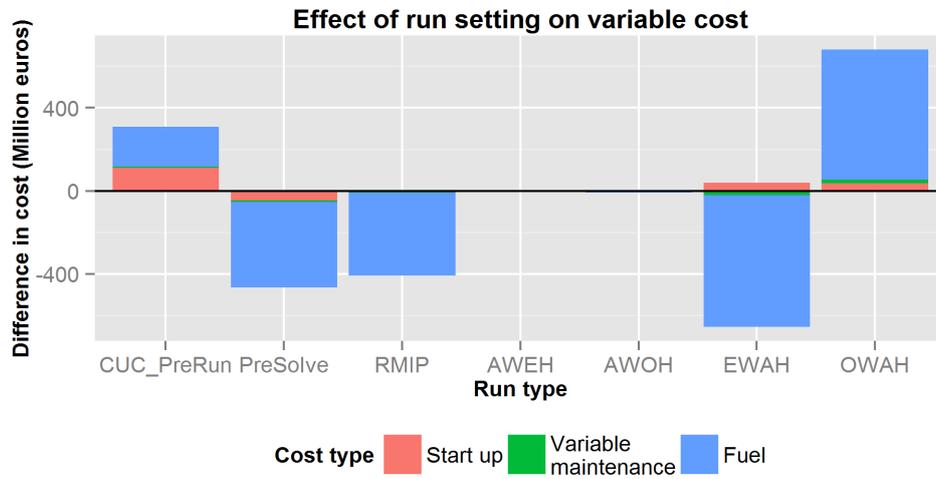


Figure 4-10: Effect of different models on absolute variable cost



Figure 4-11: Relative effect of different models on variable cost

The reason that hydro storage has no value in an economic dispatch run can be found in the absence of start-up cost and minimum output constraints. This can be seen in Figure 4-13, which plots the behaviour of the hydro storage for different levels of technical details in the clustered unit commitment model. The model used is the AWOH model. The first graph shows the storage behaviour for the run technical details and is therefore the same as the ABOH storage behaviour in Figure. The other 3 graphs show model runs with less technical detail. First minimum output constraints are removed, this does not have a large impact on the storage. The third graph shows the model results without start-up cost, which seems to affect the behaviour of the storage but does not yet replicate the behaviour we see in the economic dispatch (PreSolve) model. Finally, removing both the start-up costs and the minimum output constraints does results in the behaviour observed in the economic dispatch model. We can therefore conclude that the observed behaviour in the economic dispatch model is not caused by a modelling error.



Figure 4-12: Effect of model type on hydro storage levels

However, this does not answer the question why the behavioural change is only observed if a CO₂ cap is introduced and not in the runs were CO₂ is not capped (subsection 0). To explain this we have to look at the marginal cost of production and the differences in marginal cost of production between the two CO₂ scenarios. Marginal costs of production are important for the functioning of a storage facility because electricity is stored when prices are low and released when prices are high; creating a value that is

equal to the price difference between the two prices. Electricity prices in the model are represented by the marginal cost of production: the cost of producing one extra unit of energy.

In a situation where CO₂ can flow freely, the marginal cost at a certain hour is determined by the most expensive generator that is running at that specific time. During off-peak hours the marginal producers are usually coal plants while during peak hours gas plants provide the most expensive energy. The cost difference between producing electricity from coal and gas determines the difference in marginal cost between off-peak and peak hours.

When the CO₂ emissions are capped the situation changes, in that case the marginal cost are also dependent on the CO₂ emissions associated with using that fuel. This will be illustrated using an example. Suppose that during an off-peak hour, a coal plant is the marginal producer. When an extra unit of energy is demanded, this energy is supplied by the coal plant; however, this increases CO₂ emissions, which is not allowed due to the CO₂ cap. To solve this, coal needs to be substituted for gas at a later point in time. Because gas has lower CO₂ emissions than coal this substitution will bring the total CO₂ emissions back under the CO₂ cap. However, gas is more expensive than coal, this will increase the total cost of producing electricity.

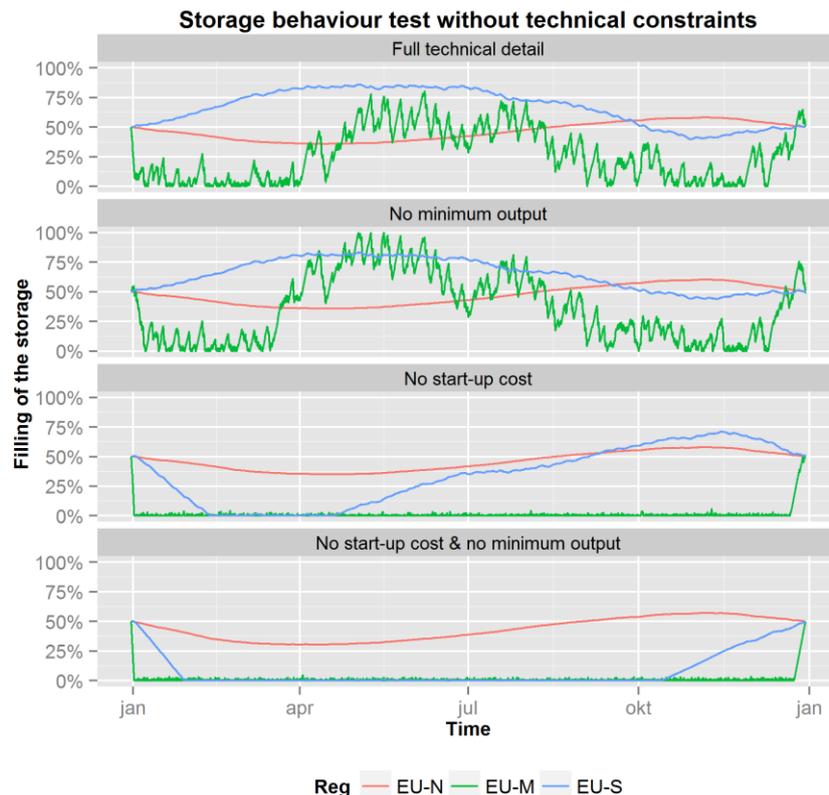


Figure 4-13: Difference in storage behaviour due to reduction of technical details

The conclusion is that, under a CO₂ cap, the marginal costs of production at a certain time are not only dependent on the marginal costs of the generator that is currently the marginal producer, but also on the ratios of production costs and CO₂ intensities of possible substitutes. This causes the inter-temporal differences in marginal cost to be lower in scenarios with a CO₂ cap.

As economic dispatch models do not consider start-up costs, the fuel costs and variable operation and maintenance costs are the only determinant for cost differences between different time periods. In unit commitment models, the cost differences between time periods are more complex as they also depend on the start-up and minimum output of individual units, creating more differences in cost between time periods. Therefore storage has more value in models that consider technical details. An economic dispatch model with a CO₂ cap is therefore not capable of determining the value of electrical energy storage.

4.1.1.3. Model selection

As can be seen from the analysis in subsection 4.1.1.1 and 4.1.1.2, there are important differences between the created models. First off all, models without integer commitment states such as the relaxed mixed integer (RMIP) model and especially the pure economic dispatch model favour large thermal generators. Secondly, the behaviour of hydro storage plants in economic dispatch models does not comply with expectations in runs where a CO₂ cap is used. This makes the clustered unit commitment model that uses results from the economic dispatch model un-reliable.

The remaining clustered unit commitment models that optimize the entire year in one go seem to be more usable. They are able to capture the implications of start-up cost and other technical constraints and value the storage better. Although these CUC models take longer to find the optimal solution, their solving time is still manageable.

Comparing the full year clustered unit commitment model with CUC models that have a resolution of two hours and the models that only optimize one out of every two weeks, we see that the latter are more influenced by wind patterns in the specific weeks they consider. The models that use a two hour time resolution show only small differences with the hourly resolution model while the time it takes to solve a two-hour resolution model is more than twice as short than solving an hourly resolution model.

Therefore a model that optimizes the full year with a resolution of two hours is favourable. The differences between the AWEH (all weeks, even hours) and AWOH (all weeks, odd hours) models are small, however, during tests the AWOH model generally came to a solution a little faster than the AWEH model. Therefore the AWOH model will be used in the rest of this thesis.

4.2. Verification and validation

Verification is the process of determining whether the model described in Chapter 3 has been correctly translated to a computer simulation model. Validation is done to

check whether the model is suited for the purpose it has been designed for. These two steps are explained below.

During the modelling process, utmost care has been taken in translating the mathematical formulas into GAMS language. The model was started with only one node and three different technologies and scaled up from there. In between implementation of additional features, runs have been done to test consistency with expectations. Nonetheless, errors can be easily made in a model that contains more than 2200 lines of code, especially when versions are split up in order to have one model that can load values from a pre-run and another that optimizes over the considered time frame in one go. Therefore, any interested reader is invited to check the source code for inconsistencies or bugs. The model code is supplied in Appendix E and can be obtained from the author upon request, including the necessary data files to execute model simulations.

In order to validate the model, the model results are compared to the operational data from the actual European power system. Because the entire European electricity network is combined into three nodes, the results are not expected to be completely similar. Figure 4-14 shows the energy mix for the entire modelled region as published in the ENTSO-E's Yearly statistics & Adequacy retrospect 2012 (ENTSO-E, 2013c) and as determined by the optimization model.

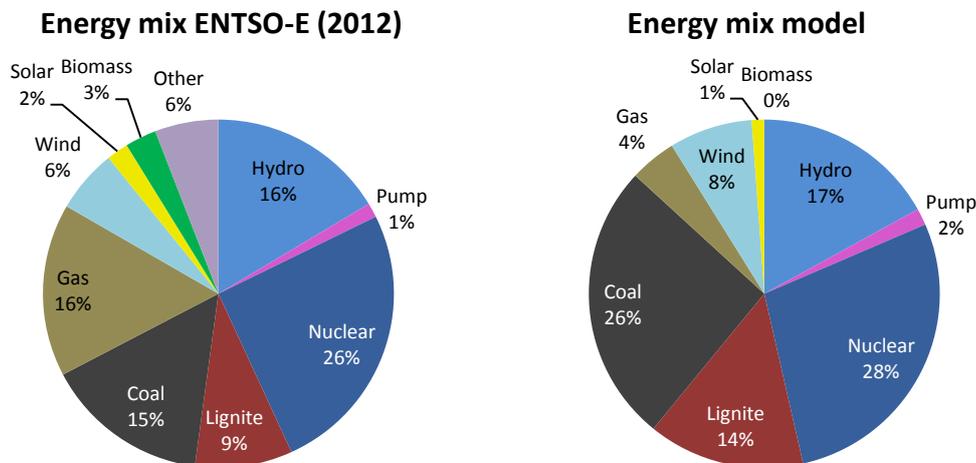


Figure 4-14: The energy mix within the modelled region. Left the actual data from 2012 (ENTSO-E, 2013c), right the model run with 2012 capacities

Although similarities can be observed between the graphs, large differences are apparent as well. The amount of energy produced by hydro power, pumping, nuclear and lignite are largely comparable. However, the amount of coal in the energy mix is far greater than the amount of coal that is observed in reality while gas fired power plants are only used to provide 4% of the total energy demand. Gas power plants are peaking plants and have higher variable cost than coal plants, so when the situation allows, coal plants are preferred over gas plants. As can be seen from the analysis of the capacity mix

in subsection 3.4.2, individual countries need their gas plants as peaking capacity, however, when many countries are combined into one node, the amount of base capacity might be enough to provide power for most of the peaks and gas is only occasionally called upon. Secondly, a part of the gas plants in Europe are used for district heating purposes⁶, which makes them must run plants. These combined heat and power plants are not considered in the model. The increase in wind energy in the mix can be explained through the availability of wind in the specific year, but no data for wind speeds of 2012 was available to test this hypothesis.

4.3. Testing intra model differences

Two separate speed-up strategies have been used so far, derated maintenance and combined reserves. However, the effect of these speed-up strategies on model results is not yet known. Therefore this subsection consecutively describes the effect of different reserve and maintenance constraints on the model results.

4.3.1. Reserve constraints

So far, two different reserve options have been described. Subsection 3.2.2.8 described primary, secondary and tertiary reserves as required by the ENTSO-E. Subsection 3.3.5 described a speed up strategy which combines the reserves into one group of reserves for up regulation and one group for down regulation. This subsection adds one more reserve option: not considering any reserves at all. Secondly, subsection 3.2.2.8 describes how special reserves for renewables need to be added to the traditional reserves.

This leaves us with the five reserve settings displayed in Table 4.2. The effect of the different reserve settings has been tested using the AWOH model (all weeks, odd hours). The table displays the effect different settings have on the time it takes to solve the model, CO₂ emissions and variable cost⁷. The combined reserves setting is used as a benchmark as this is the setting used until now.

What can be observed from the data shown is that the effect of different reserve settings is only small. Both including a 10% RES reserve and using no reserves at all does not produce a difference in cost or CO₂ emissions larger than 0.1%. However, using separate reserves increases the model time to such extend that it runs against the time out point of 10 hours. Therefore, the effect of using separate reserves cannot be measured. However, it does show that using separate reserves makes the problem much more complex.

⁶ For instance, 16% of Germany's and 13% of Great Britain's gas capacity is combined heat power (Hirth, 2013)

⁷ Which includes start-up cost, fuel cost, variable operation and maintenance cost and non-served energy cost

Table 4.2: Effect of different reserve settings on KPIs - full year

Reserve option	Solve time	CO ₂ emissions (%)	Variable cost (%)
Combined reserves	6 min 14 sec	100%	100%
No reserves	3 min 9 sec	+ 0.02%	- 0.01%
Separate reserves	> 10 hrs	-	-
Combined + RES reserves	7 min 8 sec	- 0.08%	+ 0.05%
Separate + RES reserves	> 10 hrs	-	-

Figure 4-15 shows the effect the reserves settings on the energy mix compared to the benchmark, which is the use of combined reserves. The reserve options that did not lead to a result within 10 hours are not included in this figure.

In the case of no reserves, the northern and southern region export less gas produced power, less export in the north and south means less import in the central region. This reduction is filled with coal and gas power; secondly there is more use of hydro storage. The reason that the north and the south use less gas can be explained as follows: reserves are normally provided by hydro power plants, providing these reserves results in the fact that the plants have to keep a margin between their maximum output and actual output. Hydro plants therefore produce less during their peak hours; this gap is filled by gas plants.

In the case of combined reserves and additional RES reserves, the overall reserves need to be larger. As hydro power can provide a large amount of reserves due to their high ramping rate, hydro power provides a larger part of the reserve requirements. This leads to a reduction of use of hydro pumping facilities. The latter can be loaded less frequently as the available power is used for reserves. The use of coal plants also declines when introducing RES reserves. Coal is used as a reserve as well and has to reduce output to provide a reserve margin.

To still be able to determine the effect of separate reserves on the run, a shorter version of the model is run. This model only considers 2 months of the year, the winter month February and August, a summer month. The time resolution in the model is 2 hours. Using these settings, every reserve option generated a result within the time limit. The results on KPI's are shown in Table 4.3. It can be observed that using separate reserves has almost no influence on the KPI's compared to the combined reserve benchmark. The results from the no-reserves and combined +RES runs show that using only two months instead of the full year increases the differences between the benchmark and the options.

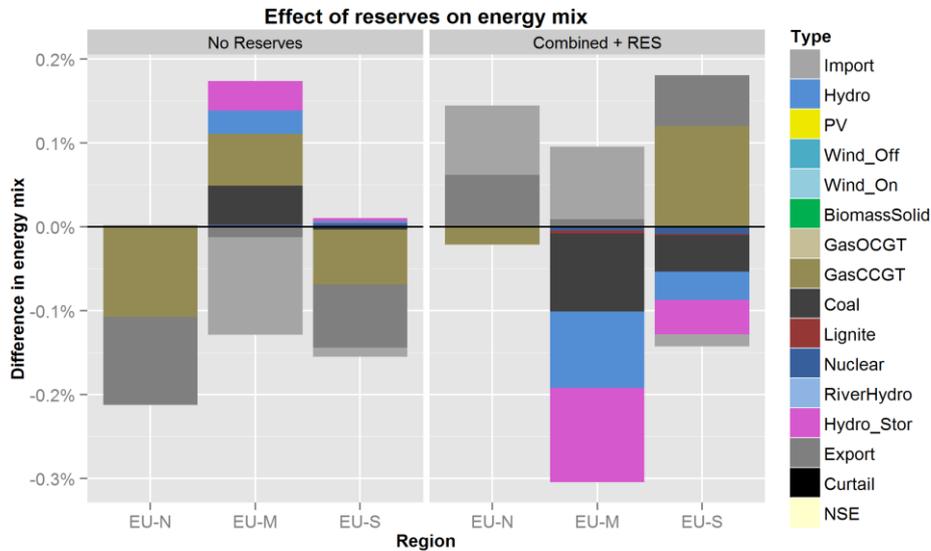


Figure 4-15: The effect of reserves on the energy mix in the 3 regions - full year

Table 4.3: Effect of different reserve settings on KPIs - only winter and summer month

Reserve option	Solve time	CO ₂ emissions (%)	Variable cost (%)
Combined reserves	28 sec	100%	100%
No reserves	22 sec	+ 0.13%	+ 0.01%
Separate reserves	40 sec	+ 0.03%	+/- 0.00%
Combined + RES reserves	29 sec	- 0.21%	+ 0.10%
Separate + RES reserves	36 sec	- 0.15%	+ 0.03%

Figure 4-16 shows the effect of different reserve settings on the energy mix in the model that only optimizes over February and August. Using separate reserves has only little effect on the energy mix. If we compare this to Figure 4-15 we see that the differences between the benchmark and the setting for no reserve and combined + RES reserves are of the same direction and type. However, the differences are smaller when running a full year.

The differences between using combined or separate reserves are only marginal and expected to be even smaller in a run where the full year is simulated. Hence, the previous and further use of combined reserves instead of the more complex separate reserves is justified. Next to this, the effect of using no reserves at all has limited effects on the model results; therefore using this option might be useful in situations where the model with combined reserves does not find a solution within the set time limit of 10 hours.

The effect of including special reserves for renewable energy sources seems large; however, the implementation of these reserve requirements requires more research as

they have unexpected effects on for instance the use of coal plants. They will therefore not be used in the rest of the analysis.

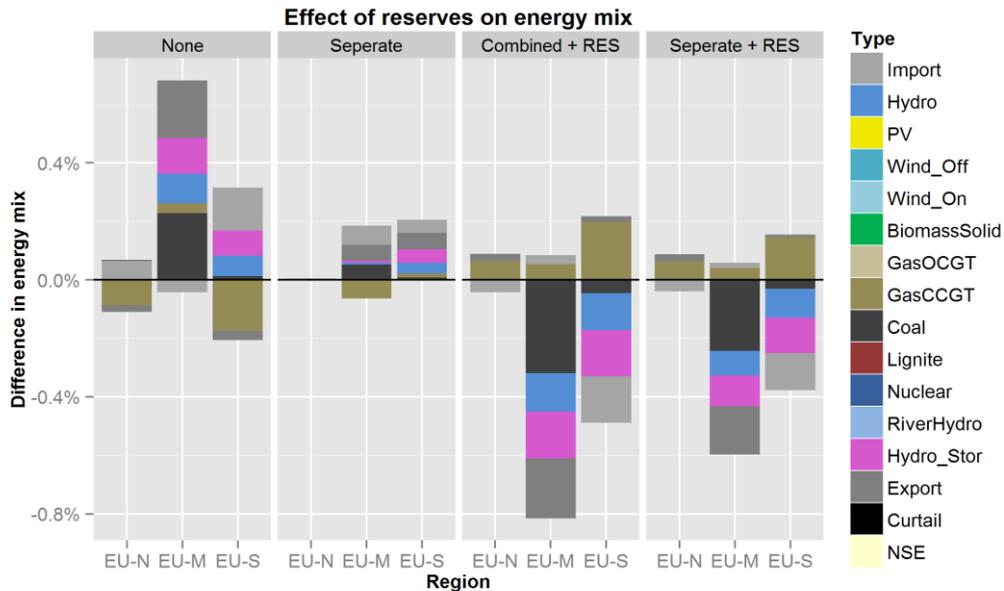


Figure 4-16: The effect of reserves on the energy mix in the 3 regions - only winter and summer month

4.3.2. Maintenance constraints

Two different maintenance options have been described until now. One of these options is to optimize the maintenance over the year; this expectedly results in more maintenance done in the summer, when demand is lower. The other option is to multiply the installed capacity with a fixed availability factor, representing the assumption that a certain percentage of the generation capacity is always under maintenance. These two options are described in section 3.2.2.7 and 3.3.4 respectively.

First, Table 4.4 shows the effect of the 2 different maintenance options on the solve time, CO₂ emissions and variable cost. Derated maintenance is used as the benchmark as this is the maintenance option used until now. It can be seen that the variable costs drop with 1.2% when using planned maintenance. However, the CO₂ emissions rise with 2 percent. Besides, the planned maintenance option increases the time to find a solution with a factor 10.

Table 4.4: Effect of different maintenance settings on KPIs

Reserve option	Variable cost (%)	CO ₂ emissions (%)	Solve time
Derated maintenance	100%	1126	3 min 28 sec
Planned maintenance	- 1.2%	+ 2.0%	35 min 12 sec

The reason for the observed changes in cost and CO₂ emissions becomes visible in Figure 4-17, which shows the difference in energy mix caused by the planned maintenance option. The usage of gas plants declines while electricity production from coal increases, coal is a cheaper fuel than gas but contains more CO₂. This explains the observed cost decrease and CO₂ increase.

In a situation with planned maintenance, more maintenance is being done during periods of low demand. These periods are generally the summer months. In winter months, when demand is high, a smaller part of the capacity is under maintenance. Figure 4-18 shows the amount of capacity under maintenance over the course of the year for the derated maintenance and the planned maintenance. As expected, the derated maintenance results in a constant amount of maintenance. On the right side of the graph, we see that the maintenance is changing over time.

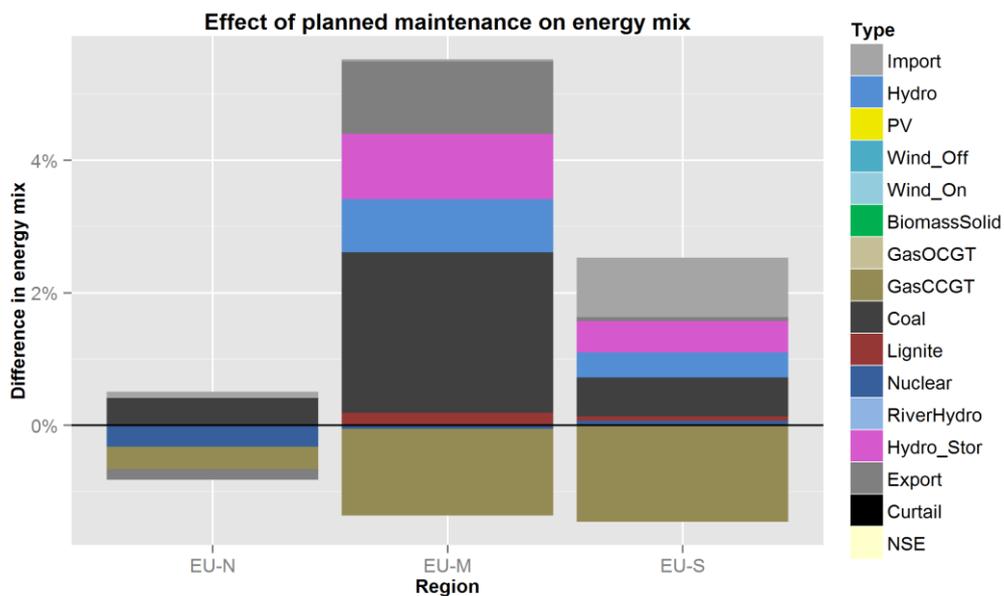


Figure 4-17: The effect of planning maintenance on the energy mix

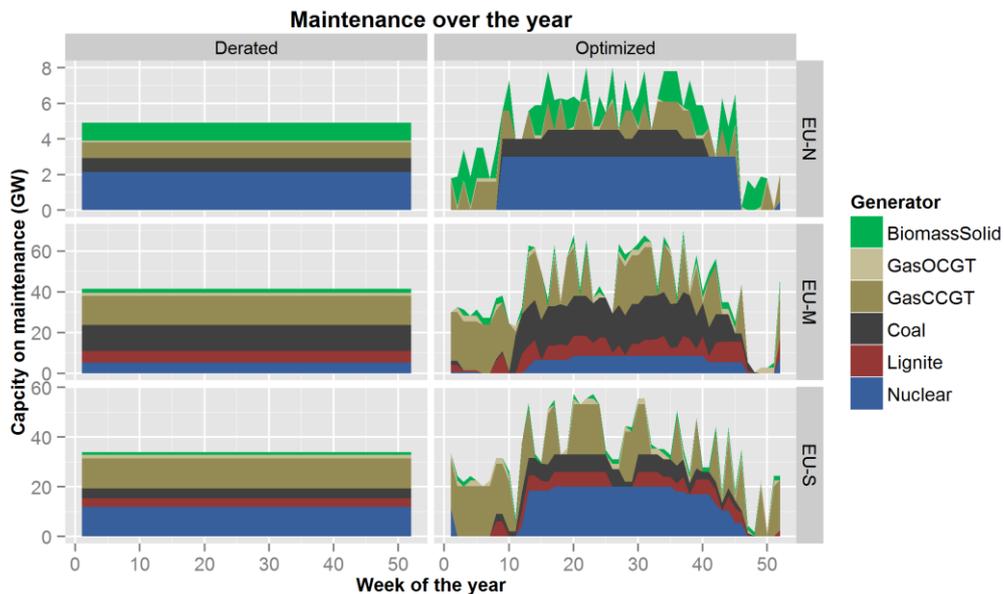


Figure 4-18: Amount of capacity under maintenance over the year

The base load plants, nuclear, lignite and coal, show a seasonal pattern. Almost no maintenance is done during the winter period while the capacity under maintenance is highest in summer. Figure 4-19 shows the dispatch over a full week; the top half of the picture shows the dispatch for a winter week while the bottom half shows the power balance of a summer week. The effects of optimized maintenance can be seen in all regions: in the winter week more base load capacity is available; this reduces the need for peaking power.

The capacity under repair for the other generator types, gas and biomass, shows less seasonal behavior and fluctuates heavily over time (Figure 4-18). As can be seen in Figure 4-19 gas plants are not used at all, the amount of cheap base load capacity is high enough to prevent gas plants from turning on in winter. During summer a little more hydro storage is used and prevents gas plants being necessary. As gas plants are almost not used, it does not matter when maintenance on these plants is executed, so the model finds an optimum at an arbitrary amount of maintenance.

Figure 4-20 shows the correlation between the average demand over a week and the amount of capacity under maintenance. The figure clearly shows the negative correlation between the demand and base load capacity under maintenance in all regions (low demand is high maintenance). There seems to be no correlation between demand and maintenance for more expensive plants, and if there is any, it is positive.

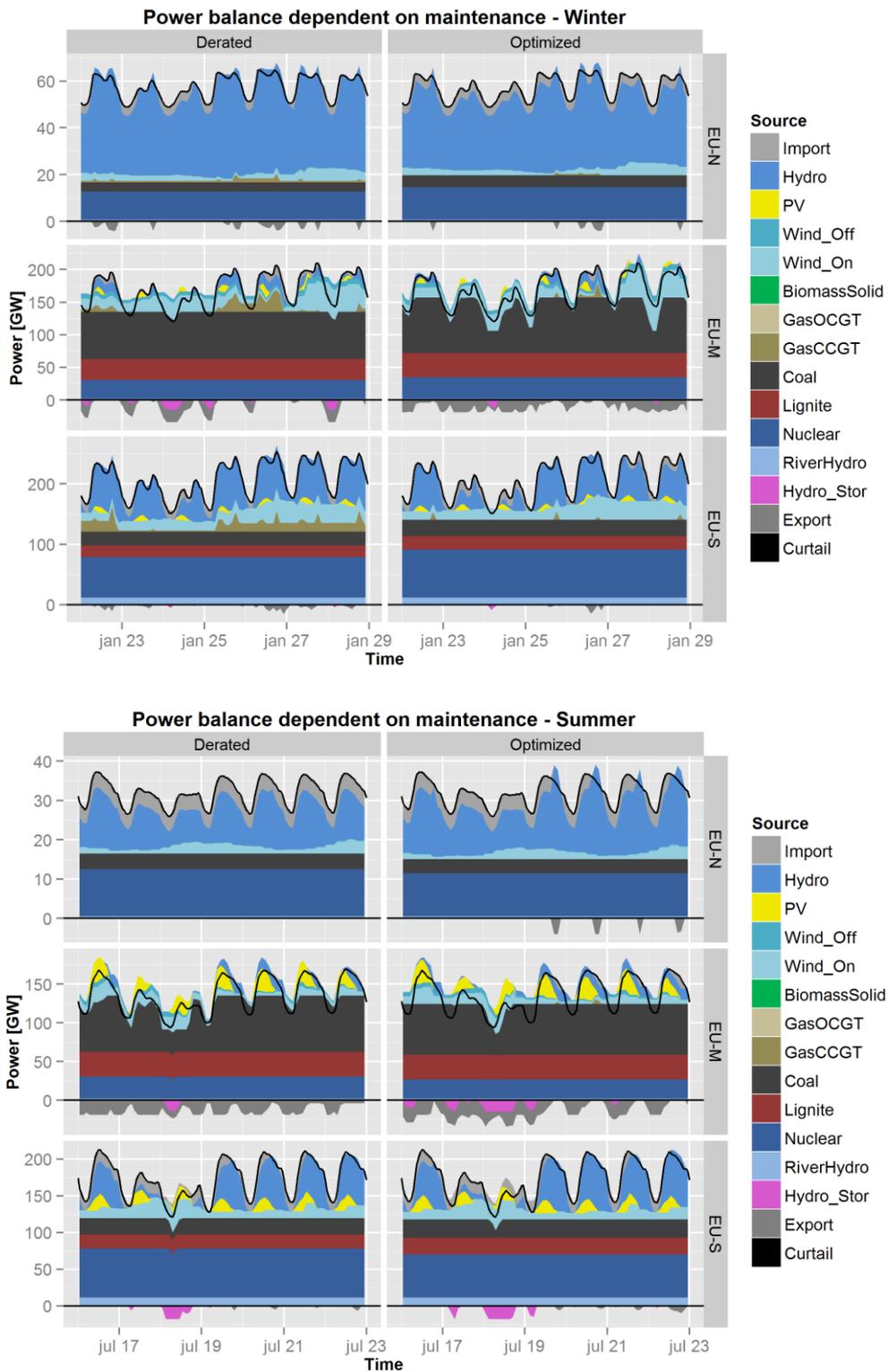


Figure 4-19: Power balance dependent on maintenance - winter week (top) and summer week (bottom)

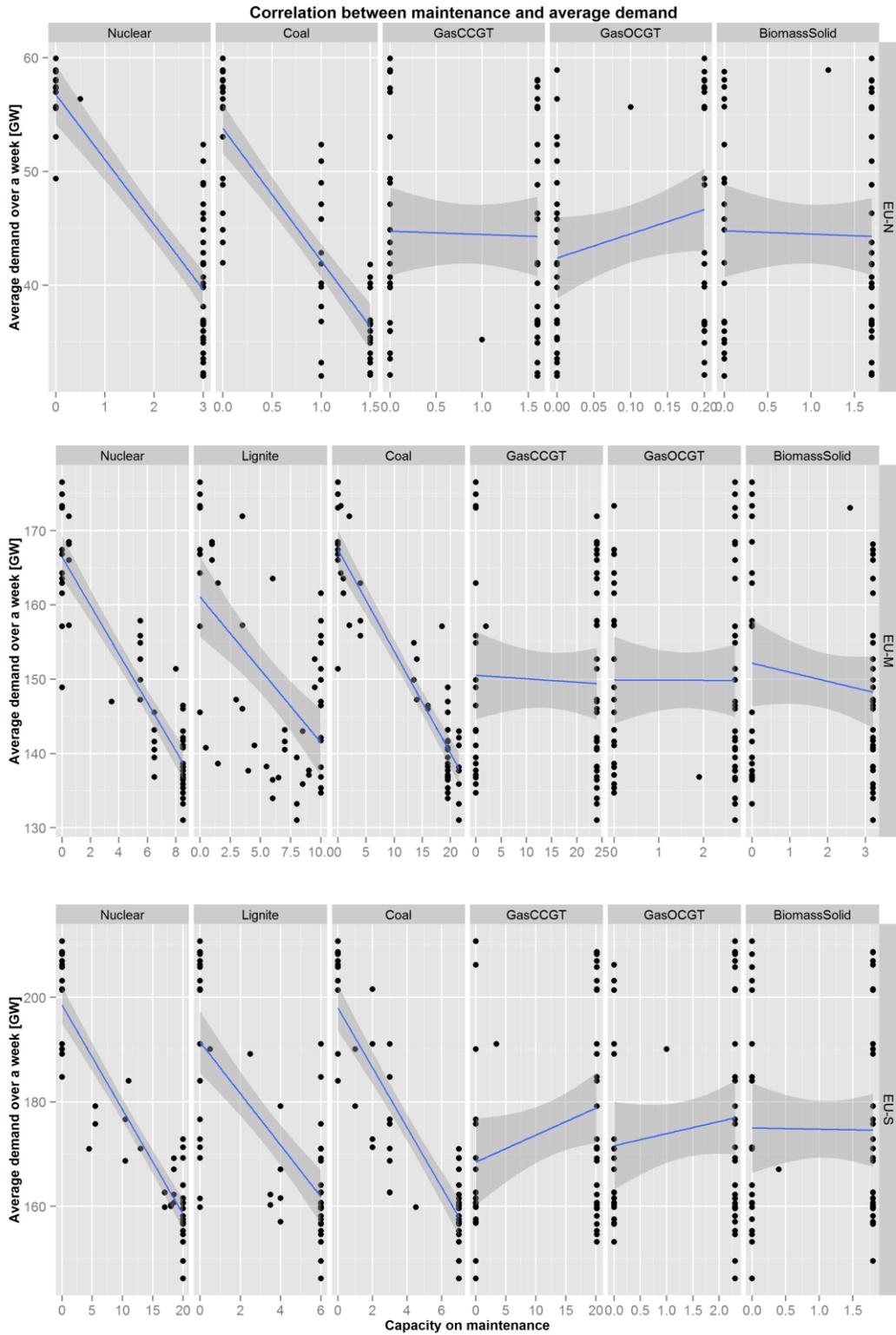


Figure 4-20: Correlation between average demand and maintenance

In Chapter 5 the model will be used to test the effect electrical energy storage has on the integration of large shares of renewables. Hence, the effect of planned maintenance in a situation with large shares of renewables needs to be tested. For this test we use, as described in subsection 3.4.3, 2030 capacities from ENTSO-E’s Scenario Outlook and Adequacy Forecast Vision 3 (ENTSO-E, 2013b). A very high renewable scenario is added by doubling the installed renewable capacities.

Figure 4-21 shows the capacity under maintenance over the year. As can be seen, using the 2030 capacities already causes the maintenance to lose a large part of the seasonal cycle. Especially central Europe, where installed renewable capacities are highest, shows fluctuating behaviour. Doubling the amount of renewables further increases the fluctuation of maintenance, also in the other regions.

The reason for this can be found in the effect that renewables have on the load, more specifically the residual load (the load after subtracting the output of renewables). As the amount of renewables increases, the residual load is more and more affected by the weather patterns instead of the daily and seasonal demand patterns. This means that during weeks with for instance high wind output, less generation capacity is necessary and more maintenance can be done.

Maintenance therefore loses its correlation with the average demand; however, some correlation between residual load and maintenance can now be expected. Figure 4-22 shows the correlation between capacity on maintenance and the average residual demand over a week. The correlations are weaker than the ones shown in Figure 4-20 because using the average residual demand might show large variations over the week compared to average demand. For instance, there might be extremely strong winds in the beginning of the week and low wind in the end of the week, resulting in an average wind week. In this average week, still enough capacity is necessary for the period with low wind output and can therefore not be on maintenance.

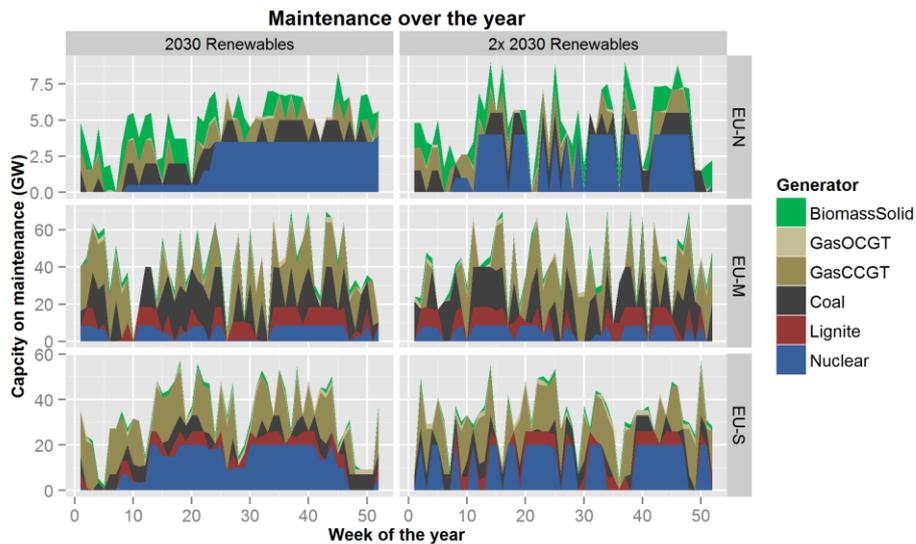


Figure 4-21: Planned maintenance in scenario with more renewables

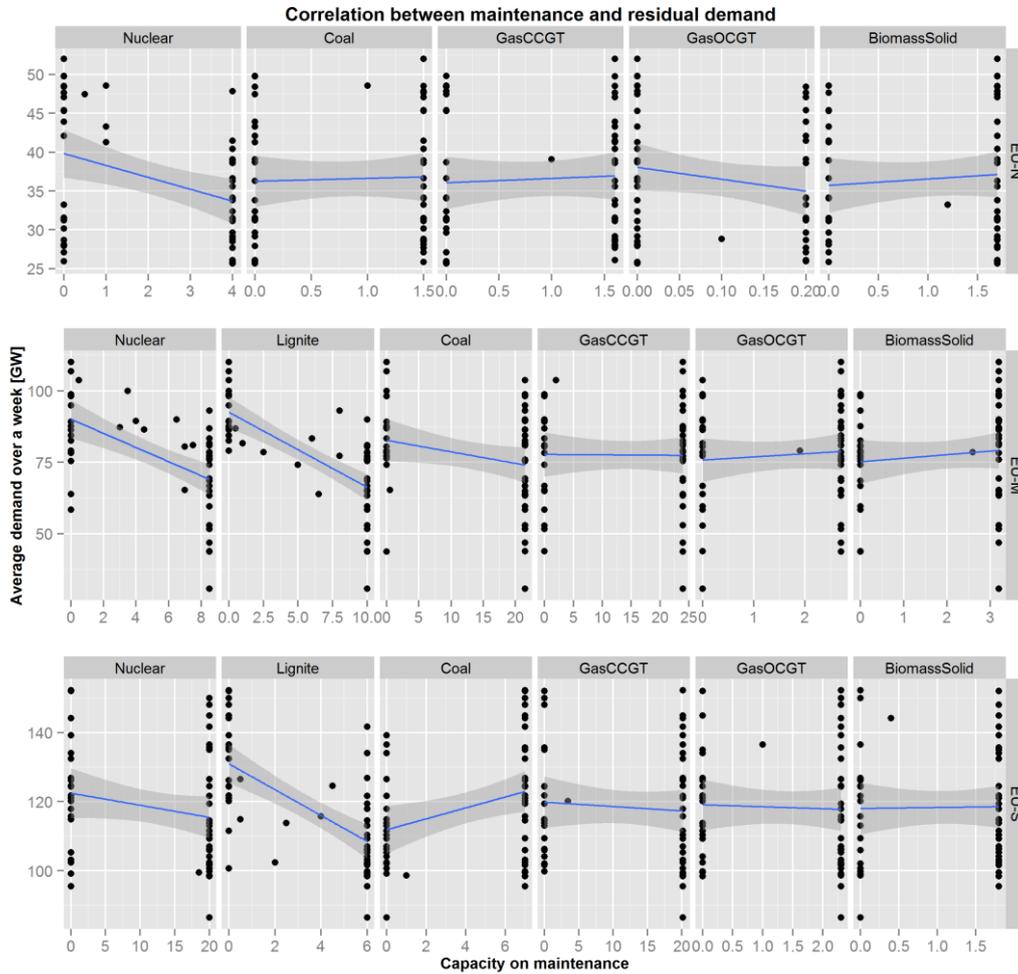


Figure 4-22: Correlation between maintenance and residual load in the 2x 2030 capacity scenario

The effect of planned maintenance behaves as expected; cost minimization is achieved when planning maintenance around periods of low demand. However, the use of gas plants, which was already low compared to values observed in reality, further declines. This further emphasizes the fact that the model does not contain transmission constraints within regions, which is an undesirable effect.

However, when introducing larger shares of renewables, the maintenance is planned around periods of high renewable output, which, although dependent on the seasons, is not fully predictable. Because the model is completely deterministic it is possible to plan maintenance around these periods of high output.

Although planned maintenance helps in finding the lowest cost solution, it will not be used in the further analysis. The reason for this is threefold. In scenarios with large shares of renewable energy planned maintenance is done during periods of unpredictable high renewable output. Besides, it reduces the use of gas plants. Finally, the time it takes to find the optimum increases significantly.

Chapter 5

EXPERIMENTATION

To test the role of electrical energy storage in a future electricity grid, the created model will be used to execute a number of experiments. These experiments are used to determine the effects of storage on the electricity system in various scenarios. The scenarios are based on the scenario data as presented in subsection 3.4.

5.1. Scenario setup

The reference scenario uses the installed generation capacities from ENTSO-E's Vision 3 (ENTSO-E, 2013b). The reference scenario is analysed twice, first without a CO₂ cap and secondly with the introduction of a 500 Mton CO₂ cap. The CO₂ emission in the runs with installed capacities from 2012 without a CO₂ cap are approximately 1200 Mton (see subsection 4.1.1.1), so introducing a 500 Mton cap could be regarded as reducing CO₂ emissions with 60% compared to the 2012 values. This is a trend that is comparable to that of the CO₂ reduction in the power sector as described by the European Commission (European Commission, 2011).

Secondly, a scenario with a large amount of renewables is analysed. This scenario is created by multiplying the renewable capacities from Vision 3 with a factor two. The amount of traditional capacity is kept constant. Again, this scenario is analysed both without and with a CO₂ cap. The introduced CO₂ cap is 100 Mton, reducing CO₂ emissions with more than 90% compared to the 2012 run (European Commission, 2011). Table 5.1 shows an overview of the considered scenarios, Figure 5-1 shows the installed capacities compared to demand and residual load in the two scenarios.

Table 5.1: Considered scenarios

Scenario	Generation capacity		CO ₂ cap (Mton CO ₂)
	Conventional sources	Renewable sources	
Reference – No CO ₂ cap	ENTSO-E Vision 3	ENTSO-E Vision 3	none
Reference – CO ₂ cap	ENTSO-E Vision 3	ENTSO-E Vision 3	500
High renewables – No CO ₂ Cap	ENTSO-E Vision 3	2x ENTSO-E Vision 3	none
High renewables – CO ₂ cap	ENTSO-E Vision 3	2x ENTSO-E Vision 3	100

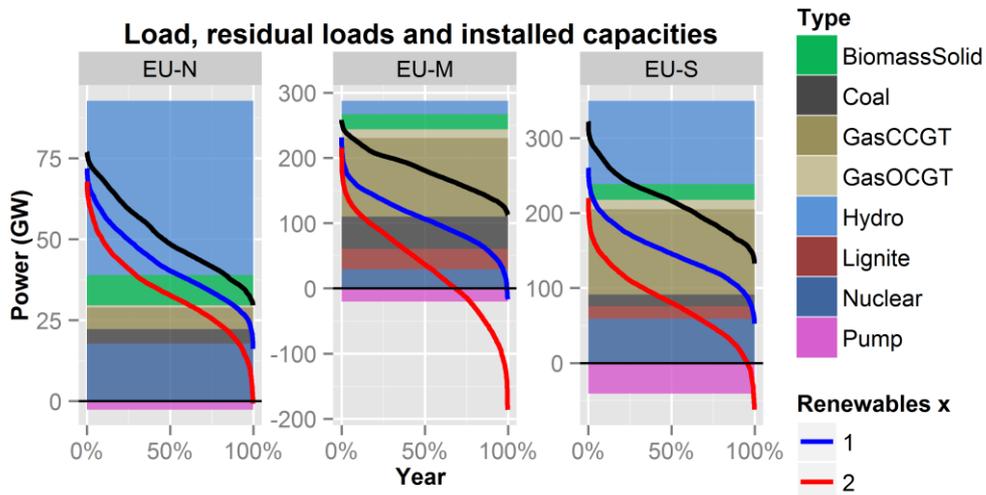


Figure 5-1: The load, installed dispatchable capacity and residual load with 1x and 2x ENTSO-E Vision 3 renewable capacities

Based on the analysis presented in subsection 2.2 (Current state of electricity storage) and 3.4.5 (Electrical energy storage properties), three storage technologies will be added to the capacity mix in the different scenarios: Flow batteries, compressed air energy storage and hydrogen (fuel cell) storage. Pumped hydro is not added because this is an accepted technology and is already present in all of the nodes. The technical characteristics of the storages are shown in Table 5.2. The considered amounts of storage capacity are 1, 5, 10, 25, 50 and 100 GW. The storage durations for each technology are fixed, so if 5 GW of flow battery is added to the system, the added storage capacity is 25 GWh⁸.

Table 5.2: Storage technology characteristics

	Power specific costs (€/kW)	Energy specific costs (€/kWh)	Storage duration (hr)	Round trip efficiency
Flow batteries	200	200	5	75%
CAES	600	50	50	70%
Hydrogen storage	4000	5	500	40%

As the amount of transmission capacity is expected to have a large influence on the effectiveness of electrical energy storage, the transmission capacity between the three nodes is also varied. Next to the transmission capacities presented in section 3.4.2, two

⁸ This disregards the efficiency of the technologies, if a 5GW, 25 GWh storage facility is fully loaded, only a part of the energy can be extracted due to the extraction losses, therefore having a storage duration that is actually shorter than 5 hours

other amounts of transmission capacity are considered. In addition to the transmission capacity that is expected in 2030, an optimistic and a pessimistic approach are taken. In the pessimistic case, only 50% of the currently planned transmission capacity is added to the system while in the optimistic case, 50% more than the expected new transmission capacity is installed. Table 5.3 shows the different amounts of transmission capacity used in the experiments.

Table 5.3: Transmission capacities considered

Transmission scenario	North ↔ Central	South ↔ Central
<i>Current capacity</i> ⁹	4.00 GW	15.00 GW
50% 2030	7.75 GW	20.25 GW
100% 2030	11.50 GW	25.50 GW
150% 2030	15.25 GW	30.75 GW

5.2. Reference scenario – ENTSO-E Vision 3

Figure 5-2 shows the reduction in variable cost dependent on the amount of storage and transmission. The marker signs show results retrieved from the model. The line behind the markers is a curve that is fitted to the model results¹⁰. In the scenario without a CO₂ cap, the curves seem to fit well. However, when a CO₂ cap is implemented, the curves fit less well. However, many model types were tested and although some of them seemed to generate a better fit; they overestimated the value of storage around zero (for instance: logarithmic functions reach infinite around zero).

In general, the curves show that small amounts of storage have a relatively large impact. The initial slope of the curves is steep and levels out when introducing more storage into the system.

Looking at the situation without a CO₂ cap, it is clear that the efficiency of a storage technology is more important than the storage duration. The flow battery, with only 5 hours of storage and a round trip efficiency of 75%, causes more cost reduction than the hydrogen storage, with 500 hours of storage and 40% efficiency. The difference between the efficiency of flow batteries (75%) and compressed air energy storage (70%) is only small; however, the difference in cost savings is relatively large.

⁹ These serve as indication, the presented current capacity is not used in the experiments of this section

¹⁰ The curves are determined by fitting the data to a function of the form:

$$Cost\ saving = \frac{StoragePower}{Storage\ Power} \cdot \alpha + \beta$$

where the sum of squared residuals is minimized by varying α and β . In general, this function fitted the observed data best.

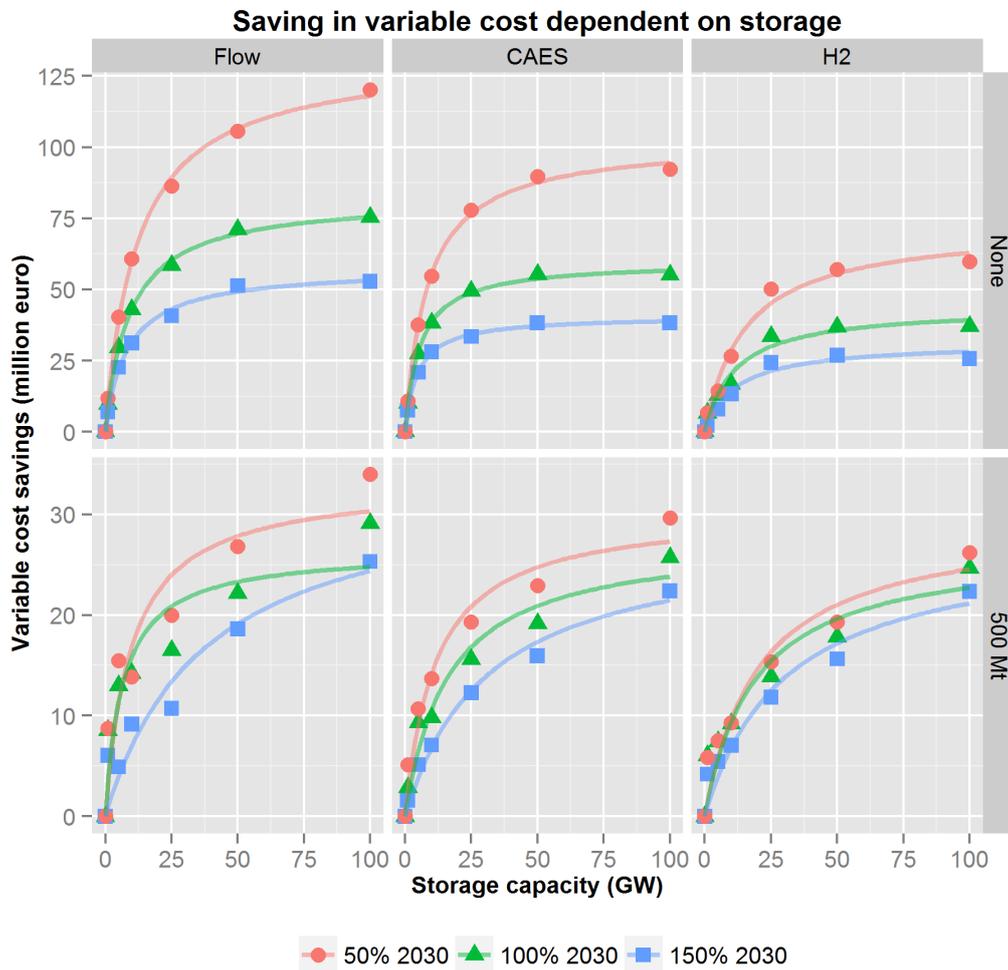


Figure 5-2: Variable cost difference based on amount of storage

Secondly, the effect of transmission capacity on is relatively large. The amount of transmission capacity added (for 150% 2030) and subtracted (for 50% 2030) from the base case is the same. However, the difference variable cost is larger when reducing transmission than when increasing transmission. This can be seen from the fact that the space between the lines is increasing when reducing the amount of transmission capacity. Figure 5-3 shows that this is caused by the fact that under all conditions, the savings in start-up cost are almost equal, however, the savings in fuel cost decrease with increasing transmission capacity.

Looking at the variable cost savings in the situation with a CO₂ cap, the observation is that the savings are significantly smaller (note the different y-axis). Also there seems to be less difference between the considered technologies and transmission capacities.

Figure 5-4 shows the marginal value of storage. The marginal value corresponds to the amount of variable cost that would be saved when introducing one extra gigawatt of storage. It is calculated by differentiating the curves that are found in the variable cost

savings from Figure 5-2. The marginal value of storage can be used to determine the amount of storage that is to be installed from a cost optimal perspective; if a flow battery would cost 5 million euro per year per GW to operate, than the amount of storage capacity to install is the interception of the horizontal line 5 and the fitted curve. The figure shows that increasing the amount of storage causes a sharp decline in the additional value of the storage. This indicates that the market for electrical energy storage will be quickly saturated.

Using Figure 5-2, the conclusion was drawn that the efficiency of the storage technology is more important than the storage duration; however, a closer look at the marginal cost presented in Figure 5-4 learns that the marginal value of CAES is higher for small amounts of storage but decreases faster when increasing the amount of storage capacity. Hence, there is room for storage with longer storage duration but the amount of storage power can only be small to be more beneficial than a higher efficiency. Secondly, the conclusion doesn't hold for storage technologies with very low efficiencies such as hydrogen storage, as can be seen from Figure 5-4.

Figure 5-4 also shows the marginal value of storage in a situation with a CO₂ cap. Due to fitting errors (especially in the case of flow batteries), the results are not very accurate. The values at 0 GW of storage power should be higher than depicted; the savings on variable cost of the first GW of installed storage capacity ranges from 8 million euros for a flow battery in a situation with low transmission to 4 million euros for hydrogen storage in a high transmission scenario, as can be seen in Figure 5-3. Nonetheless, the conclusion remains that a CO₂ cap has a negative influence on the value of storage.

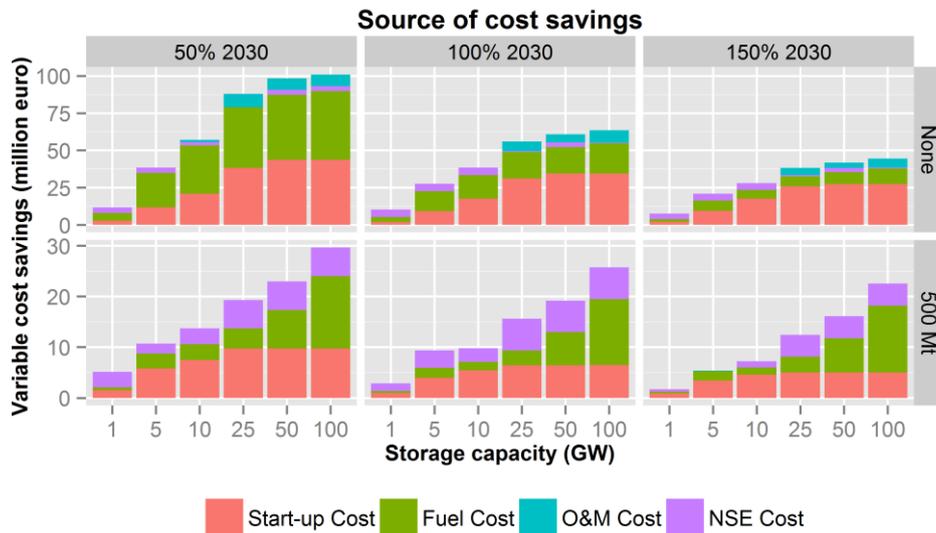


Figure 5-3: Source of variable cost savings due to storage (for flow battery storage)

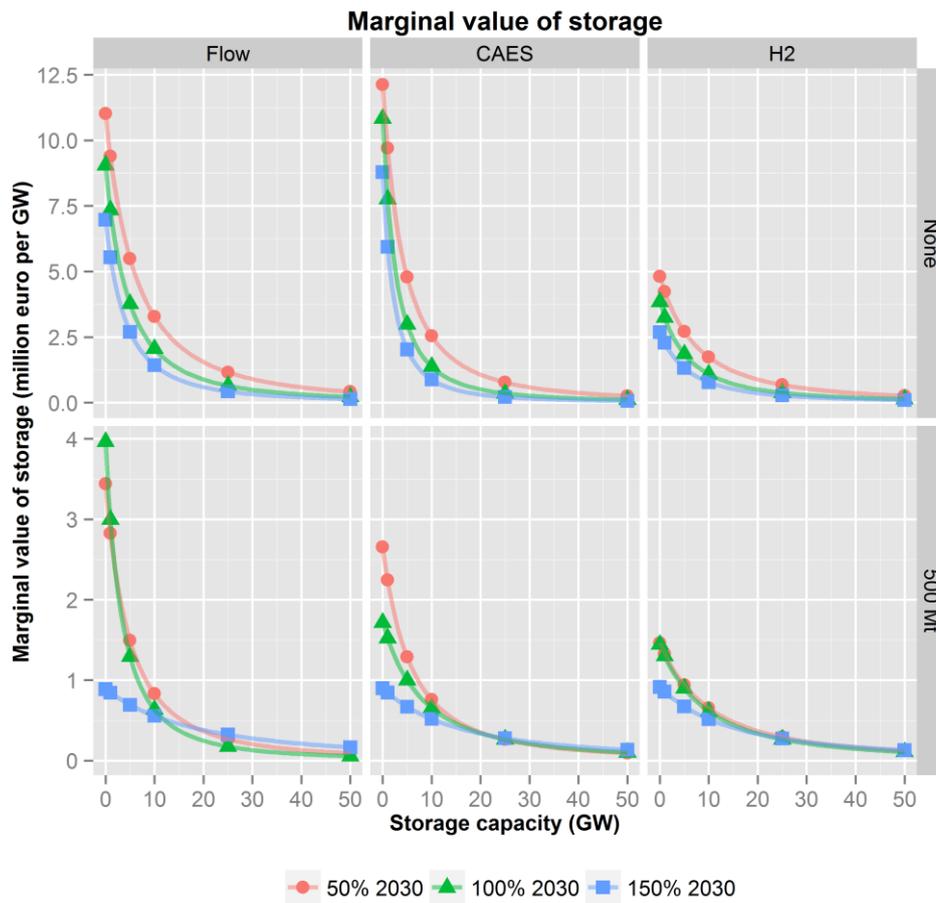


Figure 5-4: The marginal value of storage

The mechanism behind the effects electrical energy storage has on the variable costs can be explained using the energy mix that results from adding storage. The energy mix in before adding storage is shown in Figure 5-5. Figure 5-6 shows the percentage difference in energy mix of all the three regions in the runs with storage compared to a system without additional electrical energy storage. The used transmission capacity is 100% 2030, the same results hold for the different transmission scenarios.

Starting at the top left of the figure, flow battery storage without a CO₂ cap, it can be seen that an increase in storage capacity causes the amount of gas that is used to be reduced. The reduction of gas plants is mainly replaced by coal but there is also a slight increase in use of nuclear and lignite plants. Secondly, we see an increase of approximately the same size in the use of the flow batteries. This indicates that energy from coal, nuclear and lignite plants is being stored in the batteries during low demand, when a part of these base load plants would normally be idle and being released in periods of high demand, when gas would be used to cover the peaks). Thirdly, the amount of transportation (im- and export) also increases. This indicates that storage does not only

have an influence on the region where it is deployed, but also affects other regions. Finally, there is a slight decrease in necessary curtailment (indicated by the little black stripe below the reduction of gas use).

Looking at the other storage technologies, compressed air energy storage and hydrogen energy storage, we see roughly the same results, although the effects are slightly smaller for CAES storage and a lot smaller for H2 storage. What is interesting here is the effect of H2 on the variable cost compared to the effect on the energy mix. More specifically, H2 has a very marginal effect on the energy mix, almost four times smaller than the effects of a flow battery, nonetheless, the marginal cost savings are only about twice as small as the savings that are achieved with a flow battery. This indicates that a large part of the variable cost savings lies in small changes of the energy mix.

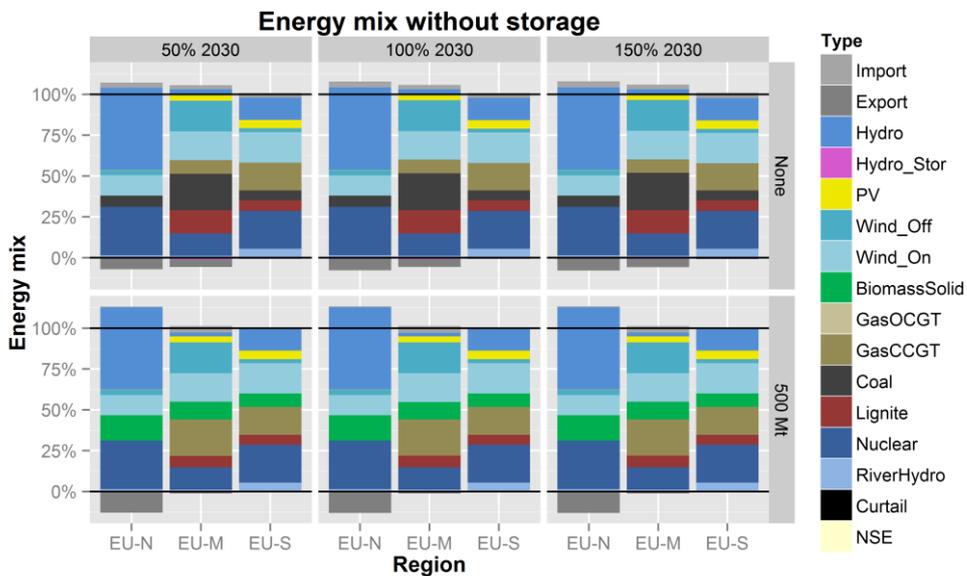


Figure 5-5: Energy mix without storage

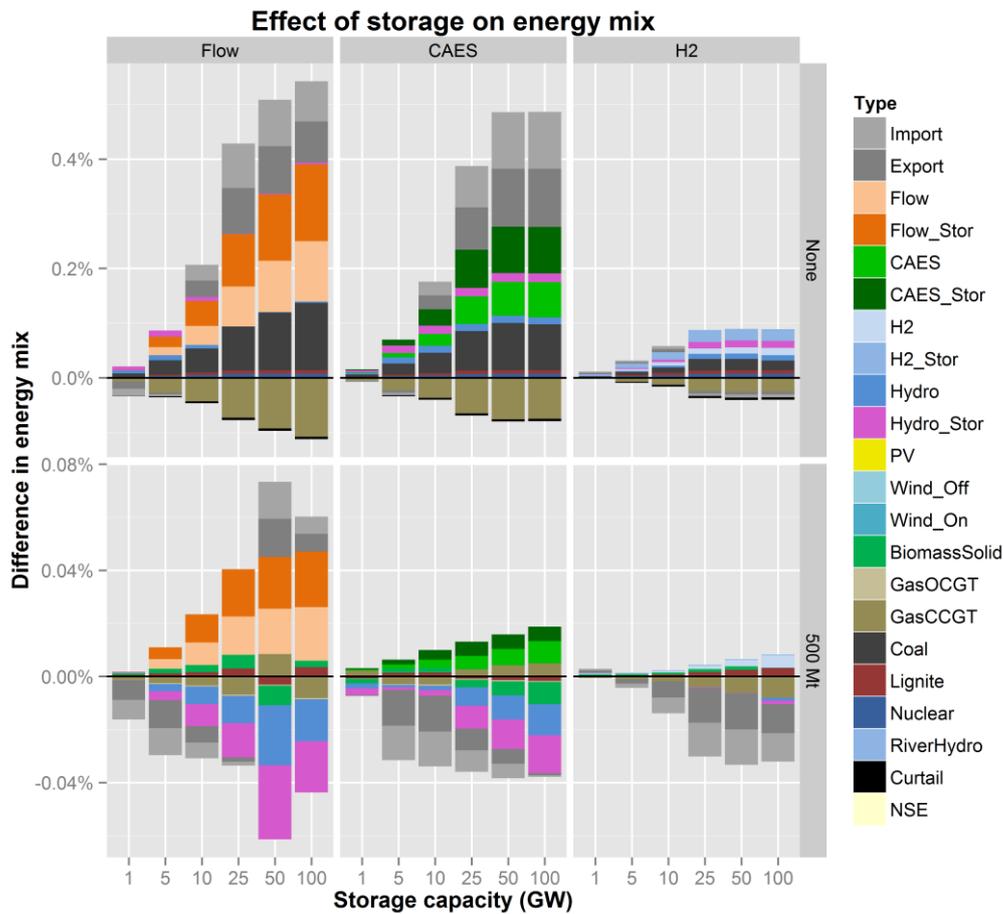


Figure 5-6: Effect of storage on total energy mix (transmission used is 100% 2030)

As already observed, adding a CO₂ cap reduces the effect that storage has on the operations of the system. The reason for this is now clear, as the CO₂ is capped at a certain level, CO₂ intensive coal and lignite plants are not able to replace the relatively CO₂ poor gas plants. Nonetheless, the change in energy mix does show interesting behaviour. When introducing a small amount of storage, transportation is reduced. However, when adding more storage, the reduction in transport becomes smaller and is replaced by a reduction in the use of the already present pumped hydro storage plants. Really large amounts of storage (50 and 100 GW flow batteries) even cause an increase in transmission.

To explain the change in the amount of energy that is transported, we can zoom into the effects of energy storage in the various regions. Figure 5-7 shows the effects of two different flow battery sizes, 5 and 50 GW, in the different regions. Again, the 100% 2030 transmission scenario is used.

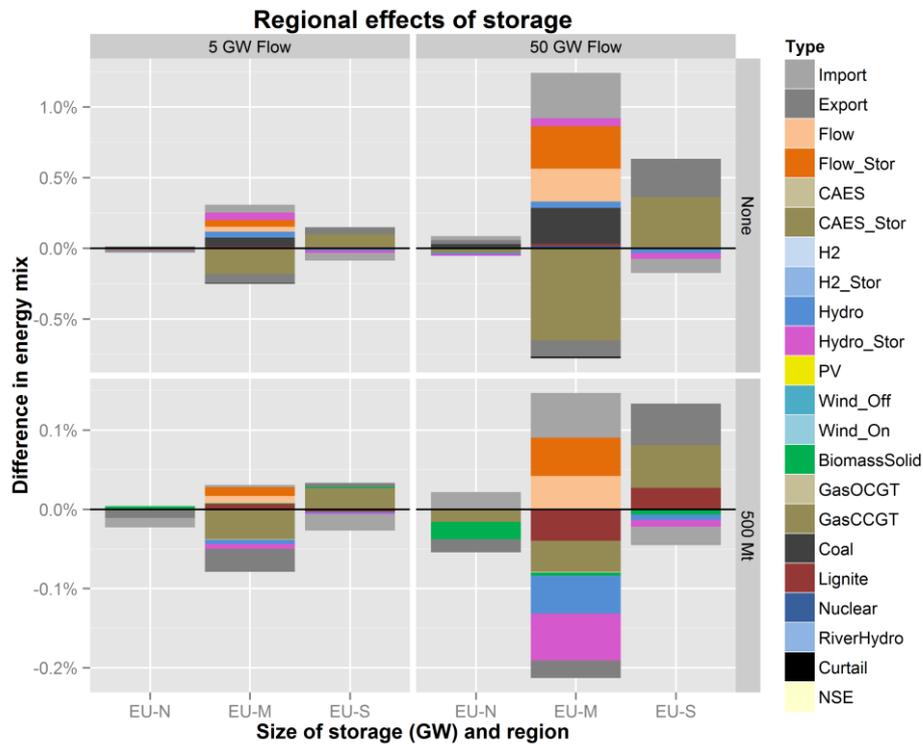


Figure 5-7: Regional effects of storage for two storage capacities, using flow battery storage and 100% 2030 transmission

First look at the scenario without a CO₂ cap. In the situation where 5 GW of flow battery is added to the central node, the gas use in the central node is reduced, and replaced by coal plants. Secondly, although the total amount of transmission does not change much, the export to the south is reduced while the import from the south is increased. The gap in the southern node, caused by more exports and less imports less, is filled with gas.

Increasing the storage capacity to 50 GW's amplifies this result. The central node, where the storage is added, reduces its gas consumption while increasing coal consumption. The transport to the south is reduced about the same amount as in the 5GW case, however, the import from the south increases significantly. Again, the south changes the emergent gap with gas.

As it seems now, the middle region reduces its gas production while importing more gas produced electricity from the south. The reason for this is unclear as production in the own region is preferred over import, as there will be transport losses. More insight is gained using Figure 5-8, which shows the cumulative difference of energy production over the year. The figure should be read as follows: a positive slope of a line means that the model with storage used more of that commodity than the model without storage.

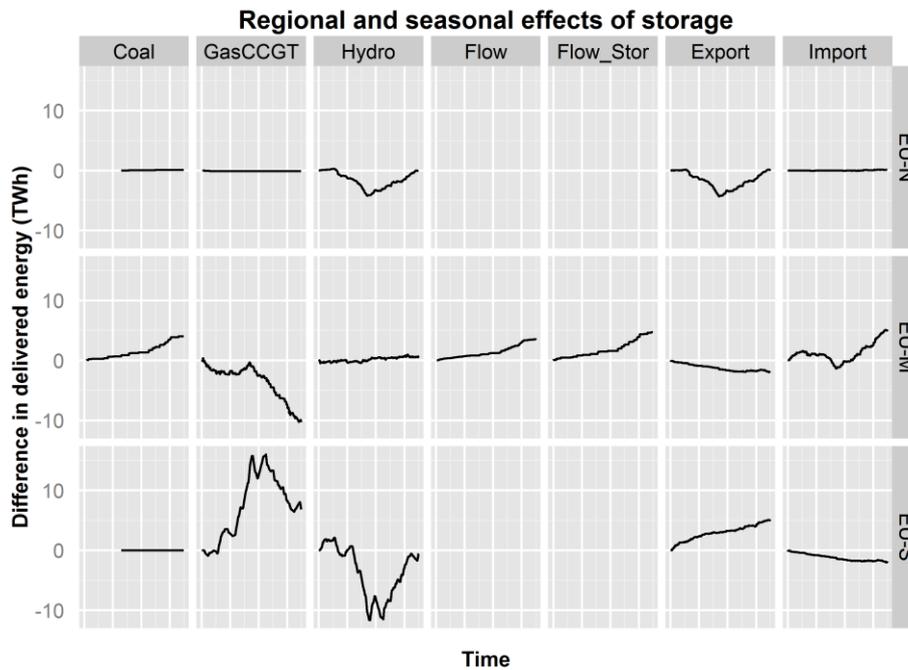


Figure 5-8: The cumulative effect of storage on the energy mix over the course of the year (50 GW flow battery compared to no additional storage, situation with no CO₂ cap and 100% 2030)

In the northern node, less hydro is being used in the beginning of the year while more is being used at the end of the year. The end result is that the same amount of hydro is used over the entire year, which is also the reason why the difference in output did not show up in Figure 5-7. Hydro shows the same behaviour in the southern node, however, the increased export, as can be seen from the positive slope, is spread over the entire year. This is because the gas usage in the southern node shows opposite behaviour to that of pumped hydro. So the additional import in the central node is mainly powered by additional hydro generation in the other two nodes. The expectation is that this is done to reduce the start-up costs.

Looking back at Figure 5-7, in the situation with a CO₂ cap, the import from the southern region is reduced approximately the same amount in both the 5 and 50 GW case. Secondly, like in the no CO₂ cap case, more energy is imported from the south, filled in by gas plants. The seasonal effects look largely the same as the ones shown in Figure 5-8 and are therefore not discussed. The largest difference caused by introducing a CO₂ cap therefore is the fact that storage is not able to replace expensive gas plants with cheaper base load plants. This reduces the variable cost savings achievable in the situation without a CO₂ cap.

Storage charges during hours of low demand, increasing the off-peak price, and discharges during hours of peak demand, decreasing the on-peak price. Therefore, it is expected to reduce price variation on the electricity market. Figure 5-9 shows a boxplot of the marginal cost observed over the year for the central region. The situations where

the marginal cost increase to the value of lost load (VOLL) are excluded from this plot. The graph shows that both storage and transmission reduce the variation in prices. Especially in situations with more than 50GW of storage the variation is reduced by a large amount. However, the prices are relatively stable in the researched scenarios already and therefore no valid conclusions on the effect of prices can be drawn from this diagram.

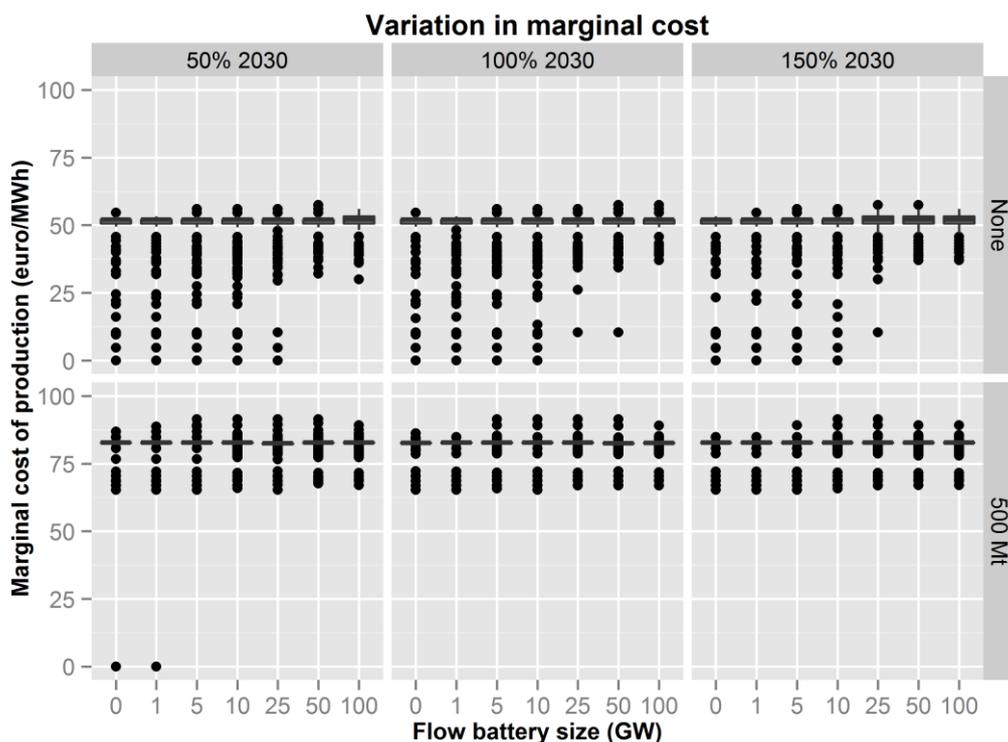


Figure 5-9: variation in marginal cost dependent on transmission and storage

5.3. Future scenario - Highly renewable power system

This section tests the effects of electrical energy storage in a system with a large amount of renewable generation capacity. The renewable generation capacity is doubled compared to the values used in the previous section, the amount of other generation capacity remains constant. The figures used to describe the effects of storage are the same and should therefore be familiar. The results of adding a very stringent CO₂ cap, equivalent to approximately 90% CO₂ reduction, are also presented.

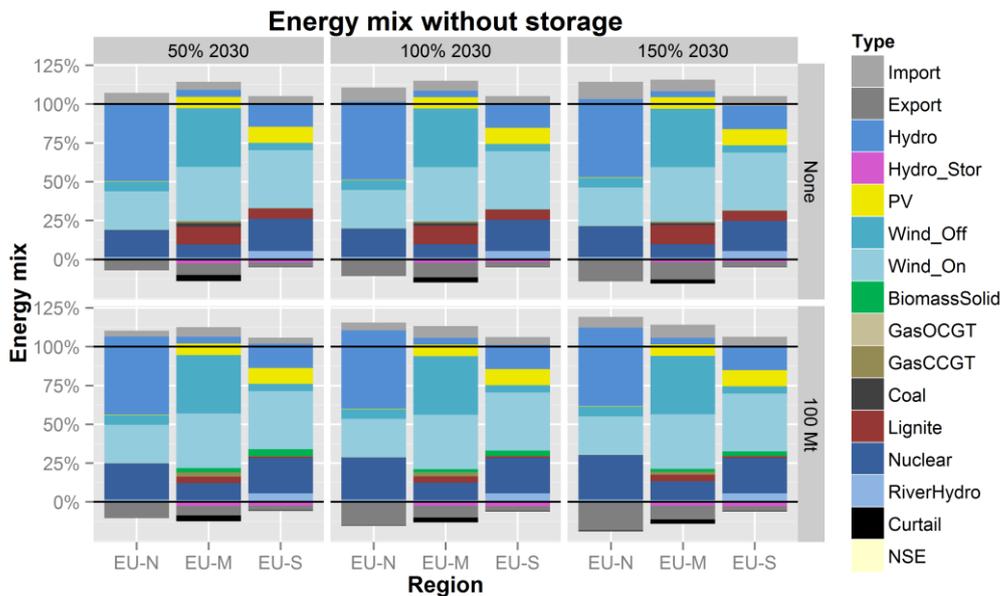


Figure 5-10: The energy mix without adding storage for different transmission capacities and CO₂ constraints

The energy mix that results from doubling the renewable capacities is shown in Figure 5-10. As can be seen, on- and offshore wind now covers a large part of the total energy demand. In total, more than 50% of the energy is supplied by wind, with more than 70% of wind production in the central node. Including solar power, more than 60% of the total energy demand is supplied by fluctuating renewables. The remaining demand is largely covered by nuclear and lignite plants in the situation without a CO₂ cap, when a CO₂ cap is introduced some of the lignite is replaced with gas.

Figure 5-11 shows the savings in variable cost due to adding storage to the central node. Again, a curve¹¹ is fitted to the data retrieved from the model in order to more easily see the trend in the results. The same type of curve fits all the scenarios equally well. The reduced variable costs are shown for both the situation with and without CO₂ cap.

The first thing to notice is the large increase in savings compared to the previous section. The maximum savings in the previous case were 125 million euros for a 100GW flow battery, in the absence of a CO₂ cap. The variable cost savings in this scenario, where the amount of renewables are doubled compared to the previous subsection, surpasses 2500 million euros. This is an increase of more than a factor 20.

Secondly, the most valuable storage technologies are the long term storage technologies. Previously, the flow batteries were able to reduce variable cost most, followed by

¹¹ The curves are determined by fitting the data to a function of the form:
 $Cost\ saving = \alpha \cdot (1 - e^{-\beta x})$
 where the sum of squared residuals is minimized by varying α and β .

compressed air energy storage and hydrogen storage, following the order of reducing efficiency. However, in the high renewable scenario, the value of storage is highest for CAES, which has storage duration of 50 hours and a slightly worse efficiency than the flow battery (70% versus 75%).

Even more striking is the increase in savings that are achieved by hydrogen storage compared to the other technologies. Hydrogen storage has a storage capacity of 500 hours and although H₂ storage only has a round trip efficiency of 40%, it still outperforms the flow battery storage. Next to that, it approaches the value of CAES storage. Apparently, an increase in renewable energy penetration increases the value of long term storage technologies.

Another observation is that the slope of the cost savings curve does not flatten out as quickly in this scenario. In the scenario with a small amount of renewable, the addition of storage capacity above 25GW has only limited additional effects. However, the average value of storage remains relatively high over the entire range of tested storage capacities. Doubling the amount of renewable energy capacity allows the addition of more than double the storage capacity.

Looking at the effects of the transmission capacity on the value of storage, we see that storage is most valuable in a situation with little transmission capacity. However, comparing the results to the low renewable scenario from the previous section, the lines are more evenly distributed and closer together. The reason for this can be found in Figure 5-12. By far the largest part of the cost savings now lies in fuel cost. An increase in transmission capacity does decrease the reduction of fuel cost and therefore decreases the value of the storage.

The bottom part of Figure 5-11 shows the savings in variable cost in the situation with a CO₂ cap. The value of storage almost doubles compared to the value of storage without a CO₂ cap, for all three technologies. In the previous analysis the value of storage reduced due to the introduction of a CO₂ cap. Looking at the source of these cost savings (Figure 5-12) it can be concluded that the cost saving primarily comes from savings in fuel cost, similar to the scenario without a CO₂ cap. The second largest source of the savings comes from savings in start-up costs.

Figure 5-13 is used to show the marginal value of storage, the reduction of variable cost that is achieved by introducing 1GW of additional storage. Although the marginal value declines quickly, it still does not completely level out after introducing the maximum tested capacity of 100GW. Figure 5-13 also shows that the marginal value of storage is higher if the energy can be stored for longer periods of time, as can be seen from the higher value of CAES and H₂ storage, despite of their low efficiencies.



Figure 5-11: Variable cost savings dependent on storage technology

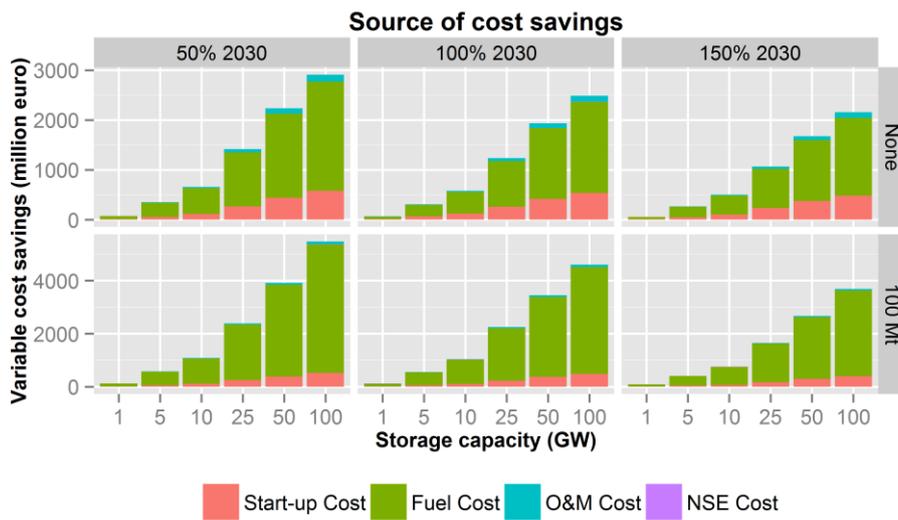


Figure 5-12: Source of variable cost savings for CAES

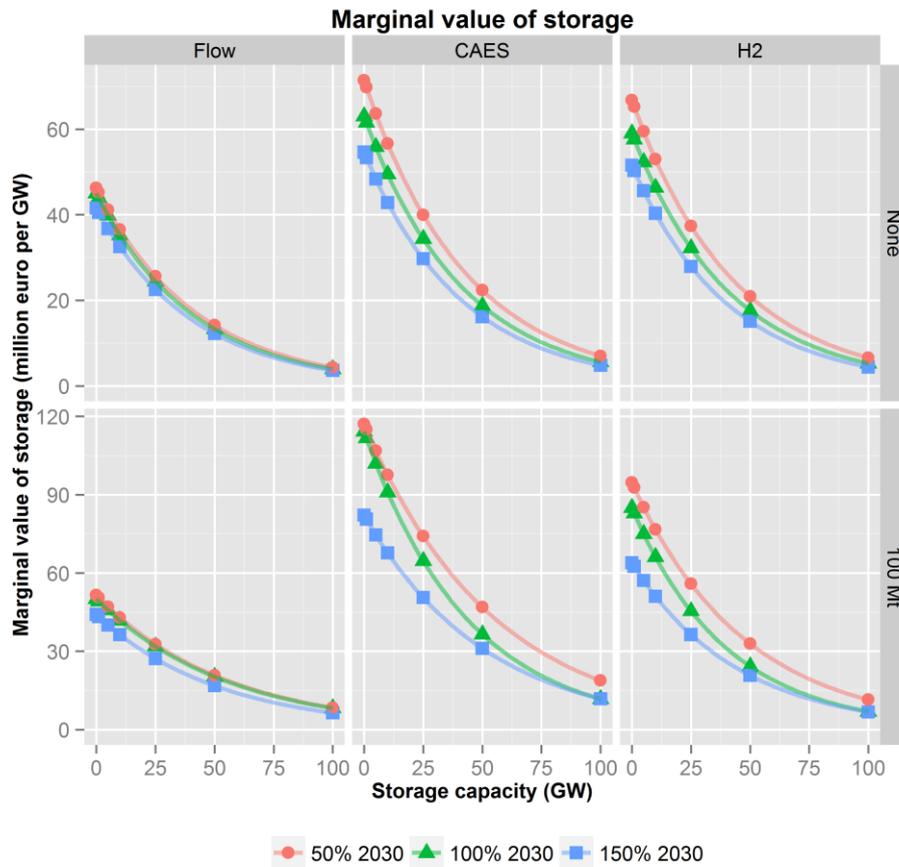


Figure 5-13: Marginal value of storage technologies

The energy mix resulting from doubling the renewable capacity was shown in Figure 5-10, Figure 5-14 shows the effect of storage has on the total energy mix for the different technologies. As expected, the storage technologies introduced into the system show a large increase. The difference in efficiencies can be clearly distinguished from the figure; hydrogen needs to store a lot more (darker blue) to release a small amount of energy compared to flow battery and compressed air energy storage.

Flow storage without a CO₂ cap (top left) mainly has an effect on the amount of curtailment. Curtailment is the practice of reducing the output of renewable sources that are overloading the system. This means that a reduction of curtailment has a direct effect on the total variable cost of generation. If curtailment can be prevented by storing the normally curtailed energy, the energy can be used later when renewable output is lower (or demand is higher). This reduces the need for firing up thermal power plants and therefore reduces fuel costs. As can be seen from the figure, the use of gas and coal plants declines. As these are the most expensive plants being used in the total energy mix, the conclusion is that the stored energy is primarily used during peaks.

Continuing with the other technologies, CAES and H2, we see similar effects. The technologies further reduce the use of coal plants. Secondly, CAES and H2 also increase

the use of base load plants; primarily lignite in the case of CAES and both lignite and nuclear in the case of H2. Due to the longer storage duration, more base load capacity can be kept at the maximum output level. This helps to further reduce the total cost of generation. The effects of storage on the amount of transported energy are negative; more storage leads to less transmission. However, the effects are relatively small.

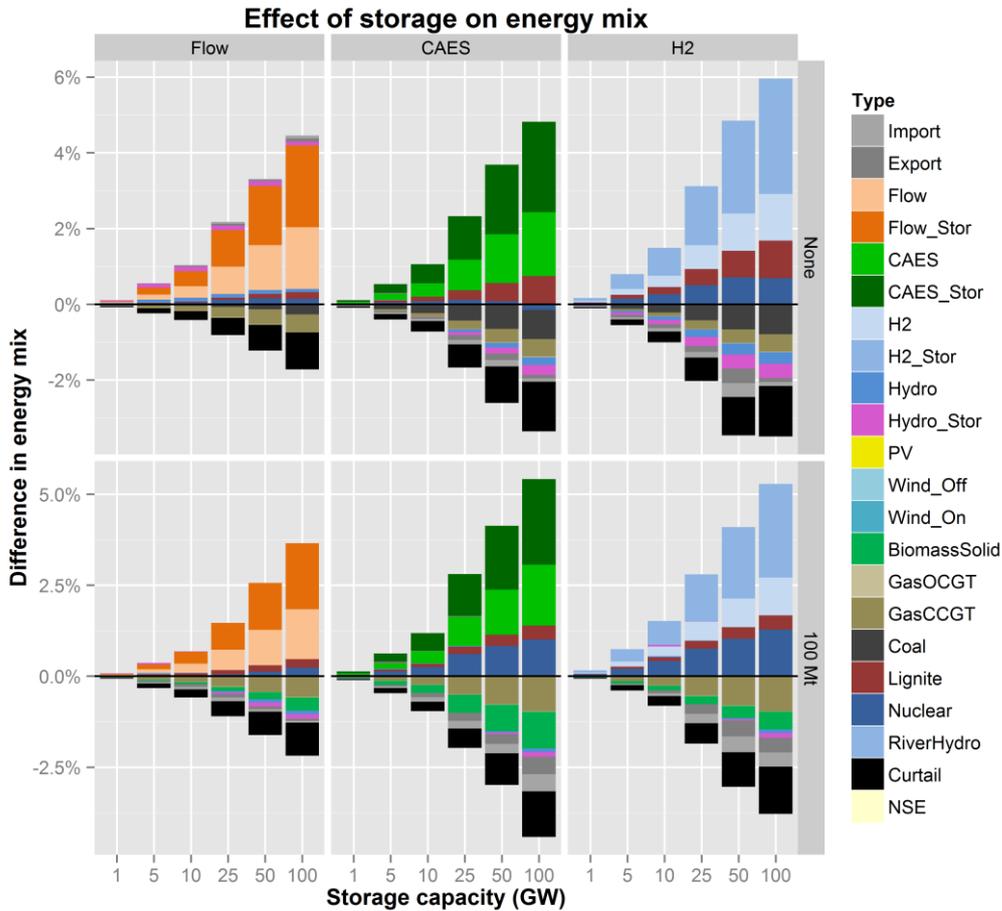


Figure 5-14: Effect of storage on total energy mix (transmission 100% 2030)

The effect of storage on the utilisation of generators can be seen in Figure 5-15, which shows a kernel density plot (smoothed histogram) for the output of nuclear, lignite and gas plants. As can be seen, the nuclear and lignite plants run at their maximum capacity more often. On the other hand, the gas fired plants are idle more often. Secondly, the maximum power required from the gas plants is reduced, from 100GW to 77GW. This means that a certain amount of gas plants can be closed down due to the introduction of storage; however, the amount of gas plants that can be taken out of order is less than the amount of storage added to the system. This means that the existing peaking capacity cannot be replaced by storage on a one to one basis.

Next to the utilization of the traditional generation technologies, the utilization rate of the storage technologies reveals how efficiently they are used. The utilization rate of storage is determined by the amount of energy they deliver on a yearly basis divided by the total storage capacity. A utilization factor of one would correspond to one load cycle per year, a utilization rate of 365 indicates that the storage is completely filled and emptied on a daily basis. Figure 5-16 shows the utilization rate of the three tested technologies. As expected, the technology with the smaller power to energy ratio has the highest utilization rate, reaching almost 150 cycles per year. The utilization rate decreases with the storage duration, hydrogen storage only operates less than one full cycle per year. However, the maximum utilization rate of hydrogen storage is also lower, as it has an energy to power ratio of 500, it would take more than a month to completely fill and empty the entire storage.

The utilization rate of both flow batteries and CAES initially increases when introducing more storage capacity. This is caused by the fact that energy storage for a large part depends on energy that would normally be curtailed, as the amount of curtailment follows the output of renewables, the curtailment is often volatile. A larger storage power can help store a larger part of the normally curtailed energy.

Storage has a larger effect on the variable cost when a CO₂ cap is introduced to the system because it replaces more expensive power sources than in the situation without a CO₂ cap. The bottom part of Figure 5-14 shows that the output of gas and biomass plants is reduced in favour of cheaper base load plants such as nuclear and lignite. The imposed CO₂ cap does not allow the amount of lignite to be increased much; therefore the use of less economically efficient nuclear plants is increased. In the situation with a CO₂ cap, the price differences between the fuels that are substituted are higher than in the situation without a CO₂ cap; the savings in fuel cost are therefore higher.

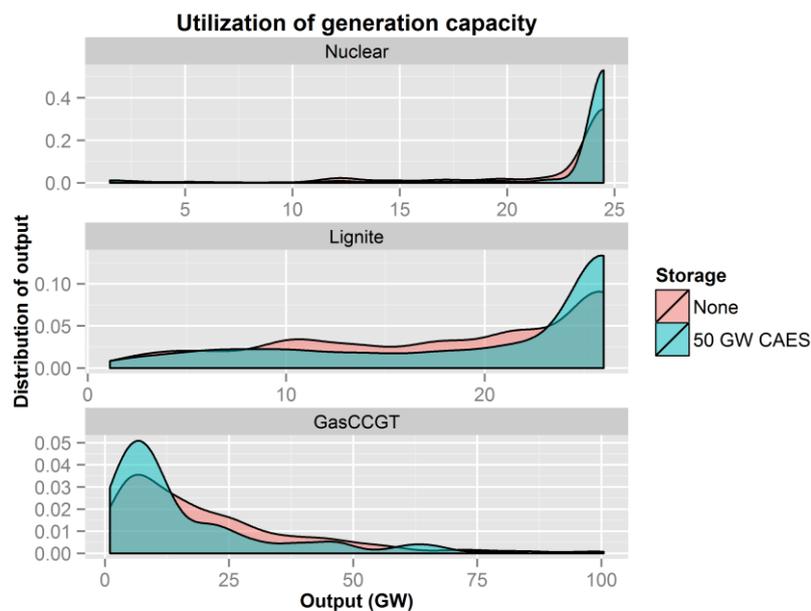


Figure 5-15: Utilization of generation capacity in the central region, situation with a CO₂ cap

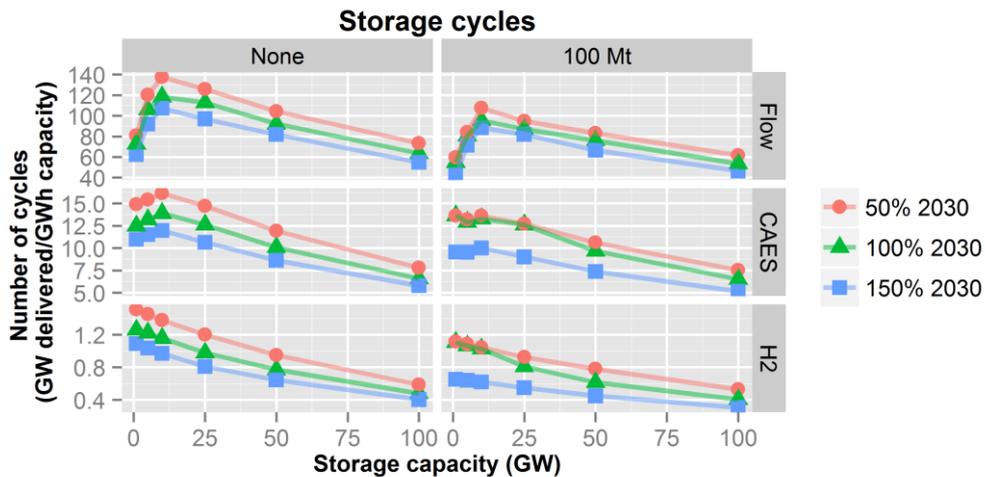


Figure 5-16: Utilization of storage technologies

In the previous subsection, where a situation with less renewables was analysed, the storage added to the central node also changed the energy mix in the northern and southern nodes. The expectation is that increasing the amount of renewables would also increase the regional differences storage has, as during periods of high renewable output, more energy can be exported while during periods of low demand, imports increase. However, Figure 5-17 shows that the inter-regional effects of storage are small compared to the local effects. The changes observed in Figure 5-14 mostly source from the central node. Only in the situation with a CO₂ cap and a large amount of storage (bottom right) the amount of nuclear power increases in the northern node. This increase in nuclear output is counter balanced by a decrease in import and an increase in export.

As we have seen before, the energy mix or change in energy mix might not be able to show all the effects of adding storage to the system. There might be seasonal changes in the use of power sources, even if the total amount of energy used over the entire year remains equal. However, Figure 5-18 shows that this phenomenon is not the case in the scenario currently under study. The differences observed emerge gradually over the year.

The effect storage has on the energy mix translates to changes in CO₂ emissions. As seen before, fuels with lower CO₂ emissions are replaced with base load capacity in the form of nuclear and lignite plants. Although nuclear power does not have any CO₂ emissions, lignite has very high carbon emissions. Figure 5-19 shows the CO₂ emissions, again, dependent on storage type, storage size and transmission capacity. The highest CO₂ emissions occur in the situation with a small amount of transmission; this is because during periods of high renewable output, the overcapacity cannot be exported to other regions and therefore the other regions require more fossil fuels to meet demand.

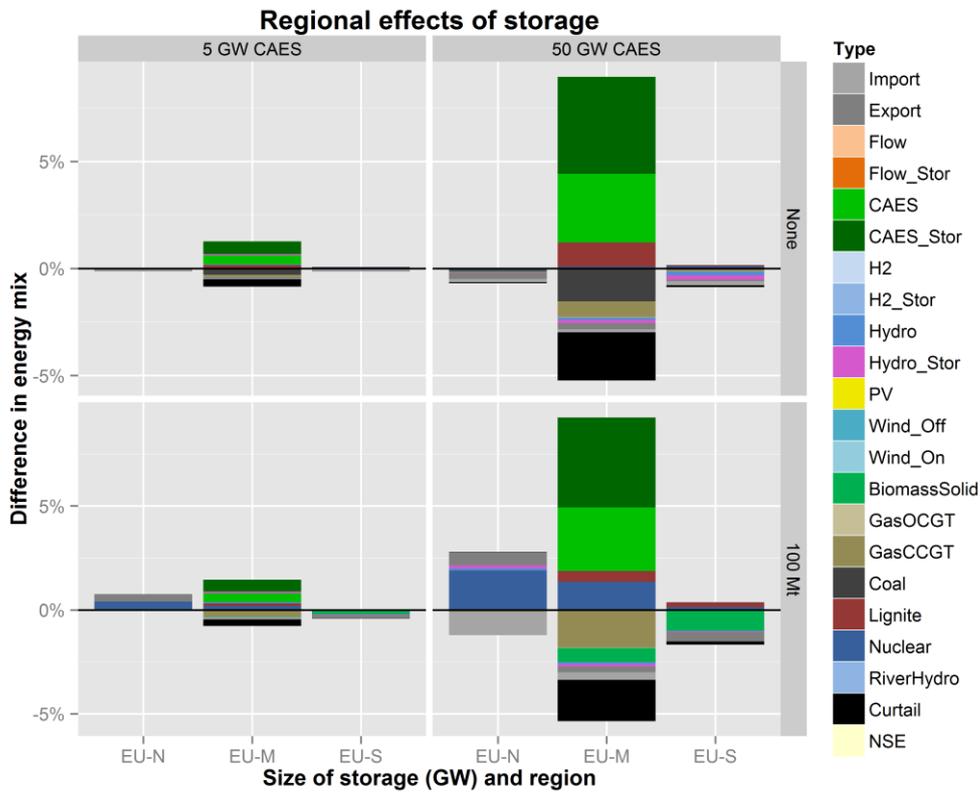


Figure 5-17: Regional effects of storage for two storage capacities, using CAES and 100% 2030 transmission capacities

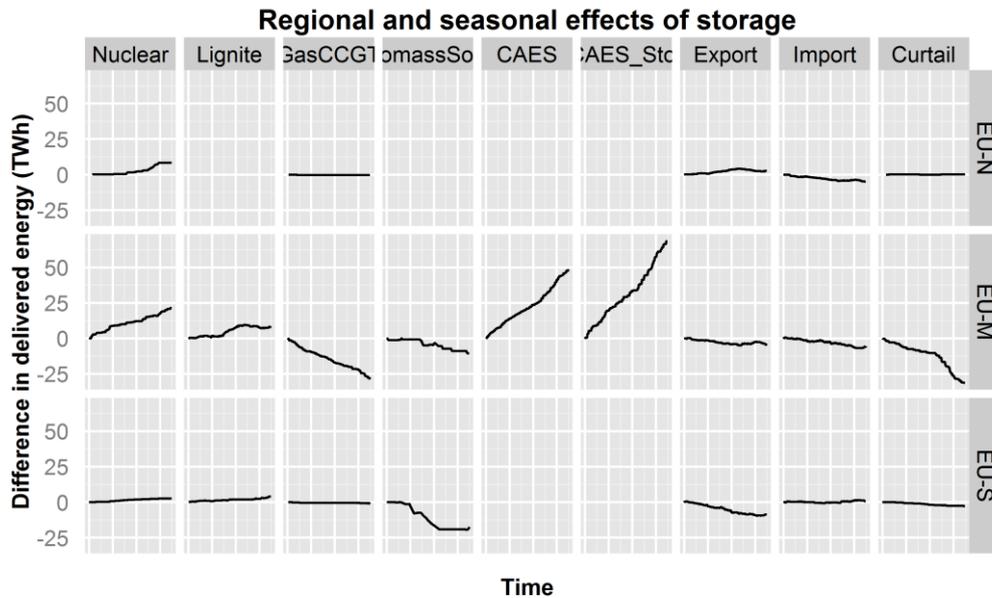


Figure 5-18: The cumulative effect of storage on the energy mix (50 GW CAES compared to no additional storage, situation with CO₂ cap and 100% 2030 transmission)

Looking at the change in CO₂ emissions caused by introducing more storage capacity, difference behaviour is observed between the storage technologies. Flow batteries only reduce the amount of CO₂ emissions, while hydrogen storage increases emissions. CAES first causes a decrease after which the CO₂ emissions increase. The decrease in emissions can be explained by the reduction of curtailment. The increase in CO₂ emissions are caused by the increased use of lignite plants. As flow has mostly an effect on curtailment, the CO₂ emissions decline. After introducing hydrogen storage, the lignite plants are directly utilised more and CO₂ emissions rise. In the case of CAES, first curtailment is reduced; later the emissions from lignite increase enough to surpass the CO₂ decrease from the reduction in curtailment. This effect is strengthened by the efficiency of the technologies; H₂ for instance has a round trip efficiency of 40%, so only 40% of the stored lignite power can be used, but might still be cheaper than other options such as using gas peaking plants.

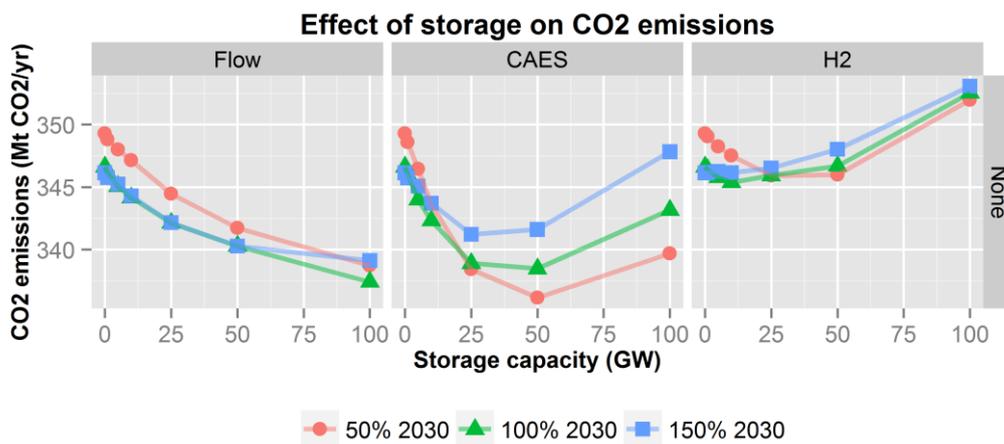


Figure 5-19: The effect of storage on CO₂ emissions

Finally, the variation in marginal cost is shown using a boxplot in Figure 5-20. In the situation without a CO₂ cap, the marginal costs are low. The marginal producer is either a renewable source such as wind or solar, which results in a marginal price of zero or a cheap base load plant such as lignite or nuclear. The observed outliers, higher prices, only occur when the base load capacity cannot supply the entire demand and coal or even gas plants are used to supply the load.

The effect of storage on the prices seems relatively small compared to the effect of transmission. Although difficult to see, increasing the transmission from 50% to 100% 2030, an increase of 4 GW between north and central and 5 GW between central and south, has a larger effect than adding 50 GW of storage capacity to the central node.

After introducing a CO₂ cap, the variation in marginal cost rise significantly. The explanation can be found in the fuel price difference of the used generators. Often, the output of renewables is so large that it exceeds demand, resulting in a marginal cost of

zero. However, when wind is not available, the stringent CO₂ cap requires generation with low carbon generators such as gas or biomass plants. These plants have higher marginal cost than nuclear, lignite or coal plants. Therefore the marginal costs can vary significantly over the course of a day.

Again, introducing storage does have an impact on the variability of the prices. However, this effect is only noticed when large amounts of storage are introduced. Secondly, the effect of increasing the transmission capacity is larger. The increase from 50% to 100% 2030 levels does not show much improvement but increasing transmission to 150% 2030 significantly reduces price variation. The effect of storage is not distinguishable any more at these high transmission capacities.

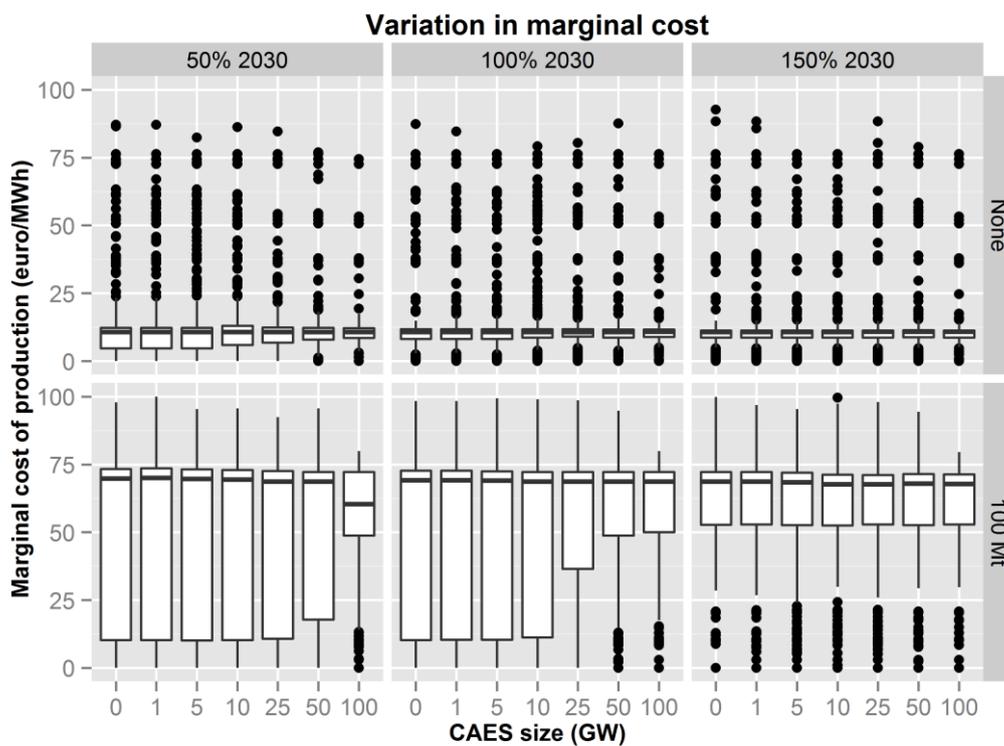


Figure 5-20: Variation in marginal cost of production in the central node

5.4. Sensitivity analysis - Effect of renewable capacity on energy storage

The previous analysis has shown that the variable cost savings of electrical energy storage are highly dependent on the amount of uncontrollable renewable energy sources in the mix. The difference in value between the two scenarios, the expected capacity mix in 2030 and the 2030 capacity mix with doubled renewable sources is large. However, a snapshot taken at two moments in time does not give insights into how the

value of storage increases as a function of the amount of renewables. Therefore, this subsection analyses the effect of renewables on the value of storage.

To keep the terminology consistent with the two previous subsections, the amount of expected renewable capacities for 2030 as described in ENTSO-E’s Scenario Outlook and Adequacy Forecast (2013b) are used. In this analysis however, the renewable capacity in 2030 is multiplied from 80% to 300% with steps of 20%. Figure 5-21 shows the installed renewable capacities over the tested renewable scenarios. The central region clearly has the highest installed capacity of volatile energy sources compared to their maximum demand.

To give insight in the size of the renewable energy compared to the demand, the residual load curves for the three regions are given shown in Figure 5-22. The thick black line is the demand; the coloured lines below show the residual demand curves that result from increasing the renewable capacity. After multiplying 2030 SO&AF capacities with a factor three, there is a positive residual demand in only about one third of the year in the central region. The southern region also shows a considerable negative demand at the maximum renewable capacity.

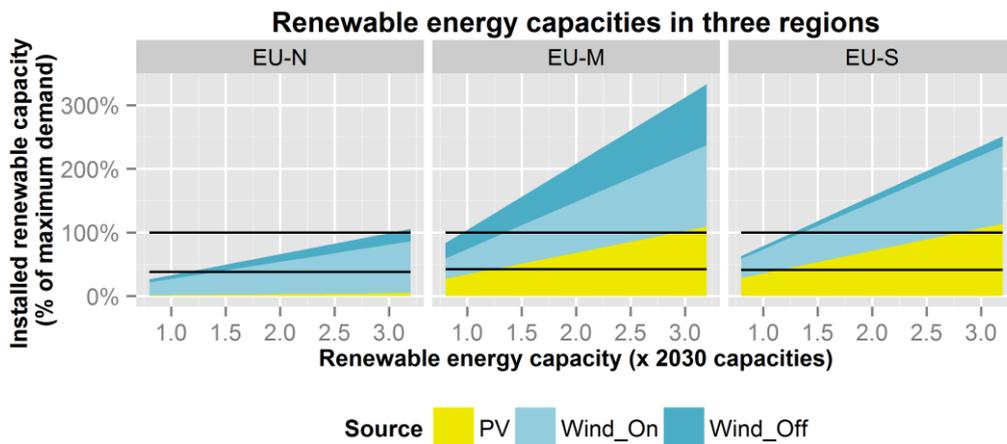


Figure 5-21: Installed capacities as a ratio to maximum demand, the black lines are the regions maximum and minimum demand.

The previous analysis has already shown most of the detailed effects of electrical energy storage on the power system. Therefore this subsection will only show the relation between the renewable capacities and the cost reduction that is caused by adding storage to the system.

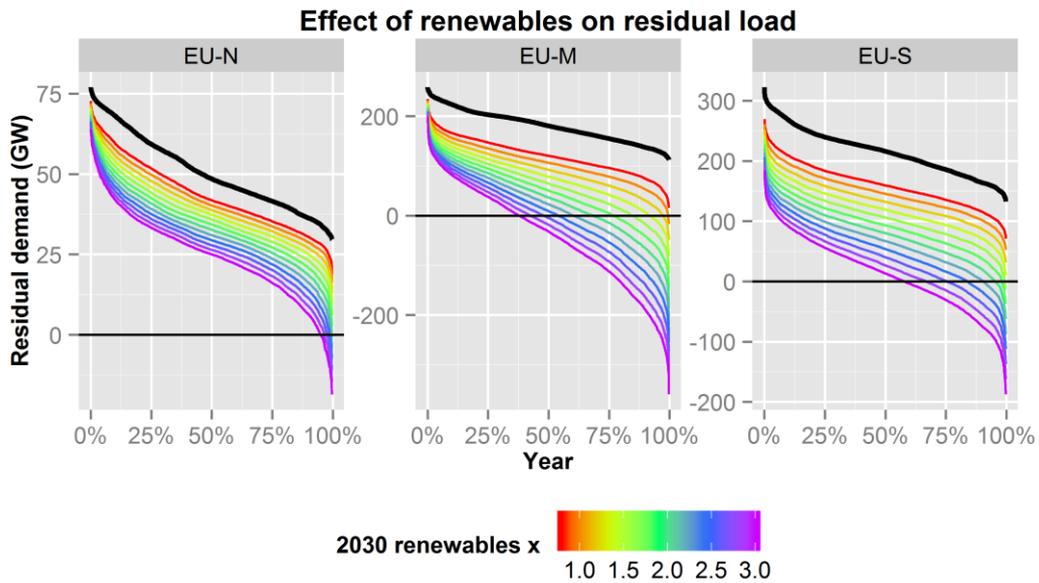


Figure 5-22: Residual load curves after introducing more renewables. The black line is the initial load.

Figure 5-23 shows the change in total variable cost dependent on storage technology. The savings at 100% and 200% correspond to the values found in subsection 5.2 and 5.3 respectively. What was already known from subsection 5.2 is that flow batteries have the highest value in the situation with little renewable energy integration, followed by CAES and hydrogen storage. Following both the reducing storage duration and round trip efficiency. However, the values lie close together.

Increasing the penetration of renewables causes the value of storage to increase. From around 150%, the value of CAES surpasses the value of flow battery storage. Looking at Figure 5-22, we see that, the central node, the residual load curve is negative for about 10% of the time at 150% renewable capacities in the central region. Some of the energy can be exported to other regions during negative residual load. When the excess load either becomes too big to export to the other regions or the other regions also suffer from negative residual loads, energy has to be curtailed. At these moments storage can be used to reduce curtailment and save fuel costs at a later point in time by releasing the energy. The fact that CAES is more valuable than flow batteries at 150% renewable capacity indicates that these periods off access demand last longer than 5 hours, otherwise the flow batteries would be able to store the excess energy, at a higher efficiency.

Compressed air energy storage has the highest maximum value which it reaches at a renewable capacity between 180 to 200%. After this, the value of CAES starts to decline. The other storage technologies reach their maximum value a little later, flow batteries at 200% and H2 storage between 200 and 220%. However, the decline in storage value for the storages with less lengthy storage duration declines faster than the technologies

with longer storage durations. After 240% of 2030 renewable capacities, hydrogen storage is more valuable than both CAES and flow battery storage.

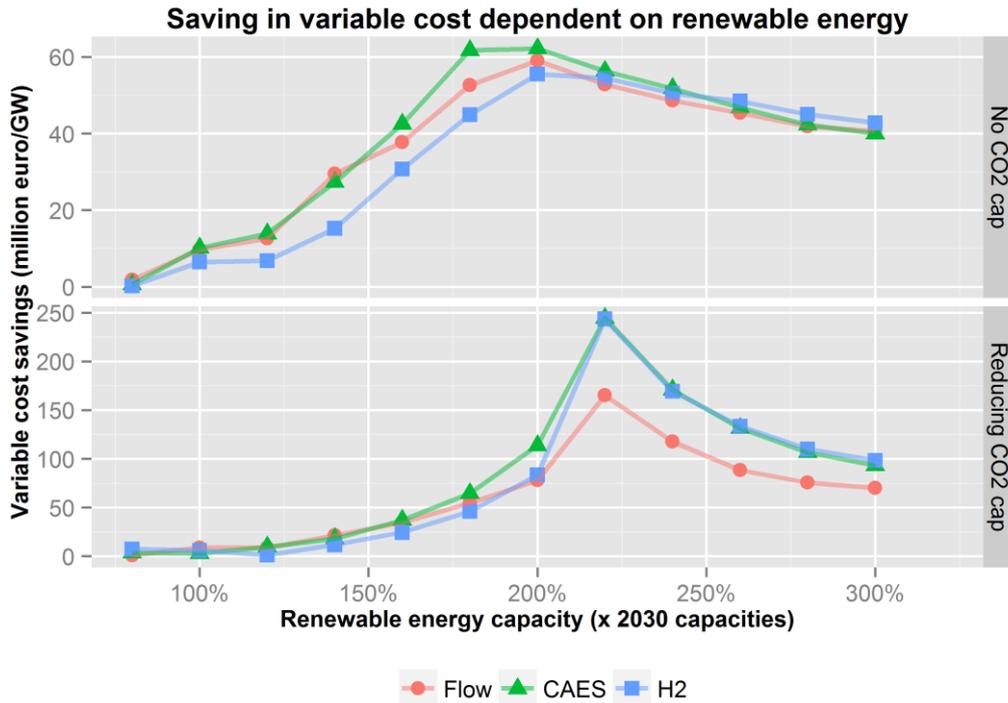


Figure 5-23: Effect of renewable capacity on storage value

Storage loses value after introducing more and more renewables. When renewables are increased, there is an increase in periods where renewable output exceeds demand. The cost reductions achieved using storage are highest when periods of excess supply and supply shortage quickly follow each other, frequently charging and discharging the storage. However, when the renewable capacity is further increased, the periods of excess supply will last longer and less periods of shortage, in which energy can be released, will be encountered. This reduces the benefits of electricity storage.

In the previous subsections, two different CO₂ caps were enforced upon the system. In the reference case (section 5.2) a 500 Mt CO₂ cap was introduced, while in section 5.3 a 100 Mt CO₂ was used. In this analysis, the CO₂ cap is reduced linearly between these two points. However, this would mean that the cap would become negative at renewable capacities of more than 220%. Therefore, the CO₂ cap reduces up to the point where only 20 Mt of CO₂ emissions are allowed (see Figure 5-24).

The results of this analysis can be seen in the bottom part of Figure 5-22. At first, the value of storage is lower than the situation without a CO₂ cap, as we know from the analysis in section 5.2. However, with the increasing renewables and stricter CO₂ caps, the value of storage increases exponentially until the CO₂ cap stops to decrease at 240%

renewable capacity. Due to the fact that the installed renewable energy capacity does keep increasing, it becomes less difficult to stay under the imposed CO₂ cap.

An important conclusion of this last section is that the correlation between renewable energy capacity and value of storage is not purely positive. Increasing the RES capacity past a certain point has a negative influence on the value of storage. However, the higher RES penetration does favour increasingly long storage durations.

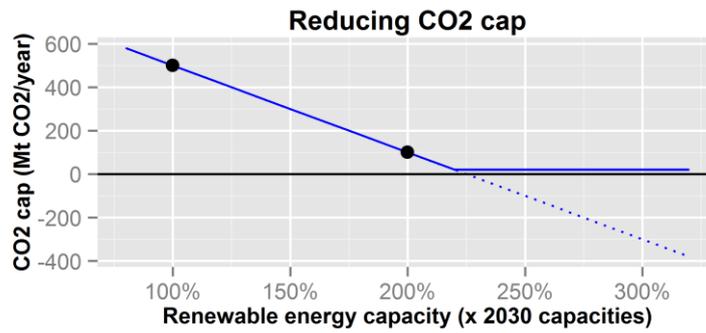


Figure 5-24: Changing CO₂ cap with increasing renewables

Chapter 6

DISCUSSION

The discussion is used to interpret the results and translate these results into real world meanings while considering the shortcomings of the thesis. This section therefore subsequently discusses the results, the implications of the results for the electricity sector and the used modelling technique.

6.1. Discussion of model results

This thesis set out to research the value of storage in a future sustainable electricity system, using an innovative modelling approach. The research shows that electrical energy storage can cause significant savings in operational cost in the electricity sector. Although the amount of transmission capacity does have an influence on the savings that are achieved using storage, the largest influence on the effectiveness of storage is the amount of renewable capacity that is integrated in the system. Although high storage durations have positive effects on systems with many renewables, the largest part of the savings are captured by systems with relatively short storage durations.

With the installed capacities in 2030, the value of the first installed gigawatt of storage ranges from 4 €/kW for systems with low efficiency and a CO₂ cap to more than 12 €/kW for a high efficiency flow battery without CO₂ cap. Increasing the amount of renewable capacity drastically increases the value of storage. Doubling the previously mentioned 2030 renewable capacities results in values between 120 €/kW for medium term (50 hour) compressed air energy storage and 40 €/kW for short term storage solutions. Increasing the renewable capacity even further decreases the value of storage as fewer opportunities to unload storage plants are present. The literature shows results in the same order of magnitude.

In a very complete analysis of the benefits of storage for the future electricity system of Great Britain, Strbac et al. (2012) find a value of storage of more than 500 €/kW¹² in 2030. However, this includes deferred investment in generation, transmission and distribution capacity. Secondly, the model uses a stochastic dispatch approach and

¹² Conversion rate: £ 1 equals € 1.25

uncertainty in weather predictions, all parameters that increase the value of storage. Stripping these away leaves a value between 75 and 150 €/kW.

Strbac et al. also find that storage, even with short duration, is able to replace other capacity on a one to one basis. This is different from the results obtained from this thesis. The explanation might be that storage would behave differently if actual capacity is taken out of the capacity mix.

Sioshansi, Denholm, Jenkin and Weiss (2009) use historical system cost of the PJM region (139 GW) to test the value of a small storage device that would not influence prices. They find that storage would have a value between 30 and 60 €/kW¹³, depending on the price data used. Although the area does not have much renewable capacity integrated into the system, the values are higher than the ones found in this thesis. However, the prices in PJM vary significantly due to market effects, increasing the value of storage. Secondly, further analysis shows that the value could be reduced with up to 25% if the storage would influence market prices, as it naturally would if it would operate on a free market.

In a second analysis of the same writers, an optimization model is used to test the performance of an electrical energy storage (EES) near a wind farm that has limited transmission capacity to the main grid (Denholm & Sioshansi, 2009). They find storage values between 40 and 65 €/kW for a 20 hour CAES storage, dependent on the location of the wind farm and the system it is connected to. Because these values are found in a system with transmission constraints they can be compared to simulations with high renewable penetration used in this study.

EPRI (2010) calculates the value that storage would currently have in different systems. For plants that are only able to deliver energy services they conclude that the value of storage lies between 100 and 200 €/kW. However, this also includes deferral in generation and transmission capacity.

The observed reduction in value of EES after introducing larger amounts of renewable capacity can be found in the analysis of Grünewald et al. (2011). They find that the value of storage starts to decline after introducing approximately 70 GW of renewables in the GB power system which has a peak demand of 60 GW. In this thesis, the reduction of storage value is observed after installing a renewable capacity of approximately 2x maximum demand. The reason for this difference could be the fact that Grünewald et al. do not include transmission to other regions. Transmission helps in reducing the effects of negative residual load by exporting excess energy, no transportation therefore results in higher negative loads and fewer moments to unload the storage at lower renewable capacities.

In general, storage and transmission can be seen as substitute solutions. They both reduce operation cost by leveling out differences in supply and demand, either in a temporal or spatial manner. In some studies, storage and transmission were found to be complementary to each other (Carlo Brancucci Martínez-Anido, 2013; Verzijlbergh et al., 2014). This thesis set out to gain more insight in the effects that storage and

¹³ Conversion rate: \$ 1 equals € 0.75

transmission have on each other. The analysis has shown an effect of transmission on storage and vice versa. In situations with high renewable energy penetration rates, a small amount of storage reduces the amount of export from the region where the storage is introduced. Increasing the storage capacity increases the import to that region during periods where the local storage is either full or already used at maximum charging capacity. So the complementarity of storage and transmission can be confirmed.

However, the complementarity observed is merely of technical nature. Although the total energy stored or transmitted might increase in situations where one of the two capacities is increased, this does not positively affect the value generated by the storage. Transmission capacity generally reduces the variation in system marginal cost, the very source of the value of electrical energy storage. In other words, storage and transmission are not economical substitutes, increasing the amount of transmission capacity does not make storage more valueable.

6.2. Implications for the power sector

As we have seen, the value of EES is dependent on many different locational and environmental factors. On an operational level, it is influenced by the generation mix, renewable energy penetration and transmission possibilities. Private investors will only develop storage if they are relatively certain that the revenues storage is able to generate exceed their costs. The investment costs of storage as discussed in subsection 3.4.6 are too high to be recovered by the reduction in the system's variable cost observed in this study.

However, extra value might be generated by incorporating more factors into the analysis. As the results from this study and the literature suggest, storage also replaces investment in generation capacity and is able to deter investments in transmission and distribution capacity. Secondly, results from other studies indicate that the value of storage can be higher than the values found in this thesis if the storage would operate in a stochastic market with uncertainty about demand and weather patterns. Congestion between countries, which is lost due to the aggregation of the ENTSO-E members into three nodes, might increase revenues even further.

Next to these increases in storage value, improvements in technology might reduce the investment cost of storage technologies. Currently, the US is drafting technology support policies with the aim of achieving a storage system with a total system cost under 150 \$/kWh (U.S. Department of Energy, 2013). The increasing interest and accompanying R&D investments of the transport sector in fuel cell technology in the might reduce power specific cost of hydrogen storage to less than 100 €/kW (Tsuchiya, 2004), compared to the 4000 €/kW this is a massive reduction.

Combining both the possible increases in value and reduction of costs might cause electrical energy storage to become an investment option to consider in the future. If it does, three particular parties will be positively interested in the technology. These

parties include current operators of large base load power plants, renewable power plant owners and finally the operators of the transmission and distribution networks.

As the analysis has shown, base load plants will primarily be able to benefit from energy storage by being able to output at a more stable level. Base load plants are often large, have relatively high fixed costs, low variable cost and considerable start-up costs. Secondly they take long to start up and have limited ramping capabilities. They therefore benefit from a stable output profile at their maximum capacity. During periods of low demand or high RES output these base load plants have to reduce output or shut down. However, when storage plants are charged during these periods, the base load plants are able to remain at a high output level. Hence, introducing storage will change the energy mix to include more base load energy.

Whether this is a desired situation is up for debate. The current base load generators include nuclear, lignite and coal plants. Nuclear plants suffer from societal debate around their safety and waste handling. Both lignite and coal plants are heavily discussed due to their CO₂ and particulate matter emissions. On the other hand, nuclear power forms a CO₂ free energy source and adding carbon capture and storage (CCS) to lignite and coal plants reduces their downsides significantly. However, literature suggests that these relatively cheap options will not be able to operate efficiently in a highly renewable system due to the excessive ramping and start-up cycles they would have to make (Nagl et al., 2012; B. S. Palmintier, 2013). Storage would make integration of these options possible. As a second advantage of storage is the fact that it will increase prices during off-peak hours by charging during periods of low demand.

Renewable power plant owners can benefit from storage if their output is spread over time more evenly. As we have seen from the model results, the integration of renewable energy causes electricity prices to vary significantly, they are low during periods of high output and high during periods of low output. This automatically means that renewable energy suppliers will have increasing difficulties in recovering their investments if RES penetration is increased. Storage is able to partly disconnect renewable energy output and use, through this it reduces price variation. Secondly, EES reduces the necessary amount of curtailment, which increases the usage of renewables, possibly generating more revenues for renewable energy sources.

Finally, the operators of the transmission and distribution systems are interested in storage as it is able to deter investments in the network. This study did not find economical complementarity of storage and transmission. Nonetheless, other studies have concluded that in a cost optimal system, a part of investments in transmission and distribution is replaced by investments in storage systems. Currently, not all of the network operators are allowed to invest in storage (European Commission, 2013). This makes it difficult for these actors to capture the benefits storage has for their systems.

Next to the parties that view storage positively, there is one party that would oppose the deployment of storage. These are the providers of peaking services, primarily gas plants. As storage discharges during periods of high demand or low RES output, it is a direct competitor of gas peaking plants. The experiments show that storage makes it

possible to replace gas fired power with cheaper base load energy. Strbac et al. (2012) even show that storage is able to directly replace peaking capacity.

As compressed air energy storage uses technology that is very similar to a gas fired power plant, current operators of these types of plants might venture into the storage market with CAES storage plants. Specific designs of CAES plants make it possible to use the plant without storing compressed air beforehand, directly connecting the compressor and turbine.

6.3. Discussion of modelling technique

The results presented in this thesis are highly dependent on an optimization model that has been built during the execution of the thesis. As with any model based analysis, the results cannot be interpreted without knowing the limitations of the model and used modelling technique.

First and foremost, in any computer simulated model, every single line of code is an assumption. Accordingly, every model is not more than a set of assumptions about a real world system, with all its endless complexities. The created model optimizes from a central decision maker point of view. In this approach, the total system costs are minimized, constrained by technical limitations. This automatically means that market failures that are observed in the real world do not exist in the model. There are no externalities, there is perfect knowledge and foresight about the entire system and there are no monopolies or oligopolies that influence the decisions made.

In the real world, the decisions are not made by someone who wants to minimize total system costs but are based on decisions by individual actors that are primarily concerned with lowering their personal cost and increasing their revenues. In the real world, the marginal cost of production often does not correspond to the actual spot market price. This can have a large influence on the overall performance of the electricity sector and therefore creates discrepancies between model results and real world behaviour.

The created model is completely deterministic. This means no uncertainty about future demand; weather patterns, maintenance and contingencies are included in the model. This makes it possible for the model to optimize the decision variables over the entire year in one go. However, this does not match reality, as explained before, all these uncertain patterns have a large effect on the operation of the power sector and prevent the 'optimal' dispatch to be reached.

A storage technology is even better able to use this certainty about the future demand and renewable output levels than other generators. Unlike most generators, a decision to load the storage today can have large impacts on tomorrow's operations. Electrical energy storage is primarily based on the differences between price levels at different moments; the opportunity cost of not loading or unloading can be difficult to assess and hamper 'optimal' operation in real life.

However, this does not mean that the savings achieved by electrical energy storage are lower than described in this thesis. One of the major advantages of storage technology is that it can provide reserve capacity. In the created model, the providers of reserve capacity are not financially rewarded. Secondly, in a deterministic model, the reserves are never called upon. In the real system however, reserves are continuously used to match the supply to the demand. This creates yet another revenue stream for the storage technology.

The thesis set out using an innovative technique modelling technique, clustered unit commitment, which has not been widely applied on systems comparable to the European grid. After the model was finished, it showed that it was computationally impossible to solve the model for the European electricity system with individual countries. Many simplifications had to be made in order to use the model for the presented experiments.

One of the major simplifications entailed the combination of all ENTSO-E members into 3 separate nodes. This means that not only the internal congestion within individual countries is lost, but also the congestion between countries in the same node. As can be seen from the model validation, this has large effect on the energy mix, especially benefiting coal fired power generation, while flexible more expensive generators are used less. This also has an impact on the potential use of electrical energy storage, which is a flexible and expensive technology.

In the end, the question arises whether all this complexity was necessary. The analysis of the various speed-up strategies shows that some of the complex constraints, mainly maintenance and reserve requirements have only limited effects on the model results. The complicated maintenance constraints which optimized the maintenance over the year even showed to be unrealistic for systems with high RES penetration rates.

Secondly, it has been shown that using economic dispatch models or unit commitment models that use economic dispatch models as a pre-run are not always capable of capturing the real value of storage, as some part of the value of storage is derived from preventing start-up cost of large thermal generators. This is an important conclusion for future models that analyse the role of electrical energy storage.

Finally, economic dispatch models benefit large thermal generators; however this is a known and generally accepted problem. Nonetheless, the results from ED models that are currently used for policy analysis and optimization of the energy mix (investment models); need to be handled with care. Understanding that these models favour large generators like nuclear and coal plants and reduce the value of flexibility options is highly important in systems where more and more unpredictable renewables are added.

Chapter 7

CONCLUSIONS & RECOMMENDATIONS

This final chapter will present the conclusions that can be drawn from the work and makes recommendations for actors in the power sector. Finally, directions for future research will be given.

7.1. Conclusions

This project set out to gain more insights into the role electrical energy storage can play in the transition to a sustainable electricity grid. The main conclusion is that energy management services provided by electrical energy storage (EES) can cause significant reductions in variable operating t.

The value of storage in systems with relatively low renewable energy penetration primarily lies in allowing cheaper base load generators to run at a more constant output level, avoiding start-up cost of these bulky generators and reducing the use of more expensive peak load generators. Introducing a CO₂ cap in this scenario reduces price variance between fuels and therefore reduces the value of storage.

The variable cost savings achieved by storage increase under the increase of renewable energy sources (RES) in the system. With increasing RES, the primary value of storage lies in the reduction of curtailment. During periods of oversupply from RES sources, energy is stored for later use. A CO₂ cap increases the value of storage in this scenario, the difference between curtailing energy and the cheapest dispatchable plant becomes larger, which benefits the storage.

After increasing the RES penetration even further, the value of energy storage reduces. In theory more energy could be loaded as periods of RES over-supply start being more frequent. However, the periods in which energy can be discharged from the storage become more infrequent.

Transmission has a negative influence on the value of storage. The fact that more energy is transmitted and stored when introducing more storage *or* transmission makes the technologies technically complementary. However, both solutions deliver the same functions: they reduce operating cost by levelling out discrepancies between supply and

demand, either in a spatial or temporal matter. Storage and transmission are therefore economical substitutes.

The focus in this research has been on bulk energy storage, a storage type used to level out hour to hour, day to day or seasonal variations in electricity supply and demand. Four different technologies are currently available for this purpose: pumped hydro storage, flow battery storage, compressed air energy storage (CAES) and hydrogen storage. Because pumped hydro is an accepted technology that is already applied in most regions of the world, the latter three were tested.

Flow battery storage has low power specific and high energy specific investment cost, making it suitable for storage of multiple hours. Hydrogen (H₂) storage has high power specific and low energy specific cost. This makes H₂ suitable for storage durations of multiple weeks. CAES is somewhere in between these technologies and most suitable for storage of a few hours to multiple days. Interestingly, the efficiency of the technologies follows the same order as their optimal storage duration. Flow batteries, CAES and H₂ have a round trip efficiency of 75%, 70% and 40% respectively.

The effect of these characteristics on their value is situation specific. Efficiency is most important in situations where storage is used to prevent base load generators from cycling. As a few hours of storage are enough to prevent this cycling, flow batteries offer the optimal solution. In scenarios with high RES penetration, where large amounts of renewables are curtailed, long storage duration is most valuable. Efficiency becomes less important as any improvement from curtailment is positive. CAES again fits in between.

The overall role of storage in the transition to a renewable system remains partly uncertain, the cost of storage are currently too high to justify its large scale deployment. Secondly, the marginal value of storage declines quickly after introducing the first GW's and although long storage duration generates most value in highly renewable systems the additional benefits might not exceed the additional cost of building facilities with very long storage durations. On the other hand, investments in R&D are expected to drastically reduce the cost of storage. In any case, storage has shown to be beneficial in several scenarios and applications and might therefore be applied for many different purposes.

7.2. Recommendations for actors in power sector

Storage will have a positive effect on the output of large traditional base load plants. These owners and operators of these plants should therefore support the development of storage facilities. If the operators notice that the integration of renewables into the system causes their plants to cycle excessively, threatening their economic viability, they should even consider funding these new storage developments.

Whether this is an acceptable development is up for political debate. As most base load generators suffer from relatively high negative externalities, the survival of these plants in a sustainable energy system might not be ethically desirable. CO₂ constraints have the capability of pushing both coal and lignite plants out of the merit order, reduc-

ing CO₂ emissions and the consequent greenhouse effects. Countries like Germany and Japan have shown that, if socially desired, even nuclear energy can be phased out of the energy mix. Although policy makers should consider the positive effects of EES on base load plants, the policies used to reduce the use of plants with negative externalities are the same as the policies that would be used when storage is not developed.

With regard to this, storage might be beneficial when creating an electrical energy system in which a large share of RES is complemented with traditional thermal generators equipped with carbon capture and storage. EES makes the combination of fluctuating renewables with large CCS plants possible. Opening opportunities for a (nearly) carbon emission free energy system.

The owners of renewable energy sources should have a positive attitude towards the development of storage. As storage makes it possible to counterbalance periods of high and low RES output, less curtailment is necessary and prices will be more stable. As the introduction of renewables will make it increasingly difficult for the owners to recover their investments, the owners of RES have to consider the option of collectively building storage to stabilize prices. Having their own storage also enables them to strategically bid in the spot market, increasing their potential profits.

With regard to this, many governments currently support renewable energy suppliers with a feed in tariff (FIT) that is used to top up revenues from the spot market to an agreed upon level. Increasing investments in renewables will increase the money that has to be spent to support these feed in tariffs. Policy makers should consider the role that electricity storage can play in stabilizing prices and, if proven beneficial, create policies that help develop storage in order to reduce FIT expenditures.

The transmission and distribution system operators could use EES to reduce the necessary investments in network reinforcement. As the network operators have the objective to deliver power in a cost optimal manner, they should consider the possibilities of storage when deciding about network reinforcements. As societal resistance against high voltage transmission cables builds due to supposed negative health effects, the position of storage as a substitute for transmission might be strengthened. As not all network operators are allowed to invest in anything other than network capacity, the development of storage will need to be either supported by sufficient market signals to make private parties benefit from the deferred transmission and distribution investments or policies will have to be changed in order to make investments in storage possible for the system operators.

Finally, this analysis and other studies clearly show that storage gains its value from a very broad spectrum of applications, reducing investment in generation, transmission and distribution, stabilizing market prices, providing reserve capacity and increasing grid stability. This broad spectrum of benefits will make it difficult for policy makers to draft policies that create the correct incentives for investors to develop electrical energy storage.

7.3. Directions for future research

Although this thesis can be improved in many different ways, this section starts with some general remarks about modelling and energy models in particular.

The biggest problem in electricity sector modelling is the following: to correctly value effects that new technologies or policies will have, including technical details in a model is absolutely necessary. In the case of electricity storage, every layer of additional details, whether it is the start-up costs included in this thesis or stochasticity and investments in networks in other researches, adds other sources of value for energy storage. However, with added details comes added complexity. This complexity makes it more difficult to solve a model and makes experimentation and analysis strenuous.

Before building any model, it is therefore absolutely critical to consider all the possible effects of a technical change or policy might have on the entire system. After this, a deliberate decision about which of these effects you want to analyse has to be taken. This decision has an effect on the size of the real world system you can include, the time period under consideration and the length of the steps taken. The size of the system can range from a district, a country or an entire continent; however, increasing the size forces you to look at a shorter time period or smaller time steps and vice versa.

Looking more specifically at energy storage modelling, the largest part of the value is already captured by technologies with storage durations of up to 50 hours. This means that the seasonal effect of storage is small; reducing the amount of time considered is therefore sensible in order to reduce model size. Secondly, transmission and congestion have a large effect on storage value, considering particular countries or even regions in a country is therefore necessary to find the value of storage in a specific context. Finally, other studies show that effects of stochasticity and uncertainty are relatively large compared to the effects of energy management that are considered in this thesis. Further analysis of the value of storage should therefore contain stochasticity and uncertainty.

Because these added complexities will probably require large computational efforts, new and innovative modelling techniques like the one used in this thesis should be kept under constant consideration and research. A thesis project is a nice opportunity to combine a methodological improvement with a practical research question.

Considering this specific thesis and the model created for this thesis, some expected changes in the future power system that could influence the value of storage were not considered. The advent of the smart grid in combination with an increased share of demand response from for instance electric cars has the potential to level out supply and demand over time; this would reduce the price variation encountered in the system and negatively influence the value of storage.

Secondly, the different characteristics of storage technologies make them suitable for different purposes. It would be interesting to find out what the effects of storage technologies on each other would be if they are all added to the system at the same time.

Another possible improvement would be to test the consistency of the results using data from different years. The data used in this thesis was from 2010, particularities that occur in that year might not be present themselves in another year. Using a different year creates a different optimal dispatch of the system and different effects of storage on the system.

Finally, the addition of CHP plants could make the operations of the electricity sector more realistic; however, this would require adding a heat market to the model, as energy can be stored in the form of heat as well. Related to this is the possibility to mix hydrogen created by fuel cells into the gas grid and using it for heating instead of storing the hydrogen and converting it back to electricity.

Chapter 8

REFLECTION

Now that you have (almost) read my entire thesis, you must be pretty tired. Hopefully you will be able to hold on a little longer while I step away from the actual content of the thesis and look into the process of which this thesis is the end product. As you already noticed, the tone will be a bit more personal.

While deciding on my thesis topic, I had multiple opportunities to choose from. Firstly, I was able to do a project at the university and extend the interesting work I had been doing for the course Agent Based Modeling of Complex Adaptive Systems. Secondly, Eneco, an employer high on my future job list, approached me with a project about district heating networks. This project built upon my past experience as an energy consultant in the built environment. However, as you have read in this thesis, I chose CPB, a renowned research institute part of the Dutch Ministry of Economic Affairs. I had two reasons for this: first of all, the scientific atmosphere made me confident that my thesis would be of sufficient scientific value and that it would not be cluttered with specific client demands. Secondly, an internship at CPB gave me the opportunity to see how a career as a civil servant would be like.

In the end, I am very content with my choice, the working environment at CPB has been very pleasant and the structure offered by an office demanded me to work full time on my thesis from the beginning on. I know for sure that I would have had difficulties with this if I would have executed my thesis at the university. From my personal experience I already knew that I have difficulties following a strict planning and to concentrate on a deadline that lies far in the future.

This showed in the first few months of the project. In February and March I was primarily reading articles, books and reports; however, I was not able to be as productive as I normally would be. As a second note I would like to add that I was doing too much reading anyway, I think more than half of the literature I read has not ended up in this thesis. Although I like to think that this literature did help me formulate and structure my own thoughts about the problem, I would have probably been more efficient if I would have stopped reading at some point. You have reached this point when, after reading some papers, you think: so what does this change about what I already knew? If the answer is 'nothing', you have read enough about the particular topic.

When I started the thesis project as an unexperienced optimization modeler, I was still under the impression that I would be able to build a stochastic hour to hour investment model of every country in Europe. This has proven not to be the case, any optimization model that considers individual hours over an entire year is extremely difficult to solve, adding investment and multiple regions makes solving the model even more difficult, let alone solving the model under uncertainty. Luckily, my supervisors were able to make my ambitions more realistic. In the end I think I have learned a lot about yet another modelling technique. I am now better able to contrast optimization with other techniques and will be better able to choose the right technique for a given problem.

After I stopped reading and had become more realistic about my goals, I started modelling. As any modeller can tell you, a model is never finished, something can always be improved. Although some improvements were absolutely necessary to be able to use the model, I kept fiddling with the model for too long. Fiddling with models is something I personally enjoy; I could have probably programmed the model more efficiently if I wasn't always trying new improvements. This fiddling also brought me into trouble approaching the deadline for the greenlight meeting, which meant that I had to do the entire analysis in one weekend. Again, sticking with a tight schedule would have been beneficial for me.

The size and complexity of the model make it difficult to execute experiments, analyse the sensitivities and examine the results. However, as has been shown in this thesis, simpler models are not able to value storage at an adequate level. Therefore I am glad I kept improving the model to the point where it is now. Hopefully, the scientific world has learned a little more about the performance of the clustered unit commitment method proposed by Palmintier (2013). Besides, I think that the CPB now has a model that can be used for other detailed power sector analysis.

Although I had the backing of both my supervisors at the University and my colleagues at the CPB, I executed this thesis very independently. Not having used the GAMS optimization language before, I experienced a steep learning curve. Secondly, although I used R before, I had never interfaced it with other programs and never used it for such extensive analysis. Through this experience my respect for people that were able to program computers before Google was around has gone up tremendously. Almost any problem I encountered, was already encountered, solved and published by someone else. Many thanks go out to Google and the people who put their questions and solutions online!

During the project I have also learned how valuable it can be to work in a project team. During my studies, I have often been frustrated with team members not meeting agreements or delivering the quality I expect from myself, however, not being able to talk and discuss about your ideas, thoughts and research directions with anyone that knows the full details about your work slows down progress and makes it difficult to structure your own mind.

Finally, I would like to conclude by saying that I really enjoyed the past half year. After starting with reading and getting familiar with a new topic, I used my new knowledge to create a complex model. After this, I was able to use the model for experimentation and eventually was able to draft conclusions about the future role of electrical energy storage. To top it off, I was able to do this while working in a pleasant and scientifically oriented environment.

REFERENCES

- Aalbers, R., & Bollen, J. (2013). EU Energy Roadmap: Learning and Intermittency.
- Baldick, R. (1995). The generalized unit commitment problem. *IEEE Transactions on Power Systems*, *10*, 465–475. doi:10.1109/59.373972
- Beaudin, M., Zareipour, H., Schellenberglobe, A., & Rosehart, W. (2010). Energy storage for mitigating the variability of renewable electricity sources: An updated review. *Energy for Sustainable Development*, *14*(4), 302–314. doi:10.1016/j.esd.2010.09.007
- Becker, S., Rodriguez, R. a., Andresen, G. B., Schramm, S., & Greiner, M. (2014). Transmission grid extensions during the build-up of a fully renewable pan-European electricity supply. *Energy*, *64*, 404–418. doi:10.1016/j.energy.2013.10.010
- Bertsch, J., Growitsch, C., Lorenczik, S., & Nagl, S. (2012). *Flexibility options in European electricity markets in high RES-E scenarios: Study on behalf of the International Energy Agency (IEA)* (pp. 1–82). Cologne, Germany.
- Brancucci Martínez-Anido, C. (2013). *Electricity without borders: The need for cross-border transmission investment in Europe* (pp. 1–210). Delft, The Netherlands.
- Brancucci Martínez-Anido, C., Vandenberghe, M., de Vries, L., Alecu, C., Purvins, A., Fulli, G., & Huld, T. (2013). Medium-term demand for European cross-border electricity transmission capacity. *Energy Policy*, *61*, 207–222. doi:10.1016/j.enpol.2013.05.073
- Chen, H., Cong, T. N., Yang, W., Tan, C., Li, Y., & Ding, Y. (2009). Progress in electrical energy storage system: A critical review. *Progress in Natural Science*, *19*(3), 291–312. doi:10.1016/j.pnsc.2008.07.014
- Dallinger, D., Gerda, S., & Wietschel, M. (2013). Integration of intermittent renewable power supply using grid-connected vehicles – A 2030 case study for California and Germany. *Applied Energy*, *104*, 666–682. doi:10.1016/j.apenergy.2012.10.065
- Denholm, P., Ela, E., Kirby, B., & Milligan, M. (2010). *The Role of Energy Storage with Renewable Electricity Generation* (pp. 1–61).
- Denholm, P., & Sioshansi, R. (2009). The value of compressed air energy storage with wind in transmission-constrained electric power systems. *Energy Policy*, *37*(8), 3149–3158. doi:10.1016/j.enpol.2009.04.002
- EA Technology. (2004). *Review of electrical energy storage technologies and systems and of their potential for the UK* (pp. 1–34).
- EEA. (2009). *Europe's onshore and offshore wind energy potential: An assessment of environmental and economic constraints* (pp. 1–90). Copenhagen, Denmark.

- ENTSO-E. (2011). NTC Matrix. Retrieved June 29, 2014, from <https://www.entsoe.eu/publications/market-reports/ntc-values/ntc-matrix/Pages/default.aspx>
- ENTSO-E. (2012a). *10-Year Network Development Plan 2012*. Brussels, Belgium.
- ENTSO-E. (2012b). *Scenario outlook and adequacy forecast 2012-2030* (pp. 1–175). Brussels, Belgium.
- ENTSO-E. (2013a). *Monthly statistics - March 2013*. Brussels, Belgium.
- ENTSO-E. (2013b). *Scenario outlook and adequacy forecast 2013-2030* (pp. 1–132). Brussels, Belgium.
- ENTSO-E. (2013c). *Yearly statistics & Adequacy retrospect 2012* (pp. 1–64). Brussels, Belgium.
- ENTSO-E. (2014a). Detailed monthly production for all countries for a specific range of time. Retrieved May 04, 2014, from <https://www.entsoe.eu/data/data-portal/production/Pages/default.aspx>
- ENTSO-E. (2014b). Hourly load values of all countries for a specific month. Retrieved May 06, 2014, from <https://www.entsoe.eu/data/data-portal/consumption/Pages/default.aspx>
- ENTSO-E. (2014c). Load and consumption data: Specificities of member countries. Brussels, Belgium. Retrieved May 06, 2014, from https://www.entsoe.eu/fileadmin/user_upload/_library/publications/ce/Load_and_Consumption_Data.pdf
- EPRI. (2003). *EPRI-DOE Handbook of energy storage for transmission & distribution applications* (pp. 1–512). Palo Alto, CA.
- EPRI. (2010). *Electricity energy storage technology options* (pp. 1–170). Palo Alto, CA.
- European Commission. A roadmap for moving to a competitive low carbon economy in 2050 (2011). Europe.
- European Commission. (2013). *DG ENER working paper: The future role and challenges of energy storage*. Brussels, Belgium.
- Evans, A., Strezov, V., & Evans, T. J. (2012). Assessment of utility energy storage options for increased renewable energy penetration. *Renewable and Sustainable Energy Reviews*, 16(6), 4141–4147. doi:10.1016/j.rser.2012.03.048
- EY. (2013). *Mapping power and utilities regulation in Europe* (pp. 1–139).
- Fürsch, M., Hagspiel, S., Jägemann, C., Nagl, S., Lindenberger, D., & Tröster, E. (2013). The role of grid extensions in a cost-efficient transformation of the European electricity system until 2050. *Applied Energy*, 104, 642–652. doi:10.1016/j.apenergy.2012.11.050
- Galiana, F. D., & Conejo, A. J. (2009). Economics of electricity generation. In *Electric energy systems: analysis and operation* (pp. 165–210). CRC Press.

-
- GAMS. (2014). General Algebraic Modeling System. GAMS Development Corporation. Retrieved from <http://www.gams.com/>
- Glachant, J., Saguan, M., Rious, V., & Douguet, S. (2013). *Incentives for investments : Comparing EU electricity TSO regulatory regimes 1* (pp. 1–110).
- Götz, B., Blesl, M., Fahl, U., & Voß, A. (2012). *Theoretical background on the modeling of policy instruments in energy system models* (pp. 1–53). Stuttgart, Germany.
- Green Rhino Energy. (2014). Annual solar irradiance Europe. Retrieved June 20, 2014, from <http://www.greenrhinoenergy.com/solar/radiation/empiricalevidence.php>
- Grünewald, P., Cockerill, T., Contestabile, M., & Pearson, P. (2011). The role of large scale storage in a GB low carbon energy future: Issues and policy challenges. *Energy Policy*, 39(9), 4807–4815. doi:10.1016/j.enpol.2011.06.040
- Heide, D., von Bremen, L., Greiner, M., Hoffmann, C., Speckmann, M., & Bofinger, S. (2010). Seasonal optimal mix of wind and solar power in a future, highly renewable Europe. *Renewable Energy*, 35(11), 2483–2489. doi:10.1016/j.renene.2010.03.012
- Herbst, A., Toro, F., Reitze, F., & Jochem, E. (2012). Introduction to energy systems modelling. *Swiss Journal of Economics and Statistics*, 148(2), 111–135.
- Hirth, L. (2013). The market value of variable renewables: The effect of solar wind power variability on their relative price. *Energy Economics*, 38, 218–236. doi:10.1016/j.eneco.2013.02.004
- IBM. (2014). IBM ILOG CPLEX Optimizer. Retrieved from <http://www-01.ibm.com/software/commerce/optimization/cplex-optimizer/index.html>
- Ibrahim, H., Ilinca, a, & Perron, J. (2008). Energy storage systems—Characteristics and comparisons. *Renewable and Sustainable Energy Reviews*, 12(5), 1221–1250. doi:10.1016/j.rser.2007.01.023
- IEA. (2010). *World energy outlook*.
- Ilic, M. D., Xie, L., & Joo, J. (2011). Efficient coordination of wind power and price-responsive demand—Part II: case studies. *Power Systems, IEEE Transactions on*, (February), 1–9. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5762581
- Ilic, M., Xie, L., & Liu, Q. (2013). *Engineering IT-enabled sustainable electricity services: The tale of two low-cost green Azores Islands* (Vol. 30). New York, NY: Springer US. doi:10.1007/978-0-387-09736-7
- International Energy Agency [IEA]. (2009). *Prospects for large-scale energy storage in decarbonised power grids*.
- International Energy Agency [IEA]. (2010). *Energy Technology Perspectives 2010: Scenarios and Strategies to 2050*. Paris.
- International Energy Agency [IEA]. (2014). *Technology Roadmap - Energy storage*. Paris, France. doi:10.1007/SpringerReference_7300

- IPCC. (2013). *Climate Change 2013: The Physical Science Basis - Summary for Policymakers*.
- Jägemann, C., Fürsch, M., Hagspiel, S., & Nagl, S. (2013). Decarbonizing Europe's power sector by 2050 — Analyzing the economic implications of alternative decarbonization pathways. *Energy Economics*, 40, 622–636. doi:10.1016/j.eneco.2013.08.019
- Jain, R., & Dirkse, S. (2014). gdxrrw: An interface between GAMS and R. Retrieved from http://support.gams.com/doku.php?id=gdxrrw:interfacing_gams_and_r
- Kaldellis, J. K., & Zafirakis, D. (2007). Optimum energy storage techniques for the improvement of renewable energy sources-based electricity generation economic efficiency. *Energy*, 32(12), 2295–2305. doi:10.1016/j.energy.2007.07.009
- Kloess, M., & Zach, K. (2014). Bulk electricity storage technologies for load-leveling operation – An economic assessment for the Austrian and German power market. *International Journal of Electrical Power & Energy Systems*, 59, 111–122. doi:10.1016/j.ijepes.2014.02.002
- Kondoh, J., Ishii, I., Yamaguchi, H., Murata, a., Otani, K., Sakuta, K., ... Kamimoto, M. (2000). Electrical energy storage systems for energy networks. *Energy Conversion and Management*, 41(17), 1863–1874. doi:10.1016/S0196-8904(00)00028-5
- Korpås, M., & Greiner, C. J. (2008). Opportunities for hydrogen production in connection with wind power in weak grids. *Renewable Energy*, 33(6), 1199–1208. doi:10.1016/j.renene.2007.06.010
- Lannoye, E., Flynn, D., & O'Malley, M. (2012). Assessment of power system flexibility: A high-level approach. *2012 IEEE Power and Energy Society General Meeting*, 1–8. doi:10.1109/PESGM.2012.6345435
- Mahlia, T. M. I., Saktisahdan, T. J., Jannifar, A., Hasan, M. H., & Matseelar, H. S. C. (2014). A review of available methods and development on energy storage; technology update. *Renewable and Sustainable Energy Reviews*, 33, 532–545. doi:10.1016/j.rser.2014.01.068
- Nagl, S., Fürsch, M., & Lindenberger, D. (2012). *The costs of electricity systems with a high share of fluctuating renewables - a stochastic investment and dispatch optimization model for Europe* (No. 01/2012). Cologne.
- Nakken, T., Strand, L. R., Frantzen, E., Rohden, R., & Eide, P. O. (2006). The Utsira wind-hydrogen system—operational experience. In *European Wind Energy Conference* (pp. 1–9).
- National Grid. (2014). Hourly load values for the UK grid.
- Northwest Power and Conservation Council. (2010a). *Sixth northwest conservation and electric power plan - Appendix I*.
- Northwest Power and Conservation Council. (2010b). *Sixth northwest conservation and electric power plan - Appendix I*.

-
- NOS. (2010, February 18). CO2-opslag Barendrecht van de baan. *NOS.nl*. Retrieved from <http://nos.nl/artikel/613003-nog-geen-besluit-over-co2opvang.html>
- NOS. (2014, November 4). Nog geen besluit over CO2-opvang. *NOS.nl*. Retrieved from <http://nos.nl/artikel/195971-co2opslag-barendrecht-van-de-baan.html>
- Palmintier, B. S. (2013). *Incorporating operational flexibility into electric generation planning: Impacts and methods for system design and policy analysis*. Massachusetts Institute of Technology.
- Palmintier, B., & Webster, M. (2011). Impact of unit commitment constraints on generation expansion planning with renewables. *2011 IEEE Power and Energy Society General Meeting*, 1–7. doi:10.1109/PES.2011.6038963
- Pérez-Arriaga, I. (2013). *Regulation of the power sector*. Madrid, Spain: Springer. Retrieved from <http://link.springer.com/content/pdf/10.1007/978-1-4471-5034-3.pdf>
- Peterson, S. B., Whitacre, J. F., & Apt, J. (2010). The economics of using plug-in hybrid electric vehicle battery packs for grid storage. *Journal of Power Sources*, *195*(8), 2377–2384. doi:10.1016/j.jpowsour.2009.09.070
- R Core Team. (2014). R: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from <http://www.r-project.org/>
- Richardson, D. B. (2013). Electric vehicles and the electric grid: A review of modeling approaches, Impacts, and renewable energy integration. *Renewable and Sustainable Energy Reviews*, *19*, 247–254. doi:10.1016/j.rser.2012.11.042
- Rodríguez, R. a., Becker, S., Andresen, G. B., Heide, D., & Greiner, M. (2014). Transmission needs across a fully renewable European power system. *Renewable Energy*, *63*, 467–476. doi:10.1016/j.renene.2013.10.005
- RStudio Team. (2012). *RStudio: Integrated Development Environment for R*. Boston, MA: RStudio, Inc. Retrieved from <http://www.rstudio.com/>
- Saber, A. Y., & Venayagamoorthy, G. K. (2010). Intelligent unit commitment with vehicle-to-grid —A cost-emission optimization. *Journal of Power Sources*, *195*(3), 898–911. doi:10.1016/j.jpowsour.2009.08.035
- Schaber, K., Steinke, F., & Hamacher, T. (2012). Transmission grid extensions for the integration of variable renewable energies in Europe: Who benefits where? *Energy Policy*, *43*, 123–135. doi:10.1016/j.enpol.2011.12.040
- Schaber, K., Steinke, F., Mühlich, P., & Hamacher, T. (2012). Parametric study of variable renewable energy integration in Europe: Advantages and costs of transmission grid extensions. *Energy Policy*, *42*, 498–508. doi:10.1016/j.enpol.2011.12.016
- Schoenung, S. (2011). *Energy Storage Systems Cost Update A Study for the DOE Energy Storage Systems Program* (pp. 1–30). Albuquerque, NM.

- Schoenung, S. M., & Eyer, J. (2008). *Benefit / Cost Framework for evaluating modular energy storage: A study for the DOE energy storage systems program* (pp. 1–40). Albuquerque, NM.
- Sioshansi, R., Denholm, P., Jenkin, T., & Weiss, J. (2009). Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects. *Energy Economics*, 31(2), 269–277. doi:10.1016/j.eneco.2008.10.005
- Steinke, F., Wolfrum, P., & Hoffmann, C. (2013). Grid vs. storage in a 100% renewable Europe. *Renewable Energy*, 50, 826–832. doi:10.1016/j.renene.2012.07.044
- Strbac, G., Aunedi, M., Pudjianto, D., Djapic, P., Teng, F., Sturt, A., ... Brandon, N. (2012). *Strategic Assessment of the Role and Value of Energy Storage Systems in the UK Low Carbon Energy Future Report for* (pp. 1–99). London, UK.
- Tsuchiya, H. (2004). Mass production cost of PEM fuel cell by learning curve. *International Journal of Hydrogen Energy*, 29(10), 985–990. doi:10.1016/j.ijhydene.2003.10.011
- U.S. Department of Energy. (2013). *Grid energy storage* (pp. 1–64).
- Verzijlbergh, R., Brancucci Martínez-Anido, C., Lukszo, Z., & de Vries, L. (2013). Does controlled electric vehicle charging substitute cross-border transmission capacity? *Applied Energy*. doi:10.1016/j.apenergy.2013.08.020
- Verzijlbergh, R., Brancucci Martínez-Anido, C., Lukszo, Z., & de Vries, L. (2014). Does controlled electric vehicle charging substitute cross-border transmission capacity? *Applied Energy*, 120, 169–180. doi:10.1016/j.apenergy.2013.08.020
- Wickham, H. (2007). Reshaping Data with the {reshape} Package. *Journal of Statistical Software*, 21(12), 1–20. Retrieved from <http://www.jstatsoft.org/v21/i12/>
- Wickham, H. (2009). *ggplot2: elegant graphics for data analysis*. Springer New York. Retrieved from <http://had.co.nz/ggplot2/book>
- Wickham, H. (2011). The Split-Apply-Combine Strategy for Data Analysis. *Journal of Statistical Software*, 40(1), 1–29. Retrieved from <http://www.jstatsoft.org/v40/i01/>
- the World Bank. (2012). *Turn down the heat: Why a 4°C warmer world must be avoided - Executive summary* (pp. 1–24). Washington DC.

APPENDICES

Appendix A COMBINED RESERVES EQUATIONS

Equations 8.1 to 8.6 replace equations 3.27 to 3.38 (system reserve requirements and maximum generator output levels with reserves).

$$\sum_{g \in G} R_{g,r,t}^{Up} + \sum_{g \in G_{Qstart}} R_{g,r,t}^{Qstart} \geq R_{r,t}^{prim} + R_{r,t}^{sec} \quad \forall r, t \quad 8.1$$

$$\sum_{g \in G} R_{g,r,t}^{Down} \geq R_{r,t}^{prim} + R_{r,t}^{sec} \quad \forall r, t \quad 8.2$$

$$P_{g,r,t} + R_{g,r,t}^{Up} \leq UC_{g,r,t} \cdot p_g^{max} \quad \forall g \in G_{UC,r,t} \quad 8.3$$

$$P_{g,r,t} - R_{g,r,t}^{Down} \geq UC_{g,r,t} \cdot p_g^{min} \quad \forall g \in G_{uc,r,t} \quad 8.4$$

$$P_{g,r,t} + R_{g,r,t}^{Up} \leq p_g^{max} \quad \forall g \notin G_{UC,r,t} \quad 8.5$$

$$P_{g,r,t} - R_{g,r,t}^{Down} \geq 0 \quad \forall g \notin G_{uc,r,t} \quad 8.6$$

The ability of generators to supply these reserves also changes. Instead of using a response time of 30 seconds for primary reserves and 15 minutes for secondary reserves, a response time of 5 minutes is used when using combined reserves. Equations 8.7 to 8.12 replace equations 3.39 to 3.51 (maximum reserve capabilities). The equation for the amount of quick start reserves remains the same.

$$R_{g,r,t}^{Up} \leq \frac{\Delta p_g^{max}}{5/60} \cdot UC_{g,r,t} \quad \forall g \in G_{UC,r,t} \quad 8.7$$

$$R_{g,r,t}^{Down} \leq \frac{\Delta p_g^{max}}{5/60} \cdot UC_{g,r,t} \quad \forall g \in G_{UC,r,t} \quad 8.8$$

$$R_{g,r,t}^{Up} \leq \frac{\Delta p_g^{max}}{5/60} \quad \forall g \notin G_{UC,r,t} \quad 8.9$$

$$R_{g,r,t}^{Down} \leq \frac{\Delta p_g^{max}}{5/60} \quad \forall g \notin G_{UC,r,t} \quad 8.10$$

The assumption is that combined reserves need to be delivered for 15 minutes. Therefore, the stored energy, $Q_{s,r,t}$, by $\frac{1}{4}$ of an hour.

$$R_{s,r,t}^{Up} \leq \frac{Q_{s,r,t}}{1/4} \quad \forall s, r, t \quad 8.11$$

$$R_{s,r,t}^{Down} \leq \frac{(q_s^{max} - Q_{s,r,t})}{1/4} \quad \forall s, r, t \quad 8.12$$

Appendix B GENERATOR AND STORAGE PARAMETERS

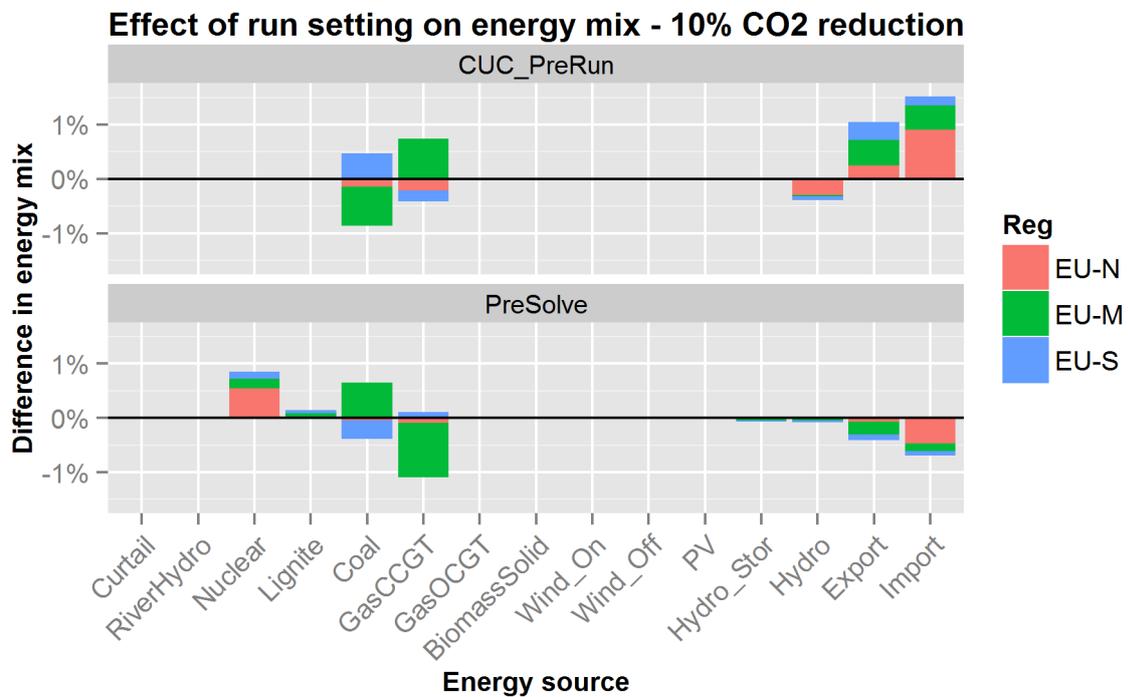
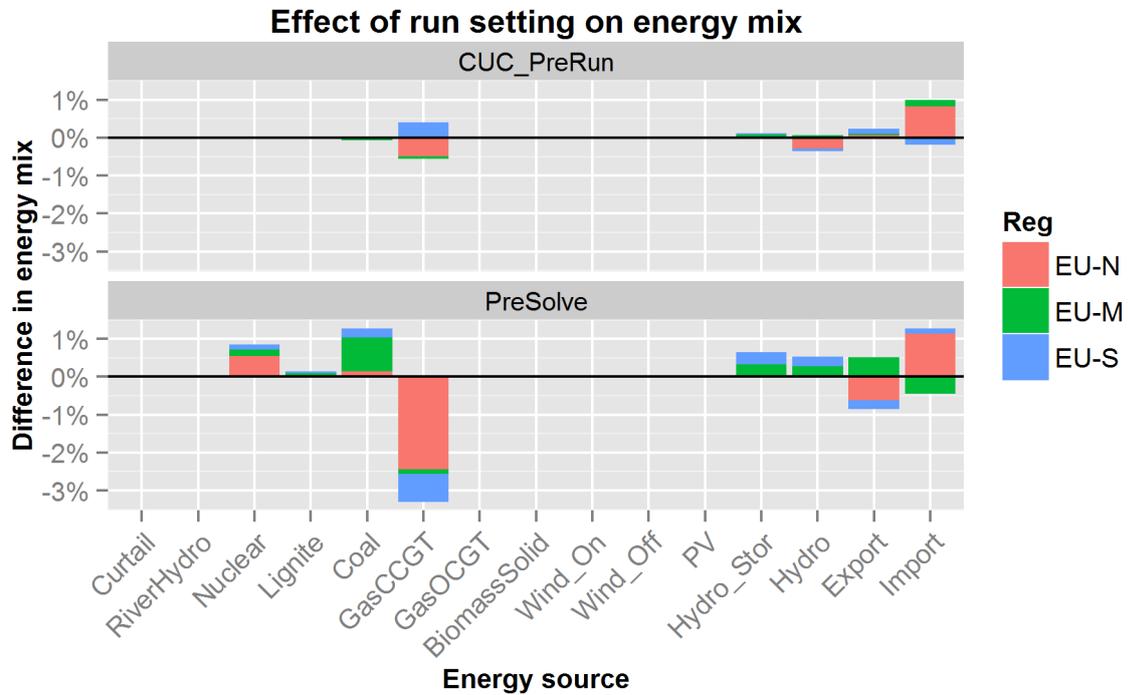
The parameters presented here are based on several sources (Bertsch et al., 2012; Fürsch et al., 2013; Hirth, 2013; International Energy Agency [IEA], 2010; Northwest Power and Conservation Council, 2010b; B. S. Palmintier, 2013).

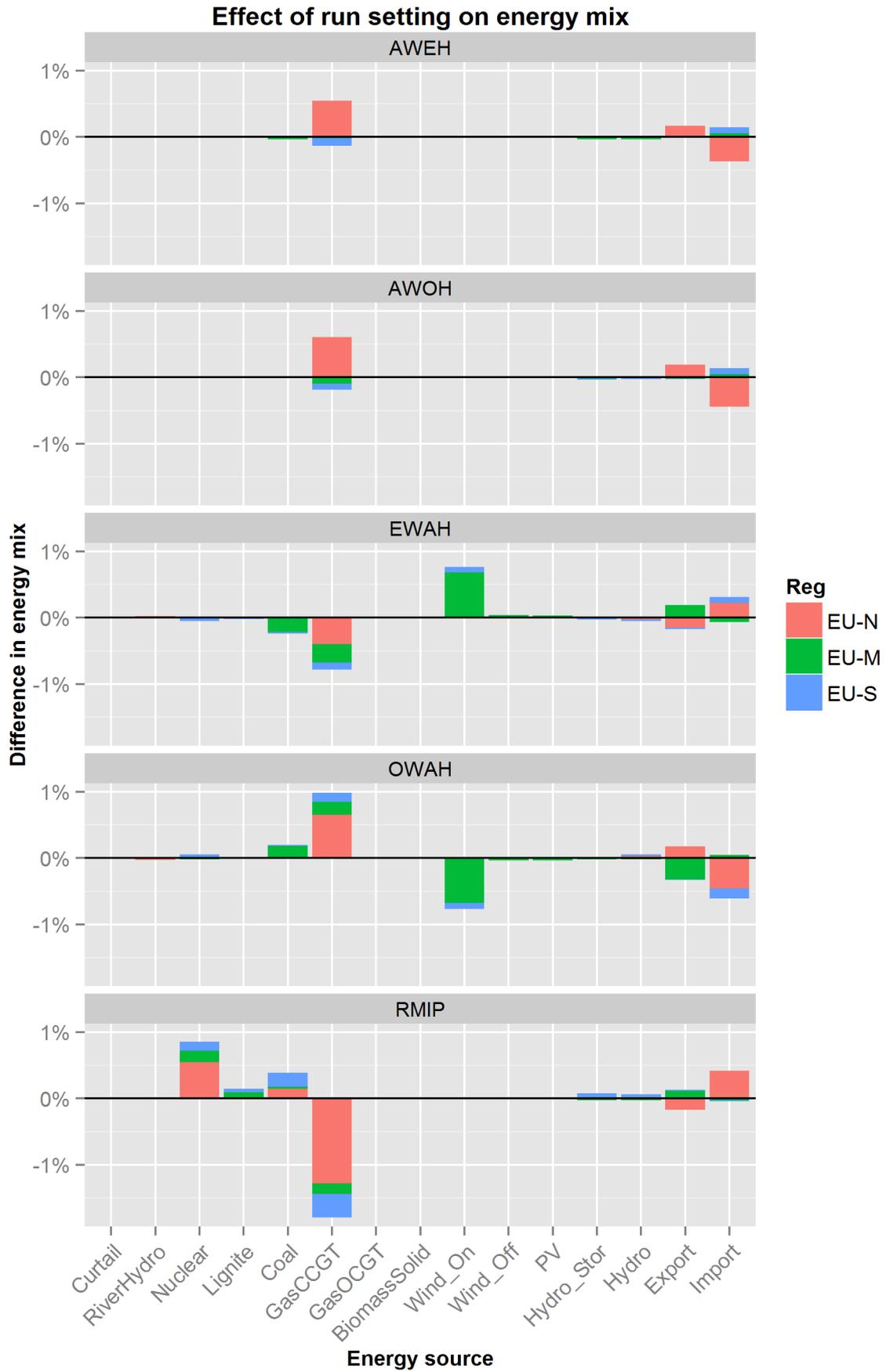
Generator type	Average plant size [GW]	Lifetime [y]	Minimum power output [%]	Output efficiency [%]	Charge efficiency [%]	Maximum ramp capacity [%/h]	Able to provide reserves?	Able to provide Quick start reserves	Capital cost [M€/GW]	Capital cost storage [M€/GWh]	Fixed O&M cost [M€/GW/y]	Variable O&M cost [M€/GWh e]	Start-up cost [M€/start]	Start-up fuel use [GWh th/start]	Scheduled maintenance [hrs/y]	Yearly availability (for non UC maintenance) [%]
Nuclear	0.5	50	0.50	0.35		0.05			3000	0	90	0.0010	0.075	2.5	1314	0.85
Lignite	0.5	45	0.40	0.40		0.08			2200	0	40	0.0010	0.025	2.5	1314	0.85
Coal	0.5	40	0.40	0.40		0.20	1		1500	0	30	0.0020	0.025	2.5	1314	0.85
GasCCGT	0.2	30	0.40	0.50		0.80	1		750	0	22	0.0020	0.008	0.011	1314	0.85
GasOCGT	0.1	25	0.20	0.35		6.00	1	1	500	0	13.7	0.0030	0.007	0.006	1314	0.85
BiomassSolid	0.1	30	0.40	0.30		0.20	1		2500	0	100	0.0020	0.025	2.5	1314	0.85
Wind_On		20	0.00	1.00		1.00			1200	0	30	0.0000	0	0	876	0.9
Wind_Off		20	0.00	1.00		1.00			2400	0	70	0.0000	0	0	876	0.9
PV		25	0.00	1.00		1.00			2200	0	30	0.0000	0	0	876	0.9
RiverHydro		50	0.00	1.00		1.00			2200	0	30	0.0000	0	0	876	0.9
CAES		30	0.20	0.80	0.8	6.00	1	1	600	25	13.7	0.0030	0.005	0.17	876	0.9
Hydro		50	0.00	0.90	0.9	12.00	1		1000	50	40	0.0000	0	0	876	0.9
H2		10	0.00	0.67	0.6	1.00	1		10000	5	0	0.0000	0	0	876	0.9

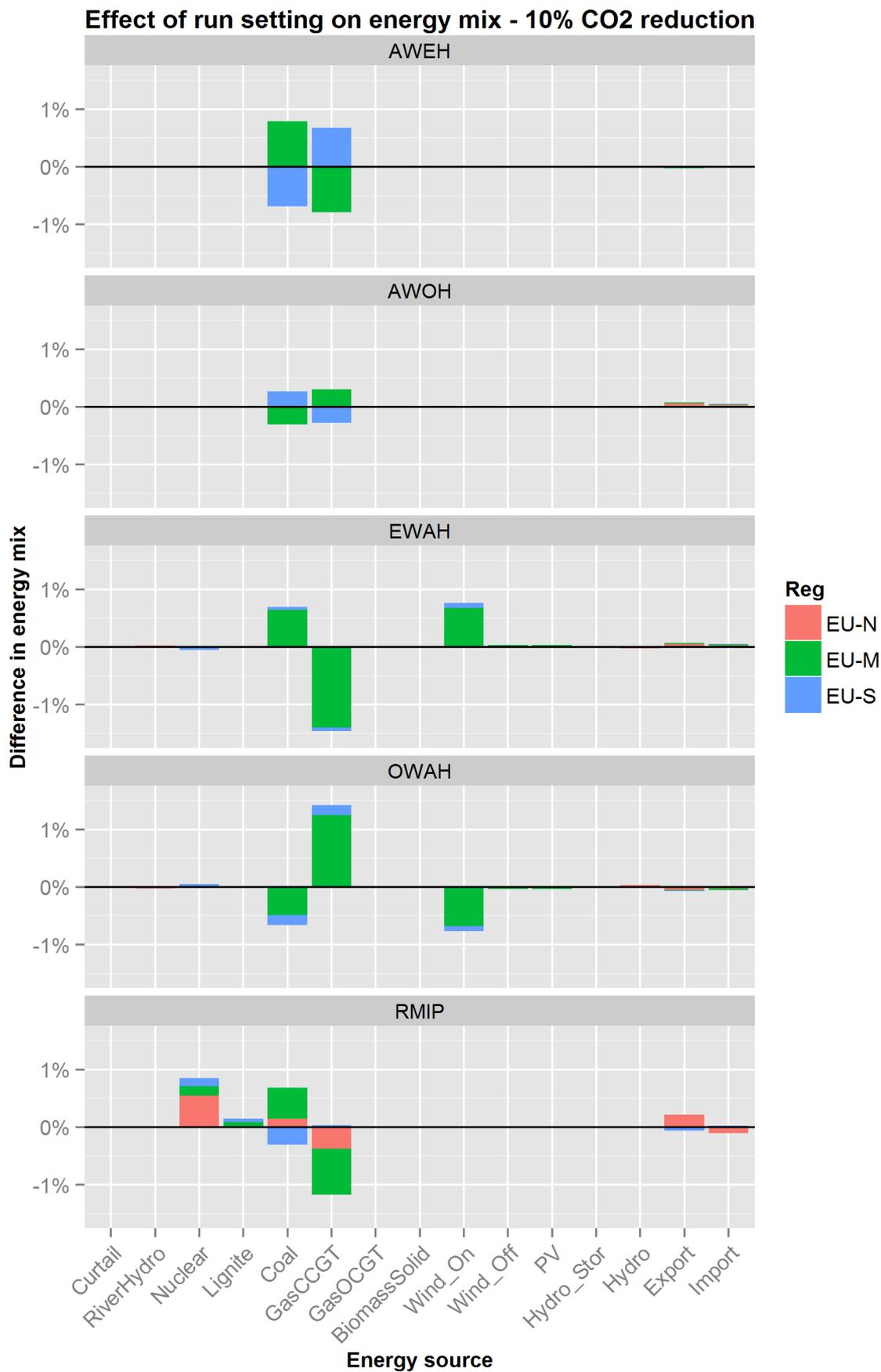
Appendix C **FUEL PROPERTIES**

	Cost [€/MWh]	CO₂ contents [ton CO₂ /MWh]
Uranium	3.3	0.000
Lignite	1.5	0.406
Coal	14.0	0.335
Gas	25.0	0.200
Bio fuel (solid)	20.0	0.000

Appendix D DETAILED EFFECTS OF DIFFERENT MODELS ON ENERGY MIX







Appendix E GAMS MODEL CODE

```
$title THE CLUSTERED UNIT COMMITMENT PROBLEM
$Author: Rick van Staveren
$Date: 23-6-2014
```

```
* ===== OPTIONS
```

```
* == Time options
```

```
*$set All_Hrs
$set Odd_Hrs
*$set Even_Hrs
```

```
$set TimeSetp_2
```

```
$set All_Blocks
*$set Odd_Blocks
*$set Even_Blocks
```

```
* == Integer options
```

```
**$set EconomicDispatch
*$set UC_LP
*$set ignore_integer
```

```
*$set PreSolve
```

```
* == Dispatch options
```

```
$set NoCO2Cap
```

```
* Non Served Energy possible?
```

```
$set No_NSE
```

```
* Turn of ramping constraints
```

```
*$set No_Ramp_Con
```

```
* == Maintenance options:
```

```
* 1 NoUCMaint uses derate factors for all maintenance (only less availability),  
Maint_LP
```

```
$set NoUCMaint
```

```
* 2 Maint LP uses separate unit maintenance functions but releases integer  
constraints
```

```
*$set Maint_LP
```

```
* == Investment options (don't forget to include capital cost)
```

```
*$set Invest_Gen
**$set Invest_Stor
*$set Invest_NTC
**$set Invest_RES
```

```
$set No_Capital_Cost
```

```
* == Reserve options
```

```
*$set Seperate_Reserves
*$set RES_Reserves
*$set No_Qstart_Reserves
```

```
*$set No_Reserves
```

```
* #####
```

```
* ===== DEFINING SETS
```

* #####

```
SETS
Counter /1*10000/

Time          Set of time increments (8760 for a hourly year) - the actual set is
loaded from Excel
*           /      t1*t120
*           /

BlockHr       Set of hours within one block (168 for a week)
/
$ifthen set All_Hrs
           1*168

$elseif set Odd_Hrs
$include Hours_Odd

$elseif set Even_Hrs
$include Hours_Even

$endif
/

Block         Set of blocks that a year is cut up in (52 for weeks - excluding
the last day of the year)
/
$ifthen set All_Blocks
           1*52

$elseif set Odd_Blocks

1,3,5,7,9,11,13,15,17,19,21,23,25,27,29,31,33,35,37,39,41,43,45,47,49,51

$elseif set Even_Blocks

2,4,6,8,10,12,14,16,18,20,22,24,26,28,30,32,34,36,38,40,42,44,46,48,50,52
$endif
/

Year         Set of years
*           /      2009
           /      2010
           /

Gen          Set of all generators
/
RiverHydro
Nuclear
Lignite
*           LigniteCCS
*           Coal
           CoalCCS
*           GasCCGT
           GasCCGTCCS
*           GasOCGT
*           BiomassGas
*           BiomassLiquid
           BiomassSolid
           Wind_On
           Wind_Off
           PV
           Hydro
*           Li-Ion
*           CAES
*           H2
/

CommitGen(Gen) Set of generators that have unit commitment constraints (min output
and start up cost)
* If Economic dispatch is used, this is an empty set
$ifthen not set EconomicDispatch
/
Nuclear
Lignite
*           LigniteCCS
```

```

*           Coal
*           CoalCCS
*           GasCCGT
*           GasCCGTCCS
*           GasOCGT
*           BiomassGas
*           BiomassLiquid
*           BiomassSolid
*           CAES
$endif /

RES(Gen) / Set of UNCONTROLLABLE renewable energy sources
           / Wind_On
           / Wind_Off
           / PV
           / RiverHydro

Stor(GEN) / Set of storage technologies
*         /
*         / Li-Ion
*         / Hydro
*         / CAES
*         / H2

oStor / Set of storage technologies used for output writing
*     /
*     / Li-Ion_Stor
*     / Hydro_Stor
*     / CAES_Stor
*     / H2_Stor

StorStor(Stor,oStor) Tuple of storages and the output set
*     /
*     / Li-Ion .Li-Ion_Stor
*     / Hydro .Hydro_Stor
*     / CAES .CAES_Stor
*     / H2 .H2_Stor

Line / Set of line types
*   / HVAC
*   / HVDC

Fuel / Set of fuels
*   / uranium
*   / lignite
*   / coal
*   / gas
*   / biogas
*   / bioliq
*   / biosol

GenFuel(Gen,Fuel) Tuple of generators and their associated fuels
*     / Nuclear .uranium
*     / Lignite .lignite
*     / LigniteCCS .lignite
*     / Coal .coal
*     / CoalCCS .coal
*     / GasCCGT .gas
*     / GasCCGTCCS .gas
*     / GasOCGT .gas
*     / GasOCGTCCS .gas
*     / BiomassGas .biogas
*     / BiomassLiquid .bioliq
*     / BiomassSolid .biosol
*     / CAES .gas

Reg / Regions
*   / EU Europe Total

```

```

EU-N   Europe North
EU-M   Europe Middle
EU-S   Europe South

*      NL      "Netherlands"
*      BE      "Belgium"
*      GE      "Germany"

/

RESReg /      Seperate regions for renewables
/      AT,BA,BE,BG,CH,CZ,DE,DK,EE,ES,FI,FR,GB,GR,HR,HU,IE,IT,
/      LT,LU,LV,ME,MK,NL,NO,PL,PT,RO,RS,SE,SI,SK

RESRegMap(Reg,RESReg) Tuple for weather regions

*      EU      .(AT,BA,BE,BG,CH,CZ,DE,DK,EE,ES,FI,FR,GB,GR,HR,HU,IE,IT,
*              LT,LU,LV,ME,MK,NL,NO,PL,PT,RO,RS,SE,SI,SK)

EU-N   .(EE,FI,LT,LV,NO,SE)
EU-M   .(BE,CZ,DE,DK,GB,IE,LU,NL,PL,SK)
EU-S   .(AT,BA,BG,CH,ES,FR,GR,HR,HU,IT,ME,MK,PT,RO,RS,SI)

*      NL      .NLDH
*      NL      .NLDM

/

;

ALIAS
(Reg,Reg2)

;

* #####

* ===== LOADING TABLES

* #####

* === Fuel data
TABLE   DataFuel(Fuel,*)      data about fuels
*           Cost              CO2int
*           (M€/Gwh th)      (MtCO2/Gwh th)
uranium  3.3e-3              0.000e-3
lignite  1.5e-3              0.406e-3
coal     14e-3              0.335e-3
gas      25e-3              0.200e-3
biosol   20e-3              0.300e-3

*
TABLE   DataNTCcost(Line,*)  data about transmission cost (from Fursch 2013 pg.
16)
*           Cable            Converter
*           (M€/(GW*km))    (M€/GW)
HVAC     0.4                 0
*HVDC    1.5                 150

* #####

* ===== DEFINING AND ASSIGNING PARAMETERS

* #####

* ===== LOADING DATA FROM EXCEL

```

```

* #####

* === loading the set of hours
$call "gdxxrw GamsData_TS.xls set=time rng=Demand!a4:a8763 rdim=1"
$gdxin GamsData_TS.gdx
$load time
*display time;

** === loading the set of years
* Only if they are not already loaded from the above code

*$call "gdxxrw GamsData.xls dset=year rng=Demand!B3:E3 cdim=1"
*$gdxin GamsData.gdx
*$load year
*display year;

** === Loading the set of regions
* Only if they are not already loaded from the above code

*$call "gdxxrw GamsData.xls dset=reg rng=Demand!B2:E2 cdim=1"
*$gdxin GamsData.gdx
*$load reg
*display reg;

* === Loading generator data
parameter DataGen(Gen,*) Generator data
$call "Gdxxrw GamsData.xls par=DataGen rng=GenType!A2:R20 dim=2 cdim=1"
$GDXin GamsData.gdx
$load DataGen
*display DataGen;

$ontext
* === Loading Net Transfer Capacity data (not working right now)
parameter DataNTCcap2(*,*) NTC of transmission from Reg to Reg 2
$call "Gdxxrw GamsData.xls par=DataNTCcap2 rng=NTC_cap!B1:AM39 cdim=1 rdim=1"
$GDXin GamsData.gdx
$load DataNTCcap2
$offtext

$ontext
* === Loading data about distances between countries (for NTC cost calculation)
parameter DataNTCdist(Reg,Reg2) Length of transmission from Reg to Reg 2
$call "Gdxxrw GamsData.xls par=DataNTCdist rng=NTC_dist!A1:AM39 cdim=1 rdim=1"
$GDXin GamsData.gdx
$load DataNTCdist
$offtext

* === Loading data about how much capacity the regions have (initially)
parameter DataCap(*,Reg) Initial generation capacity in a region
$call "Gdxxrw GamsData.xls par=DataCap rng=StartCap!A1:Z20 dim=2 cdim=1"
$GDXin GamsData.gdx
$load DataCap
*display DataCap;

* === Loading data about how much capacity the RES regions have (initially)
parameter DataCapRES(*,RESReg) Initial renewable capacity in a region
$call "Gdxxrw GamsData.xls par=DataCapRES rng=CapRES!A1:AG10 dim=2 cdim=1"
$GDXin GamsData.gdx
$load DataCapRES
*display DataCap;

* === Loading demand data
parameter DataDem(time,reg,year) Demand in a region [GW]
*$call "gdxxrw gdxxrwss.xls par=modedistance rng=sheet1!a26:e31 rdim=1 cdim=2"
$call "gdxxrw GamsData_TS.xls par=DataDem rng=Demand!A2:Z8763 dim=3 cdim=2"
$gdxin GamsData_TS.gdx
$load DataDem

* === Loading ONSHORE wind data
parameter DatawindOn(time,RESreg,year) ONSHORE wind power output in a region [%]
$call "gdxxrw GamsData_TS.xls par=DatawindOn rng=Wind_On!A1:AG8763 dim=3 cdim=2"
$gdxin GamsData_TS.gdx

```

```

$load DatawindOn
*display DatawindOn;

* === Loading OFFSHORE wind data
parameter DataWindOff(time,RESreg,year) OFFSHORE wind power output in a region [%]
$call "gdxrw GamsData_TS.xls par=DataWindOff rng=wind_Off!A1:Z8763 dim=3 cdim=2"
$gdxin GamsData_TS.gdx
$load DataWindOff
*display DatawindOn;

* === Loading SOLAR data
parameter DataSolar(time,RESreg,year) solar output in a region [%]
$call "gdxrw GamsData_TS.xls par=DataSolar rng=Solar!A2:AG8763 dim=3 cdim=2"
$gdxin GamsData_TS.gdx
$load DataSolar
*display DataSolar;

* === Loading HYDRO data
parameter DataHydro(time,RESreg,year) Hydro inflow in a region [Gwh]
$call "gdxrw GamsData_TS.xls par=DataHydro rng=Hydro!A1:AG8763 dim=3 cdim=2"
$gdxin GamsData_TS.gdx
$load DataHydro
*display DataSolar;

variable vBlockEnergyGen(Reg,Year,Block,BlockHr,Gen) Generation calculated in pre-
run      ;

$ifthen exist PreRunOutput.gdx
$GDXin PreRunOutput.gdx
$load vBlockEnergyGen
$GDXin
$endif

* #####
* ===== PARAMETERS WITH MANUAL INPUT
* #####

PARAMETERS

* === value of lost load
VOLL      /      "The value of lost load [ME/Gwh] (bijvoet, 2003)"
          /      8.6

* === CO2 policy over the years
CO2price(year) "Co2 price dependent on time [ME/Mton CO2]"
              /      set.year      0

CO2Cap(year)  "Co2 cap dependent on time [Mton CO2]"
              /      set.year      1066

* === Transfer capacity between countries/regions
*$ontext
DataNTCCap(Reg,Reg2) Net transfer capacity between countries [GW]
*
          /
          EU-M      .EU-M      0
          EU-N      .EU-M      4
          EU-M      .EU-N      4
          EU-M      .EU-S      15
          EU-S      .EU-M      15

*
          NLD      .NLD      0
*
          NLD      .BEL      2.4
*
          BEL      .NLD      2.4
*
          GER      .NLD      3.85
*
          NLD      .GER      3.0

*$offtext

```

```

*$ontext
DataNTCdist(Reg,Reg2) Net transfer capacity between countries [GW]
/
*
      EU-M      .EU-M      0
      EU-N      .EU-M      500
      EU-M      .EU-N      500
      EU-M      .EU-S      500
      EU-S      .EU-M      500

/
*$offtext

* === Size of time steps
TimeStep      "The size of time steps in the data, 1 is 1 hour"
/
$ifthen set TimeStep_2
              2
$elseif not set TimeStep_2
              1
$endif
/

* === Yearly energy demand of synchronised area
EUEnergy      The yearly energy demand of the total synchronised network (to
calculate reserve requirements) [Twh]
/
              3350
/

* === Interest rate (for annualized cost)
Intrate       The interest rate
/
              0.1
/

* === The amount of secondary reserve needed to be provided by spinning units
FracSpinReserve Secondary reserve needed to be provided by spinning units (rest
can be offline)
/
              0.5
/

* === The reserve capacity for RES (% of RES output)
RESReserve    The reserve for RES output
/
              0.1
/

* #####

* ===== PARAMETERS WITH CALCULATED INPUT (calculated later)

* #####

* === Parameters used in equations

Profiles      (RESReg,Year,Block,BlockHr,*)      Information about
the weather for renewable generation [%]
ONatInflow    (Reg,Year,Block,BlockHr,Stor)      Natural inflow in
storage (Hydro) [Gwh]

Demand        (Reg,Year,Block,BlockHr)           Demand data that
will be ordered in blocks [GW]

YearlyEnergyUse (Reg,Year)                       Yearly energy use
of a region (for reserves) [Twh]
MaxPower      (Reg,Year)                         Maximal demand of a
region (for reserves) [GW]

EACF          (*)                                Equivalent Annual
Cost Factor for generators and lines [%]

FractionOfYear year simulated [％]                The fraction of the

TotalPlantsMax (Reg,Year,Gen)                   Set upper limit to
the new number of plants [#]

```

MaxOverbuilt overbuilt capacity	[%]	Maximum fraction of
DataCapStor of the storages	(Reg,Stor) [Gwh]	The energy capacity
Reserve1 primary reserves	(Reg,Year) [GW]	The required
Reserve2 secondary reserves	(Reg,Year) [GW]	The required

* === Output parameters

oSolveStats	(*)	Solver statistics
oPowerBal balance at each node (* = gen)	(Reg,Year,time,*)	The hourly power
oEnergyBal balance at each node (* = relative, * = gen)"	(Reg,Year,*,*)	"The yearly energy
oTransport transport between 2 regions	(Reg,Reg2,Year)	The yearly
oMarginalCost cost or spot price at each node	(Reg,Year,Block,BlockHr)	The hourly marginal
oMarginalCostTs cost or spot price at each node	(Reg,Year,time)	The hourly marginal
oGenFinance cost and revenues	(Reg,Year,Gen,*)	Yearly generator
oStorFinance and revenues	(Reg,Year,Stor,*)	Yearly storage cost
oHourlyGenStartUpCost cost of generators (excl start fuel use)	(Reg,Year,Block,BlockHr,Gen) [M€]	hourly start up
oHourlyGenFuelUse seperate generators	(Reg,Year,Block,BlockHr,Gen) [Gwh]	hourly fuel use of
oHourlyTypeFuelUse fuel groups	(Reg,Year,Block,BlockHr,fuel) [Gwh]	hourly fuel use of
oHourlyFuelCost seperate generators	(Reg,Year,Block,BlockHr,Gen,Fuel) [M€]	hourly fuel cost of
oGenFuelUse generators	(Reg,Year,Gen) [Gwh]	fuel use of
oTypeFuelUse groups	(Reg,Year,fuel) [Gwh]	fuel use of fuel
oHourlyGenCO2em emissions of seperate generators	(Reg,Year,Block,BlockHr,Gen) [MtCO2]	hourly CO2
oHourlyGenCO2cost seperate generators	(Reg,Year,Block,BlockHr,Gen) [M€]	hourly CO2 cost of
oHourlyCO2em emissions	(Reg,Year,Block,BlockHr) [MtCO2]	hourly CO2
oHourlyCO2cost [M€]	(Reg,Year,Block,BlockHr)	hourly CO2 cost
oGenCO2em generators	(Reg,Year,Gen) [MtCO2]	CO2 emissions of
oTotalCO2em [MtCO2]		total CO2 emissions
oStorageLevel level	(Reg,Year,time,Stor)	hourly storage
oNTCCost	(Line,Reg,Reg2)	
oCapacityAvailable available for dispatch	(Reg,Year,Block,BlockHr)	The total capacity

;

* #####

* ===== CALCULATING PARAMETERS

```

* #####
* === Put hourly data in multidimensional tables
loop ((Block,BlockHr),
      loop(time$(ord(time) eq (Block.val-1)*card(BlockHr)*TimeStep +
BlockHr.val),
        Demand(Reg,Year,Block,BlockHr)=DataDem(time,Reg,Year);
Profiles(RESreg,Year,Block,BlockHr,'Wind_On')=DataWindOn(time,RESreg,year);
Profiles(RESreg,Year,Block,BlockHr,'Wind_Off')=DataWindOff(time,RESreg,year);
Profiles(RESreg,Year,Block,BlockHr,'PV')=MAX(DataSolar(time,RESreg,year),0);
Profiles(RESreg,Year,Block,BlockHr,'Hydro')=DataHydro(time,RESreg,year);
Profiles(RESreg,Year,Block,BlockHr,'RiverHydro')=DataHydro(time,RESreg,year);
      )
);

* === Assign values to parameters
* Fraction of year that is simulated
FractionOfYear = card(Block)*card(BlockHr)*TimeStep/8760;

* Calculate total energy use per region (if less than a full year is optimized, the
demand is scaled), used for (primary) reserves [Twh]
YearlyEnergyUse(Reg,Year)=SUM((Block,BlockHr),
Demand(Reg,Year,Block,BlockHr))/1000/FractionOfYear;

* Calculate the maximum power demand of a region, used for secondary reserves
MaxPower(Reg,Year)=SMAX((Block,BlockHr),Demand(Reg,Year,Block,BlockHr));

* Calculate the equivalent annual cost factor for generators
EACF(Gen) = IntRate / (1-(1+IntRate)**(-DataGen(Gen,'Life')));
EACF(Line)= IntRate / (1-(1+IntRate)**(-30));

* Calculate the maximum number of plants
* when investment is possible
$ifthen set Invest_Gen
      TotalPlantsMax(Reg,Year,Gen) = ceil( MaxPower(Reg,Year) /
DataGen(Gen,'AvGen') );
      TotalPlantsMax(Reg,Year,RES) = ceil( MaxPower(Reg,Year) /
DataGen(RES,'AvGen') );
* without investment
$elseif not set Invest_Gen
      TotalPlantsMax(Reg,Year,Gen) = ceil( DataCap(Gen,Reg) /
DataGen(Gen,'AvGen') );
$endif

* The margin that the total amount of capacity can have over the maximum demand (1
= 100%)
MaxOverbuilt = 1;

* Rewrite storage capacity (energy) data from the excel file in new parameter
DataCapStor(Reg,Stor) = SUM(StorStor(Stor,oStor), DataCap(oStor,Reg));

* Calculate necessary primary reserves (able to change output level in 30 sec and
last for 15 minutes)
Reserve1(Reg,Year) =
$ifthen set No_Reserves
0
$elseif not set No_Reserves
YearlyEnergyUse(Reg,Year)/(EUEnergy)*3
$endif
;
* Secondary reserves (able to reduce output in 15 minutes)
Reserve2(Reg,Year) =
$ifthen set No_Reserves
0
$elseif not set No_Reserves
SQRT(0.010*MaxPower(Reg,Year)+0.150**2)-0.150
$endif

```

```

;
oNatInflow(Reg,Year,Block,BlockHr,Stor) = SUM((RESRegMap(Reg,RESreg)),
Profiles(RESreg,year,Block,BlockHr,Stor) * DataCapRES(Stor,RESReg));
* #####
* ===== DECLARING VARIABLES
* #####

VARIABLES
vTotalCost                                objective function
(total cost)                               [M€]

vTransLoss                                Transmission losses
[GW]                                        (Year,Block,BlockHr,Reg,Reg2)

* === Declare investment variables (only if Investment in generators is set)
* == Declare generator investment
$ifthen set Invest_Gen
    POSITIVE VARIABLES
    vCapacityNew                            generator capacity
that is newly installed                    [GW]
    vCapacityClosed                        fraction of
installed capacity that is used           [%]
    (Reg,Year,Gen)

*
    INTEGER VARIABLES
    vNewPlants                              number of new
plants (to make Invest_Genments discrete) [#]
$endif

* == Declare transmission investment
$ifthen set Invest_NTC
    POSITIVE VARIABLES
    vNTCInv                                ntc capacity that
is newly installed                        [GW]
    (Reg,Reg2)
$endif

* === Declare cost variables

POSITIVE VARIABLES
vTotalFixedOMCost                         fixed operation &
Maintenance cost                          [M€]
vTotalVarOMCost                           variable operation
& Maintenance cost                        [M€]
vTotalFuelCost                             cost of fuel
[M€]
vTotalCO2Cost                             cost of CO2
emissions                                 [M€]
vTotalStartupCost                         cost of starting up
a power plant                             [M€]
* Exclude non served energy
$ifthen not set No_NSE
vTotalNSECost                             cost of non-served
energy                                    [M€]
$endif

* Exclude capital cost if specified
$ifthen not set No_Capital_Cost
vTotalCapitalCost                         capital cost for
generation set                            [M€]
vTotalNTCCost                             cost of
transmission lines                        [M€]
$endif

* === Operational variables

```

vPower generators	(Reg,Year,Block,BlockHr,Gen) [GW]	output of non served energy
vNSE	(Reg,Year,Block,BlockHr)	
* == Capacity		
vCapacityUsed	(Reg,Year,Gen) [GW]	total capacity in use
vCapacityInstalled	(Reg,Year,Gen) [GW]	total capacity that is installed
vCapacityInstalledStor	(Reg,Year,Stor) [Gwh]	the storage capacity of storages
vCapacityInstalledRES	(RESReg,Year,RES)	total RES capacity installed
vStorageLevel	(reg,year,Block,BlockHr,Stor) [Gwh]	The level of the storage
* == Reserves		
vReserveQstart	(Reg,Year,Block,BlockHr,Gen) [GW]	Quick start reserve
* = Combined reserves		
\$ifthen.SeperateReserves not set Seperate_Reserves		
vReserveUp	(Reg,Year,Block,BlockHr,Gen) [GW]	Rserve capacity for up regulation
vReserveDown	(Reg,Year,Block,BlockHr,Gen) [GW]	Reserve capacity for down regulation
* = Seperate reserves		
\$elseif.SeperateReserves set Seperate_Reserves		
vReserveUp1	(Reg,Year,Block,BlockHr,Gen) [GW]	Required combined reserve capacity for up regulation
vReserveUp2	(Reg,Year,Block,BlockHr,Gen) [GW]	Required combined reserve capacity for up regulation
vReserveDown1	(Reg,Year,Block,BlockHr,Gen) [GW]	Required combined reserve capacity for down regulation
vReserveDown2	(Reg,Year,Block,BlockHr,Gen) [GW]	Required combined reserve capacity for down regulation
\$endif.SeperateReserves		
* == Transport		
vImport	(year,block,blockhr,Reg,Reg2) [GW]	Imports of electricity between regions
vExport	(year,block,blockhr,Reg,Reg2) [GW]	Exports of electricity between regions
NEGATIVE VARIABLES		
vStoragePower	(Reg,Year,Block,BlockHr,Stor) [GW]	Storage of electricity
vCurtail	(Reg,Year,Block,BlockHr) [GW]	the renewable energy curtailed over time
* === State variables		
POSITIVE VARIABLES		
vUnitsCommitted	(Reg,Year,Block,BlockHr,Gen)	number of units running of each generator at any time
vStartUps	(Reg,Year,Block,BlockHr,Gen)	number of units starting up of each generator at any time
vShutDowns	(Reg,Year,Block,BlockHr,Gen)	number of units shutting down of each generator at any time
INTEGER VARIABLES		
vUnitsCommittedINT	(Reg,Year,Block,BlockHr,Gen)	number of units running of each generator at any time

```

vStartUpsINT          (Reg,Year,Block,BlockHr,Gen)          number of units
starting up of each generator at any time
vShutDownsINT        (Reg,Year,Block,BlockHr,Gen)          number of units
shutting down of each generator at any time

* === Maintenance variables

* If the maintenance can be calculated using LP then declare as positive variables,
otherwise it's an integer
$ifthen set Maint_LP
    POSITIVE VARIABLES
$endif

vMaint                (Reg,Year,Block,Gen)                  number of units on
maintenance during a time block

POSITIVE VARIABLES
vCapOffMaint          (Reg,Year,Block,Gen)                  capacity that is
off maintenance                                             [GW]

;

* #####

* ===== DECLARING EQUATIONS

* #####

* ===== TOTAL COST EQUATIONS

* #####

EQUATIONS

eTotalCost            objective function
[M€]

eTotalFixedOMCost     fixed operation &
Maintenance cost      [M€]
eTotalVarOMCost       variable operation &
Maintenance cost      [M€]
eTotalFuelCost        cost of fuel
[M€]
eTotalCO2Cost         cost of CO2 emissions
[M€]
eTotalStartUpCost     cost of start up
[M€]

$ifthen not set NO_NSE
eTotalNSECost         cost of non served energy
[M€]
$endif

* Exclude capital cost if specified
$ifthen not set No_Capital_Cost
eTotalCapitalCost     capital cost of generators
[M€]
eTotalNTCCost         cost of transmission lines
[M€]
$endif

* #####

* ===== INVESTMENTS

* #####

* = Generator investment equations (only when investment in generators is possible)
$ifthen set Invest_Gen
    eCapacityInstalled (Reg,Year,Gen)          amount of new capacity
installed              [GW]

```

```

[GW]      eCapacityUsed          (Reg,Year,Gen)          amount of capacity used
          eNewPlants            (Reg,Year,Gen)          amount of new plants
(discrete investments)  [#]
          eCapacityMax          (Reg,Year)            limit total amount of
capacity                                       [GW]
$endif

* = NTC investment equations
$ifthen set Invest_NTC
          eReverseNTCInv        (Reg,Reg2)            A cable can be used
by both regions                               [GW]
$endif

* #####
* ===== CONSTRAINTS
* #####

* === Power balance
eLOAD          (Reg,Year,Block,BlockHr)          load balance equation
[GW]

* === Generator state
$ifthen.ED not set EconomicDispatch
          eUnitCommitment      (Reg,Year,Block,BlockHr,Gen)  number of units
committed                                         [#]
          eMaxUnitCommitted     (Reg,Year,Block,BlockHr,Gen)  maximum number of
units comitted                                  [#]

$ifthen.UC_LP not set UC_LP
          eIntUC, eIntSU, eIntSD
$endif.UC_LP
$endif.ED

*eRESout      (Reg,Year,Block,BlockHr,RES)      output of Renewable energy
sources      [GW]
eStorageLevel (Reg,Year,Block,BlockHr,Stor)      storage level
[GWh]
eStorageLevelMax (Reg,Year,Block,BlockHr,Stor)    energy capacity of storage
level      [GWh]
eStorageLevelEnd (Reg,Year,Block,BlockHr,Stor)    the end storage level
requirement [GWh]
eStoragePowerMax (Reg,Year,Block,BlockHr,Stor)    maximum power of loading
the storage [GW]

* Already incorporated in Reserve equations
*ePMax      (Reg,Year,Block,BlockHr,Gen)          maximum power output
equation    [GW]
*ePMin      (Reg,Year,Block,BlockHr,Gen)          minimum power output
equation    [GW]

* === Ramping equations
$ifthen not set No_Ramp_Con
          eRampUpUC            (Reg,Year,Block,BlockHr,Gen)  maximum up ramp rate limit
for UC gens      [GW]
          eRampUp              (Reg,Year,Block,BlockHr,Gen)  maximum up ramp rate limit
[GW]
          eRampDownUC          (Reg,Year,Block,BlockHr,Gen)  maximum down ramp rate
limit for UC gens [GW]
          eRampDown            (Reg,Year,Block,BlockHr,Gen)  maximum down ramp rate
limit          [GW]
$endif

* === Reserve equations

```

eReserveUpUC power + reserve	(Reg,Year,Block,BlockHr,Gen) [GW]	UC generators stay below
eReserveDownUC power - reserve	(Reg,Year,Block,BlockHr,Gen) [GW]	UC generators stay above
eReserveUp + reserve	(Reg,Year,Block,BlockHr,Gen) [GW]	generators stay below power
eReserveDown - reserve	(Reg,Year,Block,BlockHr,Gen) [GW]	generators stay above power
eReserveQstart reserves	(Reg,Year,Block,BlockHr,Gen) [GW]	generators quick start
eReserveQstartMax [GW]	(Reg,Year,Block,BlockHr)	total quick start reserves
* == Combined reserves		
\$ifthen.SeperateReserves not set Seperate_Reserves		
eReserveUpReq reserves	(Reg,Year,Block,BlockHr) [GW]	calculate total required up
eReserveDownReq down reserves	(Reg,Year,Block,BlockHr) [GW]	calculate total required
*eReserveUpGenMaxUC of UC generator batch	(Reg,Year,Block,BlockHr,Gen) [GW]	maximum regulatory power
*eReserveDownGenMaxUC of UC generator batch	(Reg,Year,Block,BlockHr,Gen) [GW]	maximum regulatory power
eReserveUpGenMax non-UC generator batch	(Reg,Year,Block,BlockHr,Gen) [GW]	maximum regulatory power of
eReserveDownGenMax non-UC generator batch	(Reg,Year,Block,BlockHr,Gen) [GW]	maximum regulatory power of
eReserveUpStor reserve up a storage plant can deliver (dependent on state of storage)	(Reg,Year,Block,BlockHr,Stor)	the maximum amount of
eReserveDownStor reserve down a storage plant can deliver (dependent on state of storage)	(Reg,Year,Block,BlockHr,Stor)	the maximum amount of
* == Seperate reserves		
\$elseif.SeperateReserves set Seperate_Reserves		
eReserveUpReq1 reserves (primary)	(Reg,Year,Block,BlockHr) [GW]	calculate total required up
eReserveUpReq2 reserves (secondary)	(Reg,Year,Block,BlockHr) [GW]	calculate total required up
eReserveDownReq1 down reserves (primary)	(Reg,Year,Block,BlockHr) [GW]	calculate total required
eReserveDownReq2 down reserves (secondary)	(Reg,Year,Block,BlockHr) [GW]	calculate total required
eReserveUpGenMaxUC1 of UC generator batch	(Reg,Year,Block,BlockHr,Gen) [GW]	maximum regulatory power
eReserveDownGenMaxUC1 of UC generator batch	(Reg,Year,Block,BlockHr,Gen) [GW]	maximum regulatory power
eReserveUpGenMax1 of non-UC generator batch	(Reg,Year,Block,BlockHr,Gen) [GW]	maximum regulatory power
eReserveDownGenMax1 of non-UC generator batch	(Reg,Year,Block,BlockHr,Gen) [GW]	maximum regulatory power
eReserveUpGenMaxUC2 of UC generator batch	(Reg,Year,Block,BlockHr,Gen) [GW]	maximum regulatory power
eReserveDownGenMaxUC2 of UC generator batch	(Reg,Year,Block,BlockHr,Gen) [GW]	maximum regulatory power
eReserveUpGenMax2 of non-UC generator batch	(Reg,Year,Block,BlockHr,Gen) [GW]	maximum regulatory power
eReserveDownGenMax2 of non-UC generator batch	(Reg,Year,Block,BlockHr,Gen) [GW]	maximum regulatory power
eReserveUpStor1 reserve up a storage plant can deliver (dependent on state of storage)	(Reg,Year,Block,BlockHr,Stor)	the maximum amount of
eReserveDownStor1 reserve down a storage plant can deliver (dependent on state of storage)	(Reg,Year,Block,BlockHr,Stor)	the maximum amount of
eReserveUpStor2 reserve up a storage plant can deliver (dependent on state of storage)	(Reg,Year,Block,BlockHr,Stor)	the maximum amount of
eReserveDownStor2 reserve down a storage plant can deliver (dependent on state of storage)	(Reg,Year,Block,BlockHr,Stor)	the maximum amount of
\$endif.SeperateReserves		

```

* === CO2 Limit
$ifthen not set NoCO2Cap
    eCO2Cap                (Year)                A yearly CO2 cap
[MtCO2]
$endif

* === Maintenance
* When there is no integer maintenance
$ifthen not set NoUCMaint
    eMaintReq              (Reg,Year,Gen)        Calculate the
required maintenance (for UC plants only) [#]
$endif

eCapOffMaintUC           (Reg,Year,Block,Gen)   Amount of UC capacity
that's not on maintenance [GW]
eCapOffMaint             (Reg,Year,Block,Gen)   Amount of non-UC capacity
that's not on maintenance [GW]

* === Transports
eReverseTransport        (Year,Block,BlockHr,Reg,Reg2) Transport of electricity
between regions [GW]
eTransLoss               (Year,Block,BlockHr,Reg,Reg2) Transmission losses
[GW]
eMaxTransport            (Year,Block,BlockHr,Reg,Reg2) Maximum transport of
electricity between regions [GW]
;

* #####

* ===== MIP SOLVER HELP

* #####

* === Giving some limits to help MIP solver
* If investment in generators is possible, calculate the maximum number of new
plants
$ifthen set Invest_Gen
    vNewPlants.up(Reg,Year,Gen) = ceil(TotalPlantsMax(Reg,Year,Gen) -
DataCap(Gen,Reg) / DataGen(Gen,'AvGen'));
* If investment is not possible, fix the capacity installed and used on the current
values from the data
$elseif not set Invest_Gen
    vCapacityInstalled.fx(Reg,Year,Gen) = DataCap(Gen,Reg);
    vCapacityUsed.fx(Reg,Year,Gen) = DataCap(Gen,Reg);
    vCapacityInstalledStor.fx(Reg,Year,Stor) = DataCapStor(Reg,Stor);
$endif

$ifthen not set Invest_RES
    vCapacityInstalledRES.fx(RESreg,Year,RES) = DataCapRES(RES,RESreg);
$endif

* Provide upper limit for integer state variables (otherwise GAMS uses upper limit
of 100)
vUnitsCommitted.up(Reg,Year,Block,BlockHr,Gen) = TotalPlantsMax(Reg,Year,Gen);
vStartUps.up(Reg,Year,Block,BlockHr,Gen) = TotalPlantsMax(Reg,Year,Gen);
vShutDowns.up(Reg,Year,Block,BlockHr,Gen) = TotalPlantsMax(Reg,Year,Gen);

vUnitsCommittedINT.up(Reg,Year,Block,BlockHr,Gen) = TotalPlantsMax(Reg,Year,Gen);
vStartUpsINT.up(Reg,Year,Block,BlockHr,Gen) = TotalPlantsMax(Reg,Year,Gen);
vShutDownsINT.up(Reg,Year,Block,BlockHr,Gen) = TotalPlantsMax(Reg,Year,Gen);

* Not more than 15% of one type of generator can be on maintenance at the same time
vMaint.up(Reg,Year,Block,Gen) = ceil(0.15*DataCap(Gen,Reg) / DataGen(Gen,'AvGen'));

```

```

* Output for renewables is fixed (but can be curtailed)
vPower.fx(Reg,Year,Block,BlockHr,RES) = SUM(RESRegMap(Reg,RESReg),
DataCapRES(RES,RESReg) * DataGen(RES,'Avail') *
Profiles(RESReg,Year,Block,BlockHr,RES));

* Using pre-run results
*vPower.l(Reg,Year,Block,BlockHr,Gen) =
vBlockEnergyGen.l(Reg,Year,Block,BlockHr,Gen);
*vUnitsCommittedINT.l(Reg,Year,Block,BlockHr,Gen) =
floor(vBlockEnergyGen.l(Reg,Year,Block,BlockHr,Gen) / DataGen(Gen,'AvGen'));
*vUnitsCommitted.l(Reg,Year,Block,BlockHr,Gen) =
floor(vBlockEnergyGen.l(Reg,Year,Block,BlockHr,Gen) / DataGen(Gen,'AvGen'));

* All storages are assumed to be filled 50% at start of run
vStorageLevel.fx(Reg,Year,Block,BlockHr,Stor)$ (ord(Block) EQ 1 and ord(BlockHr) EQ
1) = DataCapStor(Reg,Stor) * 0.5;

$if set Presolve $include Presolve2

* #####

* ===== THE ACTUAL EQUATIONS AND CONSTRAINTS

* #####

* ===== OBJECTIVE (COST) FUNCTIONS

* #####

* === Total cost
* total overall cost
* Variable/Parameter          Unit
* vTotalCost                   M€
eTotalCost..
    vTotalCost
    =e=
    vTotalFixedOMCost
    + vTotalVarOMCost
    + vTotalFuelCost
    + vTotalCO2Cost
    + vTotalStartUpCost

$ifthen not set No_NSE
    + vTotalNSECost
$endif

$if set Presolve + vBlockCost

$ifthen not set No_Capital_Cost
    + vTotalCapitalCost
    + vTotalNTCCost
$endif
;

* === Fixed OM Cost
* total fixed operation and maintenance cost
* Variable/Parameter          Unit
* vTotalFixedOMCost           M€
* vCapacityUsed                GW
* DataGen(Gen,'FixedOMCost')   M€/GW/yr
* FractionOfYear               yr
eTotalFixedOMCost..
    vTotalFixedOMCost
    =e=
    SUM((Reg,Year,Gen), vCapacityUsed(Reg,Year,Gen) *
DataGen(Gen,'FixedOMCost')) * FractionOfYear
    + SUM((RESReg,Year,RES), vCapacityInstalledRES(RESReg,Year,RES) *
DataGen(RES,'FixedOMCost')) * FractionOfYear
;

```

```

* === Variable O&M cost
* total variable Operation and Maintenance cost
* Variable/Parameter          Unit
* vVarOMCost                  M€
* vPower                      GW e
* DataGen(Gen,'VarOMCost')    M€/GWh e
* TimeStep                    h
eTotalVarOMCost..
    vTotalVarOMCost
    =e=
    SUM((Reg,Year,Block,BlockHr,Gen)$(DataGen(Gen,'VarOMCost') GT 0),
vPower(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'VarOMCost') * TimeStep);

* === Total fuel cost
* total fuel cost = sum over all generators (generators total fuel consumption *
fuel cost)
* Variable/Parameter          Unit
* vTotalFuelCost              M€
* vPower                      GW e
* Timestep                    h
* DataGen(Gen,'Eff')          GWh e / GWh th
* DataFuel(Fuel,'Cost')       M€/GWh th
* vStartUps                   #
* DataGen(Gen,'StartFuelUse') GW th
eTotalFuelCost..
    vTotalFuelCost
    =e=
    SUM((Reg,Year,Block,BlockHr,GenFuel(Gen,Fuel)),
vPower(Reg,Year,Block,BlockHr,Gen) * TimeStep / DataGen(Gen,'Eff') *
DataFuel(Fuel,'Cost') )
$ifthen not set EconomicDispatch
*     + SUM((Reg,Year,Block,BlockHr,GenFuel(Gen,Fuel))$(CommitGen(Gen)),
vStartUps(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'StartFuelUse') *
DataFuel(Fuel,'Cost') )
$endif
;

* === Total CO2 cost
* CO2 cost = sum over all generators and all periods (hourly generator CO2 cost)
* Variable/Parameter          Unit
* vTotalCO2Cost               M€
* vPower                      GW e
* Timestep                    h
* DataGen(Gen,'Eff')          GWh e / GWh th
* DataGen(Gen,'CO2factor')    %
* DataFuel(fuel,'CO2int')     MtCO2/ GWh th
* CO2price(year)              M€/MtCO2
eTotalCO2Cost..
    vTotalCO2Cost
    =e=
    SUM((Reg,Year,Block,BlockHr,GenFuel(Gen,fuel)),
vPower(Reg,Year,Block,BlockHr,Gen) * TimeStep / DataGen(Gen,'Eff') *
DataGen(Gen,'CO2factor') * DataFuel(fuel,'CO2int') * CO2price(year));

* === Start up cost
* Start up cost = sum over all generators over all periods (start ups * start up
cost), this excludes start up fuel cost
* Variable/Parameter          Unit
* vTotalStartupCost           M€
* vStartUps                   #
* DataGen(Gen,'StartCost')    M€/#
eTotalStartupCost..
    vTotalStartupCost
    =e=
    0
$ifthen not set EconomicDispatch
    + SUM((Reg,Year,Block,BlockHr,Gen)$(CommitGen(Gen)),
vStartUps(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'StartCost'))
    + SUM((Reg,Year,Block,BlockHr,GenFuel(Gen,Fuel))$(CommitGen(Gen)),
vStartUps(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'StartFuelUse') *
DataFuel(Fuel,'Cost') )
$endif
;

```

```

* === Non served energy cost
* the penalty for not meeting the demand
* Variable/Parameter      Unit
* vTotalNSECost           M€
* vNSE                    GW
* VOLL                    M€/Gwh
* Timestep                 h
$ifthen not set No_NSE
eTotalNSECost..
    vTotalNSECost
    =e=
    SUM((Reg,Year,Block,BlockHr), vNSE(Reg,Year,Block,BlockHr) * VOLL *
TimeStep);
$endif

* === Capital cost

* Exclude capital cost if indicated
$ifthen.NoCapCost not set No_Capital_Cost

* == Capital cost of generators
* Variable/Parameter      Unit
* vTotalCapitalCost       M€
* vCapacityInstalled       GW e
* DataGen(Gen,'CapCost')  M€ / GW e
* EACF                     %/yr
* vCapacityInstalledStor  Gwh
* DataGen(Stor,'CapCostStor') M€ / Gwh
* EACF                     %/yr
* FractionOfYear          yr
eTotalCapitalCost..
    vTotalCapitalCost
    =e=
    (
    SUM((Reg,Year,Gen), vCapacityInstalled(Reg,Year,Gen) *
DataGen(Gen,'CapCost') * EACF(Gen))
    + SUM((Reg,Year,Stor), vCapacityInstalledStor(Reg,Year,Stor) *
DataGen(Stor,'CapCostStor') * EACF(Stor))
    + SUM((RESreg,Year,RES), vCapacityInstalledRES(RESreg,Year,RES) *
DataGen(RES,'CapCost') * EACF(RES))
    ) * FractionOfYear
    ;

* == NTC cost
* Variable/Parameter      Unit
* vTotalNTCCost          M€
* DataNTCcap             GW
* vNTCinv                GW
* EACF                   %/yr
* FractionOfYear         yr
* DataNTCdist            km
* DataNTCcost(Line,'Cable') M€/GW*km
* DataNTCcost(Line,'Converter') M€/GW
eTotalNTCCost..
    vTotalNTCCost
    =e=
    SUM((Line,Reg,Reg2),
    ( ( DataNTCcap(Reg,Reg2)
* Exclude new capacity if no investment in NTC
$ifthen.NTC set Invest_NTC
    + vNTCInv(Reg,Reg2)
$endif.NTC

    ) * EACF(Line) * FractionOfYear / 2 )
    * ( DataNTCdist(Reg,Reg2) * DataNTCcost(Line,'Cable') +
DataNTCcost(Line,'Converter') )
    )
    ;

$endif.NoCapCost

* #####

```

```

* ===== INVESTMENT DECISIONS
* #####

* == If investment is indicated
$ifthen.InvGen set Invest_Gen

* installed capacity is the current capacity + new capacity
    eCapacityInstalled(Reg,Year,Gen)..
        vCapacityInstalled(Reg,Year,Gen)
    =e=
        DataCap(Gen,Reg)
        + vCapacityNew(Reg,Year,Gen)
    ;

* used capacity is the installed capacity - closed (retired) capacity
    eCapacityUsed(Reg,Year,Gen)..
        vCapacityUsed(Reg,Year,Gen)
    =e=
        vCapacityInstalled(Reg,Year,Gen) - vCapacityClosed(Reg,Year,Gen)
    ;

* new capacity is discrete
    eNewPlants(Reg,Year,Gen)..
        vCapacityNew(Reg,Year,Gen)
    =e=
        vNewPlants(Reg,Year,Gen) * DataGen(Gen,'AvGen')
    ;

* the total maximum capacity in a certain region is the maximum demand + margin
    eCapacityMax(Reg,Year)..
        SUM(Gen, vCapacityInstalled(Reg,Year,Gen))
    =l=
        (1+MaxOverbuilt) * MaxPower(Reg,Year)
    ;
$endif.InvGen

* #####

* ===== CONSTRAINTS

* #####

* ===== LOAD CONSTRAINT

* #####

* == Load function
* Generation and use need to be equal in each node at every time
* Variable/Parameter      Unit
* vPower                   GW
* vStoragePower (negative) GW
* vImport                   GW
* vExport                   GW
* vNSE                       GW
* vCurtail                 GW
* Demand                   GW
eLOAD(Reg,Year,Block,BlockHr)..
    SUM(Gen, vPower(Reg,Year,Block,BlockHr,Gen))
    + SUM(Stor, vStoragePower(Reg,Year,Block,BlockHr,Stor))
    + SUM(Reg2, vImport(year,Block,BlockHr,Reg,Reg2))
    - SUM(Reg2, vExport(year,Block,BlockHr,Reg,Reg2))
$ifthen not set No_NSE
    + vNSE(Reg,Year,Block,BlockHr)
$endif
    + vCurtail(reg,year,Block,BlockHr)
    =e=
    Demand(Reg,Year,Block,BlockHr);

* #####

```

```

* ===== UNIT STATES
* #####

$ifthen.ED not set EconomicDispatch

* == Maximum number of generators committed
* Variable/Parameter          Unit
* vUnitsCommitted             #
* vCapOffMaint                GW
* DataGen(Gen, 'AvGen')       GW/#
    eMaxUnitCommitted(Reg,Year,Block,BlockHr,Gen)$(CommitGen(Gen))..
    vUnitsCommitted(Reg,Year,Block,BlockHr,Gen)
    =|=
    (vCapOffMaint(Reg,Year,Block,Gen) / DataGen(Gen, 'AvGen'));

* == Actual number of generators committed
* Variable/Parameter          Unit
* vUnitsCommitted             #
* vStartUps                   #
* vShutDowns                  #
    eUnitCommitment(Reg,Year,Block,BlockHr,Gen)$(CommitGen(Gen))..
    vUnitsCommitted(Reg,Year,Block,BlockHr,Gen)
    =e=
    vUnitsCommitted(Reg,Year,Block,BlockHr-1,Gen)$(ord(BlockHr) GT 1)
    + vUnitsCommitted(Reg,Year,Block-1,BlockHr--1,Gen)$(ord(BlockHr) EQ
1)
    + vStartUps(Reg,Year,Block,BlockHr,Gen) -
vShutDowns(Reg,Year,Block,BlockHr,Gen)
    ;

* States do not have to be integer if indicated
$ifthen.UC_LP not set UC_LP

    eIntUC(Reg,Year,Block,BlockHr,Gen)$(CommitGen(Gen))..
    vUnitsCommitted(Reg,Year,Block,BlockHr,Gen) =e=
vUnitsCommittedINT(Reg,Year,Block,BlockHr,Gen);
    eIntSU(Reg,Year,Block,BlockHr,Gen)$(CommitGen(Gen))..
    vStartUps(Reg,Year,Block,BlockHr,Gen) =e=
vStartUpsINT(Reg,Year,Block,BlockHr,Gen);
    eIntSD(Reg,Year,Block,BlockHr,Gen)$(CommitGen(Gen))..
    vShutDowns(Reg,Year,Block,BlockHr,Gen) =e=
vShutDownsINT(Reg,Year,Block,BlockHr,Gen);

$endif.UC_LP
$endif.ED

* #####

* ===== INDIVIDUAL OUTPUT LEVELS
* #####

* == Max and Min generator output levels

* Included in reserve equations
$ontext
ePMAX(Reg,Year,Block,BlockHr,Gen)$(not RES(Gen))..
    vPower(Reg,Year,Block,BlockHr,Gen)
    =|=
    vUnitsCommitted(Reg,Year,Block,BlockHr,Gen)$(CommitGen(Gen)) *
DataGen(Gen, 'AvGen')
    + vCapOffMaint(Reg,Year,Block,Gen)$(not CommitGen(Gen))
    ;

ePMIN(Reg,Year,Block,BlockHr,Gen)$(CommitGen(Gen) and not RES(Gen))..
    vPower(Reg,Year,Block,BlockHr,Gen)
    =g=
    vUnitsCommitted(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen, 'AvGen') *
DataGen(Gen, 'Pmin')
    ;
$offtext

```

```

* This code is omitted because variable is fixed for Renewables (calculated above)
$ontext
* == RES output calculation
* RES output is the available capacity multiplied by the natural infeed
* Variable/Parameter          Unit
* vPower                       GW
* vCapOffMaint                 GW
* Profiles                      %
eRESout(Reg,Year,Block,BlockHr,RES)..
    vPower(Reg,Year,Block,BlockHr,RES)
    =e=
    SUM(RESregMap(Reg,RESreg), DataCapRES(RES,RESreg) * DataGen(RES,'Avail') *
Profiles(RESreg,Year,Block,BlockHr,RES))
$offtext

* #####

* ===== STORAGE CONSTRAINTS

* #####

* === Calculate storage level
* The storage level is the previous storage level + storage - extraction + natural
inflow
* Variable/Parameter          Unit
* vStorageLevel               Gwh
* vStoragePower (negative)    GW
* DataGen(Stor,'ChargeEff')   Gwh stored / Gwh used
* TimeStep                    h
* vPower                       GW
* DataGen(Stor,'Eff')         Gwh del / Gwh stored
* Profiles                     %
* vCapacityInstalled          GW
eStorageLevel(Reg,Year,Block,BlockHr,Stor)$ (ord(Block) GT 1 or ord(BlockHr) GT 1)..
    vStorageLevel(Reg,Year,Block,BlockHr,Stor)
    =e=
    vStorageLevel(Reg,Year,Block,BlockHr-1,Stor)$ (ord(BlockHr) GT 1) +
vStorageLevel(Reg,Year,Block-1,BlockHr--1,Stor)$ (ord(BlockHr) EQ 1)
    - (vStoragePower(Reg,Year,Block,BlockHr-1,Stor)$ (ord(BlockHr) GT 1) +
vStoragePower(Reg,Year,Block-1,BlockHr--1,Stor)$ (ord(BlockHr) EQ 1)) *
DataGen(Stor,'ChargeEff') * TimeStep
    - (vPower(Reg,Year,Block,BlockHr-1,Stor)$ (ord(BlockHr) GT 1) +
vPower(Reg,Year,Block-1,BlockHr--1,Stor)$ (ord(BlockHr) EQ 1)) / DataGen(Stor,'Eff')
* TimeStep
    + SUM(RESregMap(Reg,RESreg), Profiles(RESreg,year,Block,BlockHr,Stor) *
DataCapRES(Stor,RESreg) * TimeStep)$ (Stor("Hydro"))
;

* === Maximum storage level
* Storage level needs to stay below storage capacity
* Variable/Parameter          Unit
* vStorageLevel               Gwh
* DataCapStor(Reg,Stor)       Gwh
eStorageLevelMax(Reg,Year,Block,BlockHr,Stor)..
    vStorageLevel(Reg,Year,Block,BlockHr,Stor)
    =l=
    DataCapStor(Reg,Stor)
;

* === End storage level
* Storage needs to have certain level at end of run
* Variable/Parameter          Unit
* vStorageLevel               Gwh
* DataCapStor(Reg,Stor)       Gwh
eStorageLevelEnd(Reg,Year,Block,BlockHr,Stor)$ (ord(Block) EQ card(Block) and
ord(BlockHr) EQ card(BlockHr))..
    vStorageLevel(Reg,Year,Block,BlockHr,Stor)
    =e=
    DataCapStor(Reg,Stor) * 0.5
;

* === Maximum storage power
* Storage loading needs to stay below storage power capacity (the upper limit is
given by generators that need to stay below max + reserves)
* Variable/Parameter          Unit

```

```

* vStoragePower          GW
* vCapOffMaint          GW
* vReserveDown(1&2)     GW
eStoragePowerMax(Reg,Year,Block,BlockHr,Stor)..
  vStoragePower(Reg,Year,Block,BlockHr,Stor)
  =g=
  -vCapOffMaint(Reg,Year,Block,Stor)$(not Stor("Hydro"))
  -DataCap("Pump",Reg)$(Stor("Hydro"))

* If combined reserves allowed
$ifthen.SeperateReserves not set Seperate_Reserves
  + vReserveDown(Reg,Year,Block,BlockHr,Stor)
* If seperate reserves required
$elseif.SeperateReserves set Seperate_Reserves
  + vReserveDown1(Reg,Year,Block,BlockHr,Stor)
  + vReserveDown2(Reg,Year,Block,BlockHr,Stor)
$endif.SeperateReserves
;

* #####

* ===== RAMPING CONSTRAINTS

* #####

$ifthen.NRC not set No_Ramp_Con

* === Maximum up UC generators up ramping
* Change in power output needs to stay below unit capabilities
* Variable/Parameter      Unit
* vPower                   GW
* vUnitsCommitted          #
* vStartUps                #
* AvGen                    GW/#
* RampMax                  %
* Pmin                     %
* Shutdowns                #
$ifthen.ED not set EconomicDispatch
eRampUpUC(Reg,Year,Block,BlockHr,Gen)$((ord(Block) GT 1 OR ord(BlockHr) GT 1) AND
(CommitGen(Gen)) AND DataGen(Gen,'RampMax') < 1)..
* Current output
  vPower(Reg,Year,Block,BlockHr,Gen)
* minus the output of the previous time step
  - (vPower(Reg,Year,Block,BlockHr-1,Gen)$(ord(BlockHr) GT 1) +
vPower(Reg,Year,Block-1,BlockHr--1,Gen)$(ord(BlockHr) EQ 1))
* is lower than
  =l=
  (
* already committed units * maximum ramp
  (vUnitsCommitted(Reg,Year,Block,BlockHr,Gen) -
vStartUps(Reg,Year,Block,BlockHr,Gen)) * DataGen(Gen,'AvGen') *
DataGen(Gen,'RampMax')
* and the amount of units that are started up * min (100%, max( unit minimum output
; unit maximum ramp ))
  + vStartUps(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'AvGen') * min(1,
max( DataGen(Gen,'Pmin') , DataGen(Gen,'RampMax') ) )
  - vShutdowns(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'AvGen') *
DataGen(Gen,'Pmin')
  ) * TimeStep
  )
;

* === Maximum down UC generators up ramping
* Change in power output needs to stay below unit capabilities
* Variable/Parameter      Unit
* see ramp up
eRampDownUC(Reg,Year,Block,BlockHr,Gen)$((ord(Block) GT 1 OR ord(BlockHr) GT 1) AND
(CommitGen(Gen)) AND DataGen(Gen,'RampMax') < 1)..
* Output in previous time step
  (vPower(Reg,Year,Block,BlockHr-1,Gen)$(ord(BlockHr) GT 1) +
vPower(Reg,Year,Block-1,BlockHr--1,Gen)$(ord(BlockHr) EQ 1))
* minus current output
  - vPower(Reg,Year,Block,BlockHr,Gen)
* is lower than
  =l=
  (
* already committed units * maximum ramp

```

```

        (vUnitsCommitted(Reg,Year,Block,BlockHr,Gen) -
vStartUps(Reg,Year,Block,BlockHr,Gen)) * DataGen(Gen,'AvGen') *
DataGen(Gen,'RampMax')
* and the amount of units that are shut down * max( unit minimum output ; unit
maximum ramp )
      + vShutDowns(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'AvGen') * min(1,
max( DataGen(Gen,'Pmin') , DataGen(Gen,'RampMax') ) )
      - vStartUps(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'AvGen') *
DataGen(Gen,'Pmin')
    ) * TimeStep
    ;
$endif.ED

*$ontext

* === Maximum ramp up for non-UC generators
* Change in power output needs to stay below unit capabilities
* Variable/Parameter          Unit
* vPower                        GW
* vCappOffMaint                 GW
* RampMax                       %
eRampUp(Reg,Year,Block,BlockHr,Gen)$((ord(Block) GT 1 OR ord(BlockHr) GT 1) AND NOT
(CommitGen(Gen)) AND DataGen(Gen,'RampMax') < 1)..
      vPower(Reg,Year,Block,BlockHr,Gen)
      - (vPower(Reg,Year,Block,BlockHr-1,Gen)$ (ord(BlockHr) GT 1) +
vPower(Reg,Year,Block-1,BlockHr--1,Gen)$ (ord(BlockHr) EQ 1))
      =|
      vCapOffMaint(Reg,Year,Block,Gen) * DataGen(Gen,'RampMax') * TimeStep
    ;

* === Maximum ramp down for non-UC generators
* Change in power output needs to stay below unit capabilities
* Variable/Parameter          Unit
* see ramp up
eRampDown(Reg,Year,Block,BlockHr,Gen)$((ord(Block) GT 1 OR ord(BlockHr) GT 1) AND
NOT (CommitGen(Gen)) AND DataGen(Gen,'RampMax') < 1)..
      (vPower(Reg,Year,Block,BlockHr-1,Gen)$ (ord(BlockHr) GT 1) +
vPower(Reg,Year,Block-1,BlockHr--1,Gen)$ (ord(BlockHr) EQ 1))
      - vPower(Reg,Year,Block,BlockHr,Gen)
      =|
      vCapOffMaint(Reg,Year,Block,Gen) * DataGen(Gen,'RampMax') * TimeStep
    ;

*$offtext
$endif.NRC

* #####

* ===== RESERVE CONSTRAINTS

* #####

* === Quick start reserves
eReserveQstart(Reg,Year,Block,BlockHr,Gen) $ (CommitGen(Gen) and
DataGen(Gen,'Qstart') GT 0)..
      vReserveQstart(Reg,Year,Block,BlockHr,Gen)
      =|
      ((vCapOffMaint(Reg,Year,Block,Gen)/DataGen(Gen,'AvGen')) -
vUnitsCommitted(Reg,Year,Block,BlockHr,Gen))
      * DataGen(Gen,'AvGen') * DataGen(Gen,'RampMax') * 15/60
    ;

* === Max quick start reserves
eReserveQstartMax(Reg,Year,Block,BlockHr)..
      SUM((GEN) $ (CommitGen(Gen) and DataGen(Gen,'Qstart') GT 0),
      vReserveQstart(Reg,Year,Block,BlockHr,Gen))
      =|
      (
* Secondary reserves
      Reserve2(Reg,Year)
* If indicated, use extra reserves for RES
$ifthen.RESreserves set RES_Reserves

```

```

+ SUM((Gen)$ (RES(GEN)), vPower(Reg,Year,Block,BlockHr,Gen)) * RESReserve
$endif.RESreserves
) * (1-FracSpinReserve)
;

* #####

* ==== COMBINED RESERVE CONSTRAINTS

* #####

$ifthen.SepRes not set Seperate_Reserves

* === Total reserve up requirement
* The total reserves provided by all generators needs to be greater then NTSOE
limits
* Variable/Parameter          Unit
* vReserveUp                   GW
* YearlyEnergyUse              GWh
* EUEnergy                     GWh
* Larges contingency           3 GW
* MaxPower                     GW
* Safety margins               0.01 GW & 0.15 GW
eReserveUpReq(Reg,Year,Block,BlockHr)$ (Demand(Reg,Year,Block,BlockHr) GT 0)..
SUM((Gen) $ (DataGen(Gen,'Reserve') GT 0),
vReserveUp(Reg,Year,Block,BlockHr,Gen))
+
SUM((GEN) $ (DataGen(Gen,'Qstart') GT 0),
vReserveQstart(Reg,Year,Block,BlockHr,Gen))
=g=
Reserve1(Reg,Year) + Reserve2(Reg,Year)
* If indicated, use extra reserves for RES
$ifthen.RESreserves set RES_Reserves
+ SUM((Gen)$ (RES(GEN)), vPower(Reg,Year,Block,BlockHr,Gen)) * RESReserve
$endif.RESreserves
;

* === Total reserve down requirement
* The total reserves provided by all generators needs to be greater then NTSOE
limits
* Variable/Parameter          Unit
* see up reserves
eReserveDownReq(Reg,Year,Block,BlockHr)$ (Demand(Reg,Year,Block,BlockHr) GT 0)..
SUM((Gen) $ (DataGen(Gen,'Reserve') GT 0),
vReserveDown(Reg,Year,Block,BlockHr,Gen))
=g=
Reserve1(Reg,Year) + Reserve2(Reg,Year)
* If indicated, use extra reserves for RES
$ifthen.RESreserves set RES_Reserves
+ SUM((Gen)$ (RES(GEN)), vPower(Reg,Year,Block,BlockHr,Gen)) * RESReserve
$endif.RESreserves
;

$ifthen.ED not set EconomicDispatch

* === UC generators stay below their maximum generating limits incl their reserves
* Variable/Parameter          Unit
* vPower                       GW
* vReserveUp                   GW
* vUnits                        #
* AvGen                         GW/#
eReserveUpUC(Reg,Year,Block,BlockHr,Gen)$ (CommitGen(Gen))..
vPower(Reg,Year,Block,BlockHr,Gen) + vReserveUp(Reg,Year,Block,BlockHr,Gen)
=|
vUnitsCommitted(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'AvGen')
;

* === UC generators stay above their minimum generating limits incl their reserves
* Variable/Parameter          Unit
* see ReserveUp
eReserveDownUC(Reg,Year,Block,BlockHr,Gen)$ (CommitGen(Gen) AND NOT Stor(Gen))..
vPower(Reg,Year,Block,BlockHr,Gen) -
vReserveDown(Reg,Year,Block,BlockHr,Gen)
=g=

```

```

        vUnitsCommitted(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'AvGen') *
DataGen(Gen,'Pmin')
;

$endif.ED

* === Non-UC generators stay below their maximum generating limits incl their
reserves
* Variable/Parameter          Unit
* vPower                       GW
* vReserveUp                   GW
* vCapOffMaint                 GW
eReserveUp(Reg,Year,Block,BlockHr,Gen)$(NOT CommitGen(Gen) AND NOT RES(Gen))..
    vPower(Reg,Year,Block,BlockHr,Gen) + vReserveUp(Reg,Year,Block,BlockHr,Gen)
    =l=
    vCapOffMaint(Reg,Year,Block,Gen);

* === Non-UC generators stay above their minimum generating limits incl their
reserves
eReserveDown(Reg,Year,Block,BlockHr,Gen)$(NOT CommitGen(Gen) AND NOT Stor(Gen))..
    vPower(Reg,Year,Block,BlockHr,Gen) -
vReserveDown(Reg,Year,Block,BlockHr,Gen)
    =g=
    vCapOffMaint(Reg,Year,Block,Gen) * DataGen(Gen,'Pmin');

* == Calculate maximum ability to provide reserves

eReserveUpGenMax(Reg,Year,Block,BlockHr,Gen)$(DataGen(Gen,'Reserve') GT 0)..
    vReserveUp(Reg,Year,Block,BlockHr,Gen)
    =l=
    (
    (DataGen(Gen,'AvGen') *
vUnitsCommitted(Reg,Year,Block,BlockHr,Gen))$(CommitGen(Gen))
    + (vCapOffMaint(Reg,Year,Block,Gen))$(not CommitGen(Gen))
    ) * DataGen(Gen,'RampMax') * 5 / 60
    ;

eReserveDownGenMax(Reg,Year,Block,BlockHr,Gen)$(DataGen(Gen,'Reserve') GT 0)..
    vReserveDown(Reg,Year,Block,BlockHr,Gen)
    =l=
    (
    (DataGen(Gen,'AvGen') *
vUnitsCommitted(Reg,Year,Block,BlockHr,Gen))$(CommitGen(Gen))
    + (vCapOffMaint(Reg,Year,Block,Gen))$(not CommitGen(Gen))
    ) * DataGen(Gen,'RampMax') * 5 / 60
    ;

* == Storage reserves
eReserveUpStor(Reg,Year,Block,BlockHr,Stor)..
    vReserveUp(Reg,Year,Block,BlockHr,Stor)
    =l=
    vStorageLevel(Reg,Year,Block,BlockHr,Stor)/0.25
    ;

eReserveDownStor(Reg,Year,Block,BlockHr,Stor)..
    vReserveDown(Reg,Year,Block,BlockHr,Stor)
    =l=
    (DataCapStor(Reg,Stor) - vStorageLevel(Reg,Year,Block,BlockHr,Stor))/0.25
    ;

* #####
* ===== SEPERATE RESERVE CONSTRAINTS
* #####

$elseif.SepRes set Seperate_Reserves

* === Reserve up

* == Determine primary reserve up requirement
eReserveUpReq1(Reg,Year,Block,BlockHr)$(Demand(Reg,Year,Block,BlockHr) GT 0)..
    SUM((Gen) $ (DataGen(Gen,'Reserve') GT 0),
    vReserveUp1(Reg,Year,Block,BlockHr,Gen))
    =g=

```

```

* Primary reserves (able to reach output level in 30 sec and last for 15 minutes)
  Reserve1(Reg,Year)
  ;

* == Determine secondary reserve up requirement
eReserveUpReq2(Reg,Year,Block,BlockHr)$(Demand(Reg,Year,Block,BlockHr) GT 0)..
  SUM((Gen) $(DataGen(Gen,'Reserve') GT 0),
  vReserveUp2(Reg,Year,Block,BlockHr,Gen))
  +
  SUM((GEN) $(DataGen(Gen,'Qstart') GT 0),
  vReserveQstart(Reg,Year,Block,BlockHr,Gen))
  =g=
* Secondary reserves (able to reach output in 15 minutes)
  Reserve2(Reg,Year)
* If indicated, use extra reserves for RES
$ifthen.RESreserves set RES_Reserves
  + SUM((Gen)$(RES(GEN)), vPower(Reg,Year,Block,BlockHr,Gen)) * RESReserve
$endif.RESreserves
  ;

* === Reserve down

* == Determine primary reserve down requirement
eReserveDownReq1(Reg,Year,Block,BlockHr)$(Demand(Reg,Year,Block,BlockHr) GT 0)..
  SUM((Gen) $(DataGen(Gen,'Reserve') GT 0),
  vReserveDown1(Reg,Year,Block,BlockHr,Gen))
  =g=
* Primary reserves (able to reduce output level in 30 sec and last for 15 minutes)
  Reserve1(Reg,Year)
  ;

* == Determine secondary reserve down requirement
eReserveDownReq2(Reg,Year,Block,BlockHr)$(Demand(Reg,Year,Block,BlockHr) GT 0)..
  SUM((Gen) $(DataGen(Gen,'Reserve') GT 0),
  vReserveDown2(Reg,Year,Block,BlockHr,Gen))
  =g=
* Secondary reserves (able to reduce output in 15 minutes)
  Reserve2(Reg,Year)
* If indicated, use extra reserves for RES
$ifthen.RESreserves set RES_Reserves
  + SUM((Gen)$(RES(GEN)), vPower(Reg,Year,Block,BlockHr,Gen)) * RESReserve
$endif.RESreserves
  ;

* === Generation limits and reserves

* == Individual generators (or batches) stay below their maximum generating limits
incl their reserves
eReserveUpUC(Reg,Year,Block,BlockHr,Gen)$(CommitGen(Gen))..
  vPower(Reg,Year,Block,BlockHr,Gen) +
vReserveUp1(Reg,Year,Block,BlockHr,Gen) + vReserveUp2(Reg,Year,Block,BlockHr,Gen)
  =|
  vUnitsCommitted(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'AvGen');

* == Individual generators (or batches) stay above their minimal generating limits
incl their reserves
eReserveDownUC(Reg,Year,Block,BlockHr,Gen)$(CommitGen(Gen) AND NOT Stor(Gen))..
  vPower(Reg,Year,Block,BlockHr,Gen) -
vReserveDown1(Reg,Year,Block,BlockHr,Gen) -
vReserveDown2(Reg,Year,Block,BlockHr,Gen)
  =g=
  vUnitsCommitted(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'AvGen') *
DataGen(Gen,'Pmin');

* == Non UC generators stay below their operating limits incl. reserves
eReserveUp(Reg,Year,Block,BlockHr,Gen)$(NOT CommitGen(Gen))..
  vPower(Reg,Year,Block,BlockHr,Gen) +
vReserveUp1(Reg,Year,Block,BlockHr,Gen) + vReserveUp2(Reg,Year,Block,BlockHr,Gen)
  =|
  vCapOffMaint(Reg,Year,Block,Gen);

* == Non UC generators stay above their operating limits incl. reserves
eReserveDown(Reg,Year,Block,BlockHr,Gen)$(NOT CommitGen(Gen) AND NOT Stor(Gen))..

```

```

vPower(Reg,Year,Block,BlockHr,Gen) -
vReserveDown1(Reg,Year,Block,BlockHr,Gen) +
vReserveDown2(Reg,Year,Block,BlockHr,Gen)
=|g=
vCapOffMaint(Reg,Year,Block,Gen) * DataGen(Gen,'Pmin');

* === Maximum reserve capabilities for generators
$ifthen.ED not set EconomicDispatch

eReserveUpGenMaxUC1(Reg,Year,Block,BlockHr,Gen)$ (CommitGen(Gen) and
DataGen(Gen,'Reserve') GT 0)..
vReserveUp1(Reg,Year,Block,BlockHr,Gen)
=|l=
DataGen(Gen,'RampMax') * DataGen(Gen,'AvGen') *
vUnitsCommitted(Reg,Year,Block,BlockHr,Gen) * 30/3600
;

eReserveUpGenMaxUC2(Reg,Year,Block,BlockHr,Gen)$ (CommitGen(Gen) and
DataGen(Gen,'Reserve') GT 0)..
vReserveUp2(Reg,Year,Block,BlockHr,Gen)
=|l=
DataGen(Gen,'RampMax') * DataGen(Gen,'AvGen') *
vUnitsCommitted(Reg,Year,Block,BlockHr,Gen) * 15/60
;

eReserveDownGenMaxUC1(Reg,Year,Block,BlockHr,Gen)$ (CommitGen(Gen) and
DataGen(Gen,'Reserve') GT 0)..
vReserveDown1(Reg,Year,Block,BlockHr,Gen)
=|l=
DataGen(Gen,'RampMax') * DataGen(Gen,'AvGen') *
vUnitsCommitted(Reg,Year,Block,BlockHr,Gen) * 30/3600
;

eReserveDownGenMaxUC2(Reg,Year,Block,BlockHr,Gen)$ (CommitGen(Gen) and
DataGen(Gen,'Reserve') GT 0)..
vReserveDown2(Reg,Year,Block,BlockHr,Gen)
=|l=
DataGen(Gen,'RampMax') * DataGen(Gen,'AvGen') *
vUnitsCommitted(Reg,Year,Block,BlockHr,Gen) * 15/60
;

$endif.ED

eReserveUpGenMax1(Reg,Year,Block,BlockHr,Gen)$ (not CommitGen(Gen) and
DataGen(Gen,'Reserve') GT 0)..
vReserveUp1(Reg,Year,Block,BlockHr,Gen)
=|l=
DataGen(Gen,'RampMax') * vCapOffMaint(Reg,Year,Block,Gen) * 30/3600
;

eReserveUpGenMax2(Reg,Year,Block,BlockHr,Gen)$ (not CommitGen(Gen) and
DataGen(Gen,'Reserve') GT 0)..
vReserveUp2(Reg,Year,Block,BlockHr,Gen)
=|l=
DataGen(Gen,'RampMax') * vCapOffMaint(Reg,Year,Block,Gen) * 15/60
;

eReserveDownGenMax1(Reg,Year,Block,BlockHr,Gen)$ (not CommitGen(Gen) and
DataGen(Gen,'Reserve') GT 0)..
vReserveDown1(Reg,Year,Block,BlockHr,Gen)
=|l=
DataGen(Gen,'RampMax') * vCapOffMaint(Reg,Year,Block,Gen) * 30/3600
;

eReserveDownGenMax2(Reg,Year,Block,BlockHr,Gen)$ (not CommitGen(Gen) and
DataGen(Gen,'Reserve') GT 0)..
vReserveDown2(Reg,Year,Block,BlockHr,Gen)
=|l=
DataGen(Gen,'RampMax') * vCapOffMaint(Reg,Year,Block,Gen) * 15/60
;

* == Storage reserves
eReserveUpStor1(Reg,Year,Block,BlockHr,Stor)..
vReserveUp1(Reg,Year,Block,BlockHr,Stor)
=|l=
vStorageLevel1(Reg,Year,Block,BlockHr,Stor)/0.25

```

```

;
eReserveDownStor1(Reg,Year,Block,BlockHr,Stor)..
  vReserveDown1(Reg,Year,Block,BlockHr,Stor)
  =1=
  (DataCapStor(Reg,Stor) - vStorageLevel(Reg,Year,Block,BlockHr,Stor))/0.25
;

eReserveUpStor2(Reg,Year,Block,BlockHr,Stor)..
  vReserveUp2(Reg,Year,Block,BlockHr,Stor)
  =1=
  vStorageLevel(Reg,Year,Block,BlockHr,Stor)/24
;

eReserveDownStor2(Reg,Year,Block,BlockHr,Stor)..
  vReserveDown2(Reg,Year,Block,BlockHr,Stor)
  =1=
  (DataCapStor(Reg,Stor) - vStorageLevel(Reg,Year,Block,BlockHr,Stor))/24
;

```

\$endif.SepRes

```

* #####
* ===== MAINTENANCE CONSTRAINTS
* #####

```

\$ifthen.ED not set EconomicDispatch

```

$ifthen.NoUCM not set NoUCMaint
  eMaintReq(Reg,Year,Gen)$(CommitGen(Gen))..
    SUM((Block), vMaint(Reg,Year,Block,Gen))
    =g=
    DataGen(Gen,'MaintReq') * Card(Block) / 8760 *
vCapacityUsed(Reg,Year,Gen) / DataGen(Gen,'AvGen')
;
$endif.NoUCM

```

```

eCapOffMaintUC(Reg,Year,Block,Gen)$(CommitGen(Gen))..
  vCapOffMaint(Reg,Year,Block,Gen)
  =e=
$ifthen.NoUCM not set NoUCMaint
  vCapacityUsed(Reg,Year,Gen) - (vMaint(Reg,Year,Block,Gen) *
DataGen(Gen,'AvGen'))
$elseif.NoUCM set NoUCMaint
  vCapacityUsed(Reg,Year,Gen) * DataGen(Gen,'Avail')
$endif.NoUCM
;
$endif.ED

```

```

eCapOffMaint(Reg,Year,Block,Gen)$(not CommitGen(Gen))..
  vCapOffMaint(Reg,Year,Block,Gen)
  =e=
  vCapacityUsed(Reg,Year,Gen) * DataGen(Gen,'Avail')
;

```

```

* #####
* ===== TRANSPORT CONSTRAINTS
* #####

```

* = Transport between countries is negatively correlated (1 from A to B = -1 from B to A)

```

eReverseTransport(year,Block,BlockHr,Reg,Reg2)..
  vImport(year,Block,BlockHr,Reg,Reg2)
  =e=
  vExport(year,Block,BlockHr,Reg2,Reg) * (1-
(DataNTCdist(Reg,Reg2)*0.05/1000));

```

```

* = Transmission losses
eTransLoss(Year,Block,BlockHr,Reg,Reg2)..
    vTransLoss(Year,Block,BlockHr,Reg,Reg2)
    =e=
    vImport(year,Block,BlockHr,Reg,Reg2) * (DataNTCdist(Reg,Reg2)*0.05/1000)
;

eMaxTransport(year,Block,BlockHr,Reg,Reg2)..
    vExport(year,Block,BlockHr,Reg,Reg2)
    =l=
    DataNTCcap(Reg,Reg2)
$ifthen set Invest_NTC
    + vNTCInv(Reg,Reg2)
$endif
;

$ifthen set Invest_NTC
    eReverseNTCInv(Reg,Reg2)$ (DataNTCdist(Reg,Reg2) GT 0)..
        vNTCInv(Reg,Reg2)
        =e=
        vNTCInv(Reg2,Reg)
;
$endif

* #####

* ==== CO2 CAP

* #####

$ifthen not set NoCO2Cap

    eCO2cap(year)..
        SUM((Reg,Block,BlockHr,GenFuel(Gen,Fuel)),
        vPower(Reg,Year,Block,BlockHr,Gen) * TimeStep / DataGen(Gen,'Eff') *
        DataGen(Gen,'CO2factor') * DataFuel(Fuel,'CO2int'))
        =l=
        CO2Cap(year) * FractionOfYear
;
$endif

* #####

* ==== SOLVE & RELATED

* #####

** Define the commitment model with all the declared
** constraints and let GAMS solve the resulting problem using a mixed-integer
solver

* An initial guess

vNSE.l(Reg,Year,Block,BlockHr)=0;
vMaint.fx(Reg,Year,Block,Gen)$ (DataGen(Gen,'MaintReq')=0)=0;

* #####

* ==== SOLVER OPTIONS

* #####

MODEL UC /ALL/;
OPTION mip=cplex;
OPTION Optcr=0.001;
OPTION reslim=36000;
OPTION profile=2;
OPTION Limcol=0;
OPTION Solprint=off;

```

```

* === Create option file for solver options
$onecho > cplex.opt

* Number of threads (0 is maximum)
threads 0

* Parallel mode, 1=deterministic & repeatable, 0=automatic, -1=opportunistic & non-
repeatable
parallelmode 1

* Absolute difference between LP and MIP solution
epopt 1e-9

* Solve algorithm for MIP solves, 0 Automatic, 1 Primal simplex, 2 Dual simplex
* 3 Network simplex, 4 Barrier, 5 Sifting, 6 Concurrent
startalg 4

* Be efficient with use of memory
memoryemphasis 1

* Ignore small infeasibilities
relaxfixedinfeas 1

* The amount of improvement in the objective function between integer solutions
* should be larger than:
relobjdif 0.00

* Turn on aggressive scaling
scaind 1

$offecho

* Include the solver option file
UC.optfile = 1;

* === Use priorities when optimizing
UC.prioropt = 1;

$ifthen set Invest_Gen
*      vNewPlants.prior(Reg,Year,Gen)=1;
$endif

$ifthen.lpmaint not set Maint_LP
$ifthen.noucmaint not set NOUCmaint
      vMaint.prior(Reg,Year,Block,Gen) = 2;
$endif.noucmaint
$endif.lpmaint

vUnitsCommittedINT.prior(Reg,Year,Block,BlockHr,"Nuclear") = 3;
vStartUpsINT.prior(Reg,Year,Block,BlockHr,"Nuclear") = 3;
vShutDownsINT.prior(Reg,Year,Block,BlockHr,"Nuclear") = 3;

vUnitsCommittedINT.prior(Reg,Year,Block,BlockHr,"Lignite") = 4;
vStartUpsINT.prior(Reg,Year,Block,BlockHr,"Lignite") = 4;
vShutDownsINT.prior(Reg,Year,Block,BlockHr,"Lignite") = 4;

vUnitsCommittedINT.prior(Reg,Year,Block,BlockHr,"Coal") = 5;
vStartUpsINT.prior(Reg,Year,Block,BlockHr,"Coal") = 5;
vShutDownsINT.prior(Reg,Year,Block,BlockHr,"Coal") = 5;

vUnitsCommittedINT.prior(Reg,Year,Block,BlockHr,"GasCCGT") = 6;
vStartUpsINT.prior(Reg,Year,Block,BlockHr,"GasCCGT") = 6;
vShutDownsINT.prior(Reg,Year,Block,BlockHr,"GasCCGT") = 6;

vUnitsCommittedINT.prior(Reg,Year,Block,BlockHr,"GasOCCGT") = 7;
vStartUpsINT.prior(Reg,Year,Block,BlockHr,"GasOCCGT") = 7;
vShutDownsINT.prior(Reg,Year,Block,BlockHr,"GasOCCGT") = 7;

vUnitsCommittedINT.prior(Reg,Year,Block,BlockHr,"BiomassSolid") = 8;
vStartUpsINT.prior(Reg,Year,Block,BlockHr,"BiomassSolid") = 8;
vShutDownsINT.prior(Reg,Year,Block,BlockHr,"BiomassSolid") = 8;

* #####

```

```

* ===== SOLVE
* #####
$ifthen set ignore_integer
  Solve UC using RMIP minimizing vTotalCost;
$elseif not set ignore_integer
  SOLVE UC using MIP minimizing vTotalCost;
$endif
* #####

* ===== OUTPUT
* #####

* ===== SOLVER STATISTICS
* #####
oSolveStats('TotalTime')      = UC.etSolve;
oSolveStats('SolverTime')     = UC.etSolver;
oSolveStats('ModelStatus')    = UC.modelStat;
oSolveStats('SolverStatus')   = UC.solveStat;
oSolveStats('DiscreteVar')    = UC.NumDVar;
oSolveStats('Equations')      = UC.NumEqu;

* #####

* ===== HOURLY POWER BALANCE
* #####

loop ((Block,BlockHr),
      loop(time$(ord(time) eq (Block.val-1)*card(BlockHr)*TimeStep+BlockHr.val),
        oPowerBal(Reg,Year,time,'Export') = SUM(Reg2, -
vExport.l(year,Block,BlockHr,Reg,Reg2)) -1e-9;
        oPowerBal(Reg,Year,time,Gen) = vPower.l(Reg,Year,Block,BlockHr,Gen)
+eps;
        oPowerBal(Reg,Year,time,oStor) = SUM(StorStor(Stor,oStor),
vStoragePower.l(Reg,Year,Block,BlockHr,Stor) -1e-9;
        oPowerBal(Reg,Year,time,'Import') = SUM(Reg2,
vImport.l(year,Block,BlockHr,Reg,Reg2)) +eps;
        oPowerBal(Reg,Year,time,'NSE') = vNSE.l(Reg,Year,Block,BlockHr)
+eps;
        oPowerBal(Reg,Year,time,'Curtail') =
vCurtail.l(Reg,Year,Block,BlockHr) -1e-9;
        * oPowerBal(Reg,Year,time,'Demand') = Demand(Reg,Year,Block,BlockHr)
+eps;

        oStorageLevel(Reg,Year,time,Stor) =
vStorageLevel.l(Reg,Year,Block,BlockHr,Stor) +eps;

        oMarginalCostTs(Reg,Year,time) = eLoad.m(Reg,Year,Block,BlockHr)
;
      )
);

*$ontext
* == Yearly energy balance (absolute numbers)
oEnergyBal(Reg,Year,'Export','Abs') = SUM(time, oPowerBal(Reg,Year,time,'Export'));
oEnergyBal(Reg,Year,oStor,'Abs') = SUM(time, oPowerBal(Reg,Year,time,oStor));
oEnergyBal(Reg,Year,Gen,'Abs') = SUM(time, oPowerBal(Reg,Year,time,Gen));
oEnergyBal(Reg,Year,'Import','Abs') = SUM(time, oPowerBal(Reg,Year,time,'Import'));
oEnergyBal(Reg,Year,'NSE','Abs') = SUM(time, oPowerBal(Reg,Year,time,'NSE'));
oEnergyBal(Reg,Year,'Curtail','Abs') = SUM(time,
oPowerBal(Reg,Year,time,'Curtail'));
oEnergyBal(Reg,Year,'Demand','Abs') = SUM((Block,BlockHr),
Demand(Reg,Year,Block,BlockHr));

* #####

```

```

* ===== YEARLY ENERGY BALANCE
* #####
oEnergyBal(Reg,Year,'Export','Rel') =
oEnergyBal(Reg,Year,'Export','Abs')/oEnergyBal(Reg,Year,'Demand','Abs');
oEnergyBal(Reg,Year,oStor,'Rel') =
oEnergyBal(Reg,Year,oStor,'Abs')/oEnergyBal(Reg,Year,'Demand','Abs');
oEnergyBal(Reg,Year,Gen,'Rel') =
oEnergyBal(Reg,Year,Gen,'Abs')/oEnergyBal(Reg,Year,'Demand','Abs');
oEnergyBal(Reg,Year,'Import','Rel') =
oEnergyBal(Reg,Year,'Import','Abs')/oEnergyBal(Reg,Year,'Demand','Abs');
oEnergyBal(Reg,Year,'NSE','Rel') =
oEnergyBal(Reg,Year,'NSE','Abs')/oEnergyBal(Reg,Year,'Demand','Abs');
oEnergyBal(Reg,Year,'Curtail','Rel') =
oEnergyBal(Reg,Year,'Curtail','Abs')/oEnergyBal(Reg,Year,'Demand','Abs');
*$offtext

* #####
* ===== ADDITIONAL COST CALCULATIONS
* #####
* == Marginal cost calculation
oMarginalCost(Reg,Year,Block,BlockHr) = eLoad.m(Reg,Year,Block,BlockHr);

* == Yearly generator cost
oGenFinance(Reg,Year,Gen,'Capital') = vCapacityInstalled.l(Reg,Year,Gen) *
DataGen(Gen,'CapCost') * EACF(Gen) * FractionOfYear;
oGenFinance(Reg,Year,RES,'Capital') = SUM(RESRegMap(Reg,RESReg),
vCapacityInstalledRES.l(RESReg,Year,RES) * DataGen(RES,'CapCost') * EACF(RES) *
FractionOfYear);
oGenFinance(Reg,Year,Stor,'CapitalStor') = vCapacityInstalledStor.l(Reg,Year,Stor)
* DataGen(Stor,'CapCostStor') * EACF(Stor) * FractionOfYear;
oGenFinance(Reg,Year,Gen,'FixedOM') = vCapacityUsed.l(Reg,Year,Gen) *
DataGen(Gen,'FixedOMCost') * FractionOfYear;
oGenFinance(Reg,Year,RES,'FixedOM') = SUM(RESRegMap(Reg,RESReg),
vCapacityInstalledRES.l(RESReg,Year,RES) * DataGen(RES,'FixedOMCost') *
FractionOfYear);
oGenFinance(Reg,Year,Gen,'VarOM') = SUM((Block,BlockHr),
vPower.l(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'VarOMCost'));
oGenFinance(Reg,Year,Gen,'Start') = SUM((Block,BlockHr),
vStartUps.l(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'StartCost'));
oGenFinance(Reg,Year,Gen,'Fuel') = SUM((Block,BlockHr,GenFuel(Gen,Fuel)),
vPower.l(Reg,Year,Block,BlockHr,Gen) * TimeStep / DataGen(Gen,'Eff') *
DataFuel(fuel,'cost'));
oGenFinance(Reg,Year,Gen,'StartFuel') =
SUM((Block,BlockHr,GenFuel(Gen,fuel))$(CommitGen(Gen)),
vStartUps.l(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'StartFuelUse') *
DataFuel(fuel,'cost'));
oGenFinance(Reg,Year,Stor,'ElPurchase')= SUM((Block,BlockHr), -
vStoragePower.l(Reg,Year,Block,BlockHr,Stor) *
oMarginalCost(Reg,Year,Block,BlockHr));
oGenFinance(Reg,Year,Gen,'CO2') = SUM((Block,BlockHr,GenFuel(Gen,Fuel)),
vPower.l(Reg,Year,Block,BlockHr,Gen) * TimeStep / DataGen(Gen,'Eff') *
DataGen(Gen,'CO2factor') * DataFuel(fuel,'CO2int') * CO2price(year));

oGenFinance(Reg,Year,Gen,'Total') = oGenFinance(Reg,Year,Gen,'Capital') +
oGenFinance(Reg,Year,Gen,'CapitalStor')
+ oGenFinance(Reg,Year,Gen,'FixedOM') +
oGenFinance(Reg,Year,Gen,'VarOM')
+ oGenFinance(Reg,Year,Gen,'Start') +
oGenFinance(Reg,Year,Gen,'StartFuel')
+ oGenFinance(Reg,Year,Gen,'Fuel') +
oGenFinance(Reg,Year,Gen,'ElPurchase')
+ oGenFinance(Reg,Year,Gen,'CO2');

* == Yearly generator revenues (from MC and power output)
oGenFinance(Reg,Year,Gen,'Revenues') = SUM((Block,BlockHr),
vPower.l(Reg,Year,Block,BlockHr,Gen) * oMarginalCost(Reg,Year,Block,BlockHr));

* == Yearly generator profits
oGenFinance(Reg,Year,Gen,'Profit') = oGenFinance(Reg,Year,Gen,'Revenues') -
oGenFinance(Reg,Year,Gen,'Total');

```

```

* == Fuel use calculations

* == Hourly fuel use per generator group
* Variable/Parameter      Unit
* oHourlyGenFuelUse      Gwh th
* vPower                  GW e
* TimeStep                h
* DataGen(Gen, 'Eff')    %
oHourlyGenFuelUse(Reg, Year, Block, BlockHr, Gen)$(NOT RES(Gen)) =
vPower.l(Reg, Year, Block, BlockHr, Gen) * TimeStep / DataGen(Gen, 'Eff');

* == Fuel use per generator group
* Variable/Parameter      Unit
* oGenFuelUse(Gen)        Gwh th
* vHourlyGenFuelUse(time, Gen) Gwh th
oGenFuelUse(Reg, Year, Gen) = SUM((Block, BlockHr),
oHourlyGenFuelUse(Reg, Year, Block, BlockHr, Gen));

* == Hourly fuel use per fuel group
* Variable/Parameter      Unit
* oHourlyTypeFuelUse(time, fuel) Gwh th
* vPower(time, Gen)       GW e
* TimeStep                h
* DataGen(Gen, 'Eff')    %
oHourlyTypeFuelUse(Reg, Year, Block, BlockHr, fuel) = SUM(GenFuel(Gen, fuel),
vPower.l(Reg, Year, Block, BlockHr, Gen) * TimeStep / DataGen(Gen, 'Eff'));

* == Fuel use per fuel group
* Variable/Parameter      Unit
* vTotalTypeFuelUse(fuel) Gwh th
* vHourlyTypeFuelUse(time, fuel) Gwh th
oTypeFuelUse(Reg, Year, fuel) = SUM((Block, BlockHr),
oHourlyTypeFuelUse(Reg, Year, Block, BlockHr, fuel));

* == Hourly fuel cost per generator type and fuel type
* Variable/Parameter      Unit
* oHourlyFuelCost(time, fuel, Gen)M€
* oHourlyGenFuelUse(time, Gen) Gwh th
* DataFuel(fuel, 'cost') M€/Gwh th
oHourlyFuelCost(Reg, Year, Block, BlockHr, Gen, Fuel)$(GenFuel(Gen, Fuel)) =
oHourlyGenFuelUse(Reg, Year, Block, BlockHr, Gen) * DataFuel(fuel, 'cost');

oHourlyGenCO2em(Reg, Year, Block, BlockHr, Gen) = SUM(GenFuel(Gen, fuel),
oHourlyGenFuelUse(Reg, Year, Block, BlockHr, Gen) * DataGen(Gen, 'CO2factor') *
DataFuel(fuel, 'CO2int'));

* == Hourly CO2 cost per generator group
* Variable/Parameter      Unit
* vHourlyGenCO2cost(time, Gen) M€
* vHourlyGenCO2em(time, Gen) MtCO2
* CO2price(time)         M€ / MtCO2
oHourlyGenCO2cost(Reg, Year, Block, BlockHr, Gen) =
oHourlyGenCO2em(Reg, Year, Block, BlockHr, Gen) * CO2price(Year);

* == Hourly CO2 emissions
* Variable/Parameter      Unit
* vHourlyCO2em(time)      MtCO2
* vHourlyGenCO2em(time, Gen) MtCO2
oHourlyCO2em(Reg, Year, Block, BlockHr) = SUM(Gen,
oHourlyGenCO2em(Reg, Year, Block, BlockHr, Gen));

* == Hourly CO2 cost
* Variable/Parameter      Unit
* vHourlyCO2cost(time)    M€
* vHourlyGenCO2cost(time, Gen) M€
oHourlyCO2cost(Reg, Year, Block, BlockHr) = SUM(Gen,
oHourlyGenCO2cost(Reg, Year, Block, BlockHr, Gen));

* == Total CO2 emissions per generator group
* Variable/Parameter      Unit
* vTotalGenCO2em(Gen)     MtCO2
* vHourlyGenCO2em(time, Gen) MtCO2

```

```

oGenCO2em(Reg,Year,Gen) = SUM((Block,BlockHr),
oHourlyGenCO2em(Reg,Year,Block,BlockHr,Gen));

* == Total CO2 emissions
* Variable/Parameter          Unit
* oTotalCO2em                  MtCO2
* oHourlyGenCO2em(time,Gen)    MtCO2
oTotalCO2em = SUM((Reg,Year,Gen), oGenCO2em(Reg,Year,Gen));

oHourlyGenStartUpCost(Reg,Year,Block,BlockHr,Gen) =
vStartUps.l(Reg,Year,Block,BlockHr,Gen) * DataGen(Gen,'StartCost');

oNTCCost(Line,Reg,Reg2) = ((DataNTCCap(Reg,Reg2)
$ifthen set Invest_NTC
+ vNTCInv.l(Reg,Reg2)
$endif
) * EACF(Line) * FractionOfYear / 2 )
* ( DataNTCdist(Reg,Reg2) * DataNTCCost(Line,'Cable')
+ DataNTCCost(Line,'Converter') );

oCapacityAvailable (Reg,Year,Block,BlockHr) = SUM((Gen),
vCapOffMaint.l(Reg,Year,Block,Gen));

```