Incorporating institutions into optimization-based energy system models

Wang, N.

DOI
10.4233/uuid:01a3ced0-59bb-484a-beeb-0bfbe4d904b8

Publication date
2022

Document Version
Final published version

Citation (APA)
Wang, N. (2022). *Incorporating institutions into optimization-based energy system models*. [Dissertation (TU Delft), Delft University of Technology]. https://doi.org/10.4233/uuid:01a3ced0-59bb-484a-beeb-0bfbe4d904b8

Incorporating institutions into optimization-based energy system models

Incorporating institutions into optimization-based energy system models

Dissertation

for the purpose of obtaining the degree of doctor
at Delft University of Technology
by the authority of the Rector Magnificus prof. dr. ir. T.H.J.J. van de Hagen,
Chair of the Board for Doctorates
to be defended publicly on
Friday 16 December 2022 at 12:30 o'clock

by

Ni WANG

Master of Science in Sustainable Energy Technology,
University of Twente, the Netherlands
born in Luoyang, Henan, China

This dissertation has been approved by the promotors.

Composition of the doctoral committee:

Rector Magnificus,	Chairperson
Prof. dr. ir. P. M. Herder,	Delft University of Technology, promotor
Dr. ir. R. A. Verzijlbergh,	Delft University of Technology, copromotor
Dr. ir. P. W. Heijnen,	Delft University of Technology, copromotor
Independent members:	
Prof. dr. ir. C. Vuik,	Delft University of Technology
Prof. dr. T. Brown,	Technical University of Berlin
Prof. dr. G. Hug,	ETH Zurich
Prof. dr. P. Mancarella,	University of Melbourne/University of Manchester
Prof. dr. ir. Z. Lukszo,	Delft University of Technology, reserve member

This research received funding from the Netherlands Organisation for Scientific Research (NWO) [project number: 647.002.007].

Keywords: Socio-technical systems, optimization, energy system planning, institutions, spatial policies, energy system optimization models, multi-objective optimization, multi-criteria decision-making, bilateral trading, externalities

Printed by: Ridderprint | www.ridderprint.nl

Front & Back: The cover is designed by Xihe Qu.

ISBN 978-94-6366-630-5

An electronic version of this dissertation is available at
`http://repository.tudelft.nl/`.

"[The sorting hat] only put me in Gryffindor,"
said Harry in a defeated voice,
"because I asked not to go in Slytherin. . . "
"Exactly," said Dumbledore, beaming once more.
"Which makes you very different from Tom Riddle.
It is our choices, Harry, that show what we truly are, far more than our abilities."

From *Harry Potter and the Chamber of Secrets*, Chapter 18, by J.K. Rowling

Contents

Summary

Introduction and problem statement
The pledge for a carbon-free energy system in 2050 requires significant investments into renewable energy sources (RES). These new RES capacities need to be planned now to avoid possible deviations from the 2050 target. The questions are: what technologies to select, where to build them, how much the capacities are, and at what cost. In order to answer these techno-economic questions, optimization models are commonly used to sketch a least-cost future energy system.

However, the energy system is far more complex than a mathematical model. Although optimization models can provide the least-cost system design, they do not guarantee that we can realize this design because some key aspects are not captured by such models: the impact of public acceptance issues, conflicting interests among stakeholders, and the imperfection of markets. In order to accommodate these aspects, models now need to be run repeatedly, which does not guarantee finding the overall optimum.

These non-technical aspects are generalized as institutions in this thesis. In a socio-technical system like the energy system, considering both the social aspects, the institutions, and the technical system, is pivotal. The results of techno-economic models would become more useful if the institutions could be included. Therefore, the goal of this thesis is *to improve optimization models by including institutions in energy system planning*.

Accordingly, the main research question is:

How can institutions be incorporated into optimization models for energy system planning?

Since institutions are not commonly mentioned in energy system planning models, this thesis starts with standardizing institutions, and we conducted a literature review. The goal is to provide a common ground for discussing institutions and find research trends and gaps in the state-of-the-art. We found that although energy system modelers rarely use the notion of institutions, there are categories of institutions that have already been included in optimization models. On the one hand, this fact enhanced our motivation to bring the institutional perspective explicitly into energy system planning models due to this lack of awareness. On the other hand, we found that optimization models are potentially good at modeling these institutions: policies, values of actors, and governance structures. We identified the following research gaps that need deliberate attention: spatial policies, collective decision-making, and bilateral trading with externalities. In this thesis, we developed three models to deal with these institutions, respectively.

Modeling spatial policies

Variable RES are characterized by intensive land-use and variable production. In existing optimization models that minimize the total cost of the energy system, land-use and land cover aspects have been largely ignored. To include renewable energy potentials that consider physical constraints and spatial policies in energy system models, we developed a spatially explicit planning approach.

In this approach, we located the residents and devised different spatial policies reflecting social acceptance. Maximum wind energy potentials were derived based on the physical constraints and spatial policies, which can be used in any energy system model.

To illustrate the influence of the maximum wind energy potentials, we formulated an energy system optimization model where the maximum wind energy potentials were incorporated as a land-use constraint. The Netherlands has been used as an exemplary case to showcase the approach. We found that with our land-use constraints, the results led to more realistic outcomes both in terms of social acceptance and physical availability. We also investigated different spatial policies where various levels of social acceptance were taken into account.

Modeling collective investment decision-making under conflicting interests

Energy system planning is a complex task where multiple actors contribute simultaneously. While social acceptance is an issue from the viewpoint of local residents, there are interests of other actors which are often conflicting. In the world of energy system models, various interests could be taken into account by multi-objective optimization models. This type of conventional modeling shows optimal solution sets regarding the various interests. However, actors are only implicitly considered. To explicitly model the actors instead of only the interests, we present an integrated multi-actor multi-objective energy system planning model.

We considered the following exemplary actors and interests. The three actor groups are governments, funders, and local residents, who have at least one of these interests, total capital expenditure, total operation & maintenance costs, land-use, and visually impacted area. We started with a multi-objective optimization model, where the different objectives were minimized. Then, the best decisions for the actors were obtained by further assessing the results by a multi-criteria decision-making method called Technique for Order of Preference by Similarity to Ideal Solution. The method has the advantage of simultaneously evaluating the results for multiple actors with different interests. A case study of Amsterdam has been employed to illustrate the approach.

Modeling bilateral trading with external costs

Although the interests of the actors have been addressed using the multi-objective optimization model, the previous method only provides a basis for discussions toward collective decision-making. However, in a liberalized electricity market, the planning decisions are directly influenced by the expected costs and benefits from trading in the market. In this part of the thesis, we focused on bilateral trading with external costs in the market.

Common energy system optimization models assume a perfectly competitive market where marginal costs decide the merit order. However, consider the motivating example

where two actors, say a large wind farm developer and an equally large industrial load, in a power system engage in bilateral trades. These energy volumes will be outside the market, and an energy system optimization model would arrive at different outcomes than if they were included. To make the cost and benefits of the actors explicit, we presented an equilibrium model first, and then a centralized optimization model was cast. In these models, different external costs have been incorporated. They are capacity-based costs, production-based costs, and bilateral trades-based costs, which can be used to represent, e.g., the social costs of technologies, carbon taxes/RES subsidies, willingness to pay, or trading barriers, respectively.

The model was demonstrated using a proof-of-concept case study of the highly renewable Dutch power system in 2030. The case study illustrated the external costs associated with bilateral trading in two different ways. Firstly, the bilateral external costs have been used to represent transaction costs. It was found that incorporating bilateral trading changed the results when compared with the conventional cost-optimal energy system optimization model in different ways. The capacity of wind energy decreased while that of solar PV increased. Regarding the geographical distribution, the generation capacities were more local regardless of the weather conditions. Secondly, we studied a situation where a group of regions had to decide on their investments to reach a common investment goal. An assumed unwillingness to invest in wind energy has been considered. It was shown that bilateral trading with external costs could work as a negotiation simulator to inform the regions about the consequences of such a preference.

Conclusions

Energy system modelers and economists currently operate worlds apart. This thesis has the objective *to improve optimization models by including institutions in energy system planning*. We conclude that optimization models are fully equipped to study institutions. This thesis has improved current models with a techno-economic focus to incorporate spatial policies, collective decision-making, and bilateral trading with externalities. Since these institutions are indispensable in a socio-technical system, including them in optimization models results in socio-technically optimal future energy system designs beyond only the techno-economic optimums.

Samenvatting

Inleiding en probleemstelling
De belofte voor een koolstofvrij energiesysteem in 2050 vereist aanzienlijke investeringen in hernieuwbare energiebronnen (HEB). De capaciteit van deze nieuwe HEB moet nu worden gepland om het behalen van de doelstelling 2050 niet in gevaar te brengen. De belangrijkste vragen hierbij zijn: welke technologieën moeten worden geselecteerd, waar moeten ze worden gebouwd, wat is de gewenste capaciteit, en wat zijn de verwachte kosten. Om deze technisch-economische vragen te beantwoorden, worden gewoonlijk optimalisatiemodellen gebruikt waarmee een toekomstig energiesysteem met de minste kosten kan worden geschetst.

Het energiesysteem is echter veel complexer dan deze wiskundige modellen. Hoewel optimalisatiemodellen een systeemontwerp tegen de laagste kosten kunnen opleveren, garanderen zij niet dat wij dit ontwerp kunnen verwezenlijken omdat dergelijke modellen geen rekening houden met een aantal belangrijke aspecten: het effect van problemen in verband met publiek draagvlak, tegenstrijdige belangen tussen belanghebbenden, en de imperfectie van de markten. Om met deze aspecten rekening te houden, moeten de modellen nu herhaaldelijk worden uitgevoerd onder verschillende condities, hetgeen niet garandeert dat het algemene optimum wordt gevonden.

Deze niet-technische aspecten, de instituties, worden in dit proefschrift daarom geïntegreerd in de modellen. In een socio-technisch systeem als het energiesysteem is het van cruciaal belang rekening te houden met zowel de sociale aspecten, de instituties, als met het technische systeem. De resultaten van techno-economische modellen zouden bruikbaarder worden als de instituties integraal konden worden meegenomen in de optimalisatie. Daarom is het doel van deze dissertatie *om optimalisatiemodellen te verbeteren door instituties integraal mee te nemen in de planning van energiesystemen.*

De hoofdonderzoeksvraag is:

Hoe kunnen instituties worden opgenomen in optimalisatiemodellen voor de planning van energiesystemen?

Aangezien instituties niet eenduidig worden gedefinieerd in planningsmodellen voor energiesystemen, begint deze dissertatie met het standaardiseren van instituties, en hebben we daarvoor een literatuurstudie uitgevoerd. Het doel is om een gemeenschappelijke basis te creëren voor het bespreken van instituties en om onderzoekstrends en hiaten in de state-of-the-art te vinden. We vonden dat, hoewel modelspecialisten van energiesystemen het begrip instituties zelden gebruiken, er categorieën van instituties zijn die al in optimalisatiemodellen zijn opgenomen. Enerzijds versterkte dit feit onze motivatie om het institutionele perspectief expliciet in te brengen in planningsmodellen voor energiesystemen vanwege dit gebrek aan bewustzijn. Anderzijds stelden wij vast dat optimalisatiemodellen potentieel goed zijn in het modelleren van deze instituties: beleid, waarden van actoren, en bestuursstructuren. Wij identificeerden de volgende onderzoekshiaten die extra aandacht behoeven: ruimtelijk beleid, collectieve besluitvorming, en bilaterale handel met externaliteiten. In dit proefschrift hebben we drie modellen ontwikkeld om met deze instituties om te gaan.

Modellering ruimtelijk beleid

Variabele HEB worden gekarakteriseerd door intensief landgebruik en variabele productie. In bestaande optimalisatiemodellen die de totale kosten van het energiesysteem minimaliseren, zijn aspecten van landgebruik en landbedekking grotendeels genegeerd. Om hernieuwbare-energiepotentiëlen op te nemen die rekening houden met fysieke beperkingen en ruimtelijk beleid in energiesysteemmodellen, hebben wij een ruimtelijk expliciete planningsbenadering ontwikkeld.

In deze benadering hebben we de bewoners gelokaliseerd en hebben we verschillende ruimtelijke beleidsmaatregelen ontworpen die de sociale acceptatie weerspiegelen. Op basis van de fysische beperkingen en het ruimtelijk beleid werden maximale windenergiepotentiëlen afgeleid, die in elk energiesysteemmodel kunnen worden gebruikt.

Om de invloed van het maximale potentieel aan windenergie te illustreren, hebben we een optimalisatiemodel voor het energiesysteem geformuleerd waarin het maximale potentieel aan windenergie is opgenomen, gegeven een beperking van het landgebruik. Nederland is gebruikt als voorbeeld om de aanpak te illustreren. We lieten zien dat met onze randvoorwaarden inzake landgebruik, de resultaten leidden tot meer realistische uitkomsten, zowel in termen van sociale acceptatie als van beschikbaarheid. We onderzochten ook verschillende ruimtelijke beleidsmaatregelen waarbij rekening werd gehouden met verschillende niveaus van sociale acceptatie.

Modellering van collectieve investeringsbeslissingen bij tegenstrijdige belangen

Energiesysteemplanning is een complexe taak waarbij meerdere actoren tegelijkertijd een bijdrage leveren. Terwijl de maatschappelijke acceptatie vanuit het oogpunt van de omwonenden een issue is, zijn er belangen van andere actoren die vaak conflicterend zijn. In de wereld van de energiesysteemmodellen kan met verschillende belangen rekening worden gehouden door middel van multi-objective optimalisatiemodellen. Dit type conventionele modellen toont optimale oplossingsreeksen met betrekking tot de verschillende belangen. Actoren worden echter slechts impliciet in aanmerking genomen. Om de actoren expliciet te modelleren in plaats van alleen de belangen, ontwikkelden wij een geïntegreerd multi-actor multi-objective energiesysteem-planningsmodel.

Wij hebben de volgende actoren en belangen als voorbeeld genomen. De drie groepen actoren zijn overheden, financiers en lokale bewoners, die ten minste één van de volgende belangen hebben: totale kapitaaluitgaven, totale exploitatie- en onderhoudskosten, landgebruik en visueel beïnvloed gebied. We begonnen met een multi-objective optimalisatiemodel, waarbij de verschillende doelstellingen werden geminimaliseerd. Vervolgens werden de beste beslissingen voor de actoren verkregen door de resultaten verder te evalueren met behulp van een multicriteria besluitvormingsmethode, genaamd ‘Technique for Order of Preference by Similarity to Ideal Solution’. Deze methode heeft het voordeel dat de resultaten voor meerdere actoren met verschillende belangen tegelijkertijd kunnen worden geëvalueerd. Een casestudy van Amsterdam is gebruikt om de aanpak te illustreren.

Modellering van bilaterale handel met externaliteiten

Hoewel de belangen van de actoren aan de orde zijn gesteld met behulp van het multi-objective optimalisatiemodel, biedt de vorige methode slechts een basis voor discussies in de richting van collectieve besluitvorming. Echter, in een geliberaliseerde elektriciteitsmarkt worden de planningsbeslissingen direct beïnvloed door de verwachte kosten en baten van handel op de markt. In dit deel van het proefschrift hebben we ons gericht op bilaterale handel met externe kosten in de markt.

Gangbare optimalisatiemodellen voor energiesystemen gaan uit van een perfect concurrerende markt waar de marginale kosten de 'merit order' bepalen. In het voorbeeld waarbij twee actoren (bijvoorbeeld een grote ontwikkelaar van een windmolenpark en een even grote industriële speler), in een energiesysteem bilaterale handel aangaan, geldt deze perfecte concurrentie echter niet meer: deze energievolumes zullen immers buiten de markt vallen, en een model voor optimalisering van het energiesysteem zou tot andere resultaten komen dan wanneer zij wel zouden worden meegerekend. Om de kosten en baten van de actoren expliciet te maken, hebben wij eerst een evenwichtsmodel ontwikkeld, en dit vervolgens omgezet in een gecentraliseerd optimalisatiemodel. In deze modellen zijn verschillende externe kosten opgenomen. Het gaat om op capaciteit gebaseerde kosten, op productie gebaseerde kosten en op bilaterale handel gebaseerde kosten, die kunnen worden gebruikt om respectievelijk de maatschappelijke kosten van technologieën, koolstofbelastingen/HEB-subsidies, betalingsbereidheid of handelsbelemmeringen weer te geven.

Het model werd gedemonstreerd aan de hand van een proof-of-concept casestudy van het hernieuwbare Nederlandse elektriciteitssysteem in 2030. De casestudy illustreerde de kosten die gepaard gaan met bilaterale handel op twee verschillende manieren. Ten eerste werden de bilaterale externaliteitskosten gebruikt om de transactiekosten weer te geven. Het bleek dat het incorporeren van bilaterale handel de resultaten in vergelijking met het conventionele kostenoptimale energiesysteemoptimalisatiemodel op verschillende manieren veranderde. De capaciteit van windenergie nam af, terwijl die van fotovoltaïsche zonne-energie toenam. Wat de geografische spreiding betreft, waren de opwekkingscapaciteiten meer lokaal, ongeacht de weersomstandigheden. Ten tweede bestudeerden we de situatie waarin een groep regio's moest beslissen over hun investeringen om een gemeenschappelijk investeringsdoel te bereiken. Er is rekening gehouden met een verondersteld onwil om in windenergie te investeren. Tevens lieten we zien dat bilaterale handel met externe kosten kan werken als een onderhandelingssimulator om de regio's te informeren over de gevolgen van een dergelijke voorkeur.

Conclusies

Modelleurs van energiesystemen en economen opereren momenteel in behoorlijk gescheiden werelden. Deze dissertatie heeft als doel *optimalisatiemodellen te verbeteren door instituties integraal mee te nemen in de planning van energiesystemen.* We concluderen dat optimalisatiemodellen geschikt zijn om instituties te bestuderen. Deze dissertatie heeft bestaande modellen met een techno-economische focus aanzienlijk verbeterd door ruimtelijk beleid, collectieve besluitvorming, en bilaterale handel met externaliteiten op te nemen. Aangezien deze instituties onmisbaar zijn in een socio-technisch systeem, leidt het opnemen ervan in optimalisatiemodellen tot socio-technisch optimale toekomstige energiesysteemontwerpen die verder gaan dan alleen de techno-economische optima.

Acknowledgments

Writing this part is the most difficult for me because I will express my gratitude to the people who helped me during this journey which I am not good at. My sincere appreciation is beyond my plain words.

Remco, I still remember the first interview for this Ph.D. position because you chose to do it on King's Day. You impressed me with your enthusiasm for research, which has been evident since our first meeting. Your enthusiasm is tied closely to your pragmatic "get-your-hands-dirty" approach, which I still benefit from every day. Besides work, I am grateful for our amiable relationship, with which we pleasantly talked about parenting, surviving in academia, and all kinds of life hack. Petra, you are my actual "daily" supervisor. We had small talks about work and life almost every day before the pandemic hit. You carefully examined every writing sample I gave and provided timely feedback. I still remember your critical comments on my first draft of the Go/No-Go proposal not long before the meeting. As soon as I started to panic, you stepped in and took me hand-by-hand to write a completely different proposal. You have a rigorous academic style and a caring attitude toward your students, which I truly learned a lot from. Paulien, you have a great view of my work and are always there to direct me to the right destination at critical moments. You taught me how to make the most significant impact on my work. You are all the time supportive. When I was a bit lost on track at the end of the journey, you gave the right kick with extreme personal care that I wholeheartedly appreciated.

Having spent the past years in E&I is a privilege. It is the best community I can think of. There is a perfect mix of seriousness and silliness. Although I naturally belong to one part, the other part makes life vivid as it should be. I miss the parties, the lunches, the coffee breaks, and even the teaching assistant experiences with many of you. I am very happy that I also gained friendship, which I value the most. I must thank the supportive staff members and secretaries; you are integral to the section and were very helpful in making my life easier. I want to thank all other colleagues at TPM that I interacted with, both academic and non-academic. You enriched my work and enlightened my life as well. I also want to thank the master students I have supervised. Seeing you was like seeing a better me in the past, baffled about the future but persevered and energetic to tackle the challenges. I want to thank my colleagues from EWI who are involved in the NWO RESS project, especially Anne and Johan. Our monthly meetings were always eye-opening, and I gained a different view of the same research problem.

I am grateful to my TNO colleagues, who offered me exciting projects to work on during the last stretch of this journey. In particular, I would like to express my gratitude to Sanne and Sebastiaan, who kindly agreed to let me work part-time, allowing me to sprint toward the end of this Ph.D. project.

All my years before coming to Delft University of Technology have been an integral part of me. I want to thank my friends and teachers at University of Twente. In particular, I am obliged to thank prof. Hoeijmakers, who is not only a great supervisor for study and work but also a great person to help me settle down and live my life in the Netherlands. I am grateful to my friends in China as well, especially Chengbin, who helped me survive the initial hard times living abroad.

Finally, I would like to say a few words to my family. Thank you, my parents-in-law. You made me recall my childhood dream of becoming a scientist. My dear parents, not for a moment I forget that I have unconditional and self-sacrificing love from you. I owe you the company time for the past years. Your son, the author of this thesis, would not be able to do independent research if he was not cultivated to have an independent personality. You can be proud of this work and your son. Hui, we met, loved, and married in the past years. Although our life has ups and downs, we always have each other's support and company. I love you. Yichang, you are so little that you do not understand these words now, just like you do not understand how much joy you have brought us. One day you will know that you are my best blessing in the world.

Ni WANG
Leiden, November 2022

Abbreviations

CapEx	capital expenditure
CC	coefficient of closeness
CLC	Corine Land Cover
EM	equilibrium models
ENTSO-E	European Network of Transmission System Operators for Electricity
ESOM	energy system optimization models
FOM	fixed operation and maintenance
GRIM	greenfield renewables investment model
LCOE	levelized cost of electricity
MCDM	multi-criteria decision-making
MOO	multi-objective optimization
NSGA-II	Non-dominated Sorting Genetic Algorithm II
O & M	operation and maintenance
P2P	peer-to-peer
RES	renewable energy sources
TC	transaction costs
TOPSIS	Technique of Order Preference by Similarity to Ideal Solution
TSO	transmission system operator
VIA	visually impacted area
VOM	variable operation and maintenance
VRES	variable renewable energy sources

Nomenclature

Chapter 2

$\mathbf{x_n}$	vector of generation capacities at node n
λ_n	energy price at node n
$\mathbf{g^I}$	vector of generation capacity limits at node n
$\mathbf{g^{II}}$	vector of network capacity limits
$\mathbf{u}$	vector of network flows
$\mathbf{y_n}$	vector of energy production at node n
$\mathbf{z}$	vector of network capacities
c^I	generation-related costs
c^{II}	network-related costs
f_1	1st objective function
f_k	kth objective function
h^I	energy balance
h^{II}	flow modeling
N	set of nodes

Chapter 3

$\alpha_{i,c}$	suitability factor for technology i, Corine Land Cover class c
f	factor that represents extra length and extra capacity considering security constraint
β_i	capacity density for technology i
$\delta_{n,m}$	length of network (n,m)
η_i^{in}	charging efficiency of storage technology i
η_i^{out}	discharging efficiency of storage technologies i
$\eta_{i,n,t}$	capacity factor for technology i at node n at time t (of wind and solar energy), 1 for other generation technologies

ω RES target

$\tau_{n,m}$ energy loss factor in line (n,m)

A_i annuity factor of generation and storage technology i, $A_i = \frac{1-\frac{1}{(1+r)^{L_i}}}{r}$

a_i fixed operation & maintenance costs of generation and storage technology i

$A_{n,m}$ annuity factor of line (n,m) , $A_{n,m} = \frac{1-\frac{1}{(1+r)^{L_{n,m}}}}{r}$

b_i variable operation & maintenance costs generation and storage technology i

$B_{n,c}$ number of Corine Land Cover units at node n for Corine Land Cover class c

C_i capital expenditure of generation and storage technology i

$C_{n,m}$ capital expenditure of network (n,m)

CLC set of Corine Land Cover classes

$CP_{i,n,t}$ energy charging of technology i at node n at time t

$D_{n,t}$ energy demand at node n at time t

$DP_{i,n,t}$ energy discharging of technology i at node n at time t

E set of network connections

G set of generation technologies

$K_{i,n}^{max}$ maximum possible installed capacity for technology i at node n

$K_{i,n}$ capacity of generation and storage technology i at node n

$K_{n,m}$ capacity of line (n,m)

L_i lifetime of generation and storage technology i

$L_{n,m}$ lifetime of line (n,m)

N set of nodes

$P_{n,m,t}^{export}$ energy export from node n to node m at time t

$P_{n,m,t}^{import}$ energy import from node n to node m at time t

$P_{i,n,t}$ energy production of technology i at node n at time t

RES set of renewable energy generation technologies

r discount rate

$S_{i,n,c}$ suitable area for technology i at node n for Corine Land Cover class c

S_{unit} area of a grid cell in Corine Land Cover data

SC set of storage conversion technologies

$SP_{i,n,t}$ stored energy of technology i at node n at time t

S set of storage technologies

t_{end} last time step in T

T set of time steps

$VRES$ set of variable renewable Energy energy generation technologies

Chapter 4

ω_m^a weight for preference m, actor a

ϕ_i land-use factor of technology i

A set of actors

CC_n^a normalized coefficient of closeness for solution n, actor a

$\mathrm{CC}_n^{\mathrm{average}}$ average normalized Coefficient of Closeness for solution n

CoCl_n^a absolute coefficient of closeness for solution n, actor a

$\mathrm{LU}^{\mathrm{max}}$ maximum land that can be used

M set of preferences

N set of Pareto-optimal solutions

TRS total roof surface

v_i visual impact of one wind turbine of type i

C^{CapEx} total capital expenditure

$C^{\mathrm{O\&M}}$ total operation & maintenance costs

D_t energy demand at time t

I_m^{a+} best point regarding preference m, actor a

I_m^{a-} worst point regarding preference m, actor a

K_i capacity of generation/storage conversion technology i

P_t^{charging} energy from charging the storage at time t

P_t^{deficit} energy deficit after deploying wind and solar energy at time t

$P_t^{\mathrm{discharging}}$ energy from discharging the storage at time t

P_i^{rated} rated power of wind turbines of type i

$P_{i,t}$ energy production/storage of technology i at time t

Q_{nm} absolute value for solution n, preference m

R_{nm} normalized value for solution n, preference m

S_n^{a+} positive distance for solution n, actor a

S_n^{a-} negative distance for solution n, actor a

V_{nm}^a weighted normalized value for solution n, preference m, actor a

$\eta_{i,t}$ capacity factor of technology i at time t

WT_i number of wind turbines of type i

LU total land-use

maximin the highest minimal normalized coefficient of closeness for all the actors, among all the solutions

minimax the lowest maximal normalized coefficient of closeness for all the actors, among all the solutions

VIA total visually impacted area

Chapter 5

Δ_l length of line l

$\lambda_{n,m,t}^{\text{bilateral}}$ bilateral trading price between node n and node m at time step t

$\lambda_{n,m,t}^{\text{grid}}$ grid price between node n and node m at time step t

$\lambda_{n,t}^{\text{pool}}$ pool trading price at node n at time step t

ω_n set of neighbors of node n on the communication graph

Φ_n percentage of trades in the bilateral market at node n

CAP^{CO_2} carbon market cap

A_l annuity factor of line l

A_i annuity factor of technology i

B_i variable costs of technology i

C_l fixed costs of line l

C_i fixed costs of generation and storage conversion technology i

CS_i fixed costs of storage technology i

$E_{n,m}^{\text{bilateral-ex}}$ product differentiation value from node n towards node m

$E_{i,n}^{\text{capacity-ex}}$ unit social cost for technology i at node n

$E_{i,n}^{\text{production-ex}}$ carbon tax/RES subsidy for technology i at node n

$f_{l,t}$ energy flow at line l at time step t

G set of generation technologies

H_i^{in} charging efficiency of storage technology i

H_i^{out} discharging efficiency of storage technology i

$k_{i,n}^{\text{storage}}$ investment capacity of storage technology i at node n

K_l existing capacity of line l

k_l investment capacity of line l

$K_{i,n}$ existing capacity of technology i at node n

$k_{i,n}$ investment capacity of generation and storage conversion technology i at node n

L set of lines

N set of nodes

$p_{n,m,t}^{\text{bilateral}}$ bilateral trades from node n to node m at time step t

$p_{i,n,t}^{\text{in}}$ charging to storage of storage technology i at node n at time step t

$p_{i,n,t}^{\text{out}}$ discharging from storage of storage technology i at node n at time step t

$p_{n,t}^{\text{pool}}$ pool trades at node n at time step t

$p_{i,n,t}$ produced energy from technology i from node n at time step t

$PTDF$ Power Transfer Distribution Factors matrix

R set of fossil-fueled generation

S set of storage technologies

$soc_{i,n,t}$ energy in storage of storage technology i at node n at time step t

T set of time steps

W_i emission of fossil-fueled technology i

$z_{n,m,t}^{\text{bilateral}}$ arbitrage energy from the transmission system operator from node n to node m at time step t in the bilateral market

$z_{n,t}^{\text{pool}}$ arbitrage energy from the transmission system operator at node n at time step t in the pool market

1

Introduction

1.1. Future energy systems need a socio-technical change

1.1.1. Investments into renewable energy are pivotal

Global warming is one of the greatest challenges of our times. Reducing greenhouse gas emissions in the long term requires a fundamental change in the energy system, from fossil fuels to clean energy. According to [1], for a net zero-carbon energy system in 2050, two-thirds of the primary energy supply comes from renewable energy sources (RES), consisting of wind, solar, hydro, and bioenergy.

The role of RES is even more significant in the electricity sector. Electricity will become the most crucial energy carrier in 2050, which contributes directly to electricity end-use or indirectly to other carriers such as methane, hydrogen, and heat through electrification. Compared to today, electricity production will grow threefold where 90% is provided by RES [2].

1.1.2. Techno-economic modeling overlooks barriers for investments

Techno-economic approaches are widely used to determine the future energy design, i.e., what technologies to choose, where to build them, and how much capacity is needed. The resulting ideal investments are renewable rich, technically feasible, and cost optimal, which correspond to the United Nations Sustainable Development goals of sustainability, reliability, and affordability [3].

While the ideal future energy system is pictured, the current investments are far from enough for that picture. The 2021 projection shows that for the net-zero energy scenario, investments into clean energy need to grow from one trillion dollars to four trillion dollars annually by 2030. However, this ambition is overshadowed since the announced investments from the globe need to be increased 75% to reach the required level [4].

From a pure techno-economic perspective, one might argue that the costs of RES need to be lower so that the investments would come. This is only partly true because cost reduction is undoubtedly one of the main drivers for the cost-optimal renewable-rich future energy systems. However, RES are already cost-competitive with their fossil-fuels counterparts in 2020 [2], but the required investments are still yet to come. This indicates that there are non-techno-economic barriers that hinder the investments for RES [5], which we briefly discuss below.

- Permits and spatial issues

  The difficulty of obtaining permits for RES investments significantly hampers the investment processes. This happens mostly for onshore wind energy, partly due to the administrative efficiency of the jurisdiction and partly due to the increasing concerns over land availability and public acceptance [6].

- Policy uncertainty

  Investments may be held back due to a lack of policy support schemes and the uncertain institutional environment, e.g., the change of carbon targets. For example, the Netherlands announced in 2019 an emission target of 49% by 2030 [7] and changed that to 55% in 2022 [8].

- Ownership and finance

  Financing is another issue. Both private parties, such as generation companies and financiers, and public actors, such as state-owned utilities, play a crucial part in providing funding [4]. The provision of funding is closely related to the ownership structures, market signals, and policies set by the governments.

- Markets & governance

  With the increasing share of decentralized generation, the traditional market design tailored to centralized power plants needs fundamental changes to incentivize RES-based generations. Different governance structures from markets, such as centralized decision-making, may play a role in local energy systems or energy systems where the markets have not yet been dominant.

1.1.3. Interactions between cost optimality and rules

All these barriers can be roughly considered as rules of the energy system. The energy system can be viewed as a socio-technical system where a technical and a social subsystem interweave. The design of the technical subsystem follows a techno-economic logic aiming for cost optimality. The social subsystem consists of actors and their decision-making under rules that need to be designed.

Incorporating rules in techno-economic models may change the way these are built and thus lead to different techno-economic designs of future energy systems. For example, the effects of various policies need to be understood in techno-economic terms. A conservative carbon target will slow down the efforts to mitigate climate change, while a too ambitious one would result in unnecessary costs that would have to be paid by everyone. Failing to consider spatial issues would result in optimistic installed capacities that are infeasible. Different governance structures, e.g., liberalized market versus vertically-integrated utilities and conventional market designs versus new market designs, will change the economic incentives for the investors so that the future energy system will be shaped accordingly.

1.2. This thesis

1.2.1. Problem description

In order to design a cost-optimal future energy system under carbon constraints, optimization models are often employed. Optimization models are strong at giving normative results, i.e., what the future energy system should be. However, they do not guarantee that we can realize this design because some key institutions are not captured. The *institutions* include actors and the rules that govern them, such as policies, ownership structures, and market designs.

Engineers who do the energy system's techno-economic design generally do not pay attention to the institutions. Vice versa, economists that focus on the institutions lack an understanding of the techno-economic modeling. Hence, the interlink between optimization models and institutions is poorly understood.

Techno-economic optimums are set to deviate in reality because of the socio-technical nature of the energy system. Therefore, including institutions in optimization models for energy system planning is crucial.

1.2.2. Research objective and questions

The question thus arises of how institutions can be included in optimization models for energy system planning. Therefore, the objective of this thesis is *to improve optimization models by including institutions in energy system planning.*

Accordingly, the main research question is formulated:

How can institutions be incorporated into optimization models for energy system planning?

To help answer this main research question, four sub-questions are formulated. Sub-question 1 is answered through a literature review in Chapter 2. In addition, this chapter provides the theoretical background for understanding this thesis and motivates the remaining three sub-questions.

1. What is the state-of-the-art on optimization-based institutional modeling for energy system planning?

2. How can renewable energy potentials that consider physical constraints and spatial policies be included in energy system optimization models?

3. How can collective energy system planning be modeled using multi-objective optimization?

4. How can decentralized planning processes considering bilateral trading be modeled?

1.2.3. Audience

Due to the interdisciplinary research objective, this thesis is relevant for multiple practitioners in the energy transition and academics.

Firstly, academics from different fields, particularly energy system modelers and economists, can obtain insights from the other disciplines and deepen their understanding in their own field of expertise. On the one hand, this thesis sheds light on how these two fields are combined, and they can be inspired to further their research. On the other hand, it provides a common ground to foster collaborations and innovations.

Secondly, multiple actors in the energy transition may find the thesis helpful. Policymakers can assess the influences of the institutions on the future energy system design so that they can make more informed decisions. Furthermore, other actors such as market participants, investors, and local residents may find this thesis interesting since it provides a methodological contribution for quantifying their values in different forms of decision-making.

1.2.4. Reading ahead

Figure 1.1 shows the structure of the thesis. After the introduction, Chapter 2 provides the theoretical background and a literature review. Chapters 3 - 5 are modeling chapters. Three optimization models incorporating different institutions that have been developed during the Ph.D. research are presented.

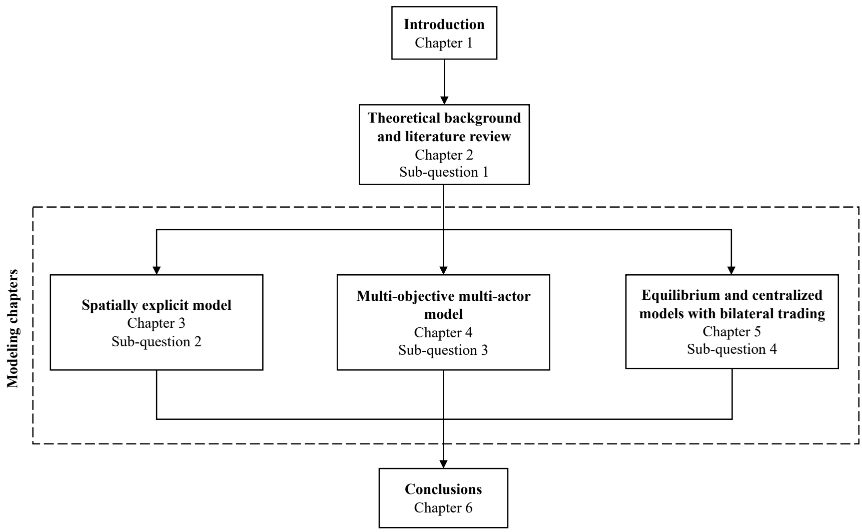

Figure 1.1: Structure of the thesis.

- Chapter 2 is based on [9]. It first equips the fundamental knowledge to understand this thesis by giving an energy system description from the socio-technical viewpoint and presenting several generic mathematical formulations of optimization models. It then treats sub-question 1 through a literature review. The state-of-the-art is analyzed, and several research gaps that motivate sub-questions 2 - 4 are identified.

- Chapter 3 is based on [10] which answers sub-question 2 by proposing a spatially explicit energy system model.
- Chapter 4 is based on [11]. It copes with sub-question 3 by presenting a multi-objective optimization model combined with a multi-criteria decision-making technique for collective decision-making.
- Chapter 5 deals with the last sub-question, which is based on [12]. An equilibrium formulation considering bilateral trading is first described, and then, an equivalent centralized model is cast.

Chapter 6 ends the thesis with conclusions, reflections, and recommendations. A complete list of publications can be found at the end of the thesis.

2

Theoretical background and literature review

2.1. Introduction

The transition to a carbon-free energy system faces significant challenges. While advances in renewable energy sources (RES) technology drive the energy transition, there are challenges from socio-economic, environmental, and institutional aspects. Firstly, the high initial costs of RES technologies act as a barrier to investments. Governments are working on various financial incentives such as RES subsidies to help tackle the problem. Secondly, RES integration becomes a spatial issue increasingly. According to [10], land use is a critical factor for estimating RES potentials, and thus, spatial policies need to be carefully designed and examined. Thirdly, there is a need for changes in market regulation, re-bundling, and forms of governance in order to promote and make full use of local RES [13]. The above are examples of the critical non-technical issues in the transition to a future energy system with a high share of RES, indicating the need for a paradigm change for the conventional fossil fuel-based energy system to accommodate increasing RES investments [14]. These aspects are generalized as institutions of the energy system, which relate to concepts such as actors, values, regulations, and their governance. Most existing literature on institutional designs is qualitative, but there is a need to align institutions with technology [15] and the current practice of techno-economic modeling should be enhanced to include institutions [16].

Optimization models are widely used in energy systems research, from which optimal generation and network investment can be derived. They are considered powerful tools to guide the decision-making for relevant stakeholders [17]. For example, national and international energy system optimization models are deployed by policy-makers to figure

This chapter is based on the paper N. Wang, R. A. Verzijlbergh, P. W. Heijnen, and P. M. Herder, "A review and analysis on the institutional paradigms in optimization models for energy system planning", Submitted, 2022. The first author of the paper, also the author of this thesis, conceptualized and conducted the research. The other authors performed an advisory role.

out the cost-optimal investment portfolio to reach a carbon target, from which they may design specific policies to incentivize promising technologies. Generation companies or network operators would treat the model outcomes as a basis for their generation or network expansion plans. Considering institutions in optimization models can enhance their capabilities for investment and policy decision-support where policies, actors, and values play an indispensable role.

Due to this broad area of applications, optimization models applied to energy systems have been reviewed extensively in the literature in recent years. However, most reviews present general challenges and state-of-the-art in energy system modeling, such as [18], [19], where social and policy aspects are only partially discussed. Several reviews focus on specific aspects regarding institutions, e.g., [20] for multi-level governance and [21] for social factors. So far, existing literature reviews do not systematically review and analyze optimization models applied in energy systems from the institutions' viewpoint.

To assess the state-of-the-art, this chapter has two goals. The first goal is to give the theoretical background that is necessary for understanding this thesis. To start with, the energy system is described from a socio-technical system viewpoint. Then, three typologies of mathematical formulations of optimization models are presented. The second goal is to provide a literature review and find research trends and knowledge gaps that motivate the sub-questions 2 - 4.

This thesis focuses on the planning of power systems. By planning, we mean the capacity expansion of generation technologies, storage technologies, and networks from either a greyfield assumption or a greenfield assumption. Accordingly, the geographical scope of the reviewed literature ranges from regional models to continental models.

The remainder of the thesis is structured as follows. First, Section 2.2 gives a socio-technical system description. Next, Section 2.3 presents generic mathematical formulations for three optimization typologies. Afterward, Section 2.4 reviews the existing literature and highlights the trends and research gaps. Section 2.5 concludes this chapter.

2.2. Energy system description from a planning perspective

This section describes the energy system from a planning perspective. Since it is meant to provide a socio-technical system viewpoint, we discuss the social aspects of the energy system in detail, particularly its institutions and actors, while an extensive technical description is beyond the scope of the thesis.

2.2.1. Socio-technical worldview

The term socio-technical system was initially proposed by Emery and Trist (1960) [22]. It refers to a complex system that technical, human, social, and organizational factors co-exist in various settings [23], [24].

An energy system is a typical socio-technical system. The technical subsystem includes technical assets such as generation, storage, and networks. The social subsystem includes actors such as producers, consumers, policy-makers, market operators, and the required institutions, *rules of the game*. Under this worldview, the energy system can be regarded as a unification of a technical subsystem and a social subsystem, where the interplay is pivotal. Combining the two subsystems leads to the increased complexity of the energy system, meaning that its performance depends on both subsystems and the degree to which they effectively interact. For the successful functioning of the energy system, the two subsystems cannot be analyzed separately.

2.2.2. Technical system description

Although the energy system consists of many technical components, its simplest version conceptualized in this thesis will now be introduced.

The physical electric power system includes the flow of energy from generation to end-users and the related infrastructure. Electricity is first generated by fossil fuels or RES. Next, it is transmitted to other locations through electricity networks. The network infrastructure is further divided into transmission networks and distribution networks. Transmission networks are high-voltage overhead lines that allow efficient electricity transmission over long distances. In large power systems such as the national power systems, transmission networks serve as the backbone. They are designed so that any interruptions such as a broken line would not decrease the reliability of the power system. When the energy has been transmitted to a location near the end-user in the transmission network, the voltage will be transformed to lower levels at substations, after which the energy enters the distribution network. Compared to the transmission network, the distribution network is a local network that delivers energy to the end users.

Due to the increasing share of RES, the existing, conventional way of operating the power system has changed. From the generation perspective, more variability and uncertainty are introduced with RES. RES generation fluctuates with variable weather conditions both temporally and spatially. In addition, inaccurate weather forecasts bring unpredictability to the power outputs. These features make the load-generation balance more complicated to maintain than the power systems with a lower share of RES. From the network perspective, the growing share of RES calls for re-design and reinforcement of the networks. Traditional generation is done in centrally-operated fossil-fueled power plants, whereas nowadays, energy generation has become more decentralized and distributed. The conventional unidirectional delivery of energy from generation sources to end-users has changed as bi-directional energy flows emerge and will gradually become the norm. Because in modern power systems, the end-users consume energy and generate energy through RES. When there is surplus energy beyond the need for demand and storage capacity, it has to be fed back to the grid. This would result in energy flows from end-users to the distribution and transmission networks. Since the networks were built many years ago and were not designed to cope with such flows, issues such as congestion may occur.

These technical issues related to the integration of RES into modern power systems highlight the need for a system-level re-design. In addition, social aspects need to be examined as well in this process.

2.2.3. Social system description: institutions and actors

Embedded institutions using institutional analysis framework Institutions are defined as "systems of established and prevalent social rules that structure social interaction" [25]. Despite the definition, under the context of energy system planning, the scope of relevant institutions is always not clear.

In this thesis, we adopt a framework called the institutional analysis framework. It was proposed by Williamson (2005) [26] and is widely used in energy-related research. The advantage of utilizing a framework is that it can provide the basic vocabulary of concepts and terms in an institutional design [27] so that the institutions can be studied in a comprehensive and structured manner based on this common ground. The framework contains four levels (see Figure 2.1).

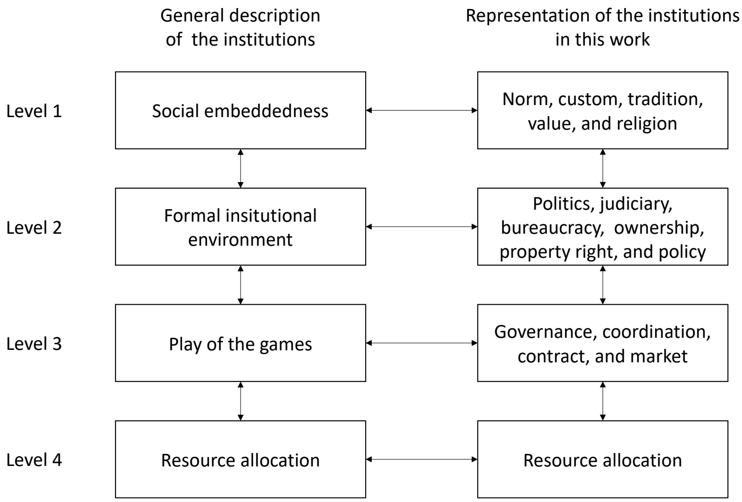

Figure 2.1: Schematic of Williamson's four-level institutional analysis framework and its representation in this work (adapted from [26]).

The top level is the social embeddedness level. It represents the informal institutions that are embedded in society. Examples are norms, customs, traditions, values, and religions. These institutions are rooted deeply in people's minds and would only change in hundreds to thousands of years. In the context of energy system planning, since the lifetime of energy infrastructure is at the magnitudes of decades, those informal institutions would remain unchanged.

The second level is the formal institutional environment. The institutions at this level are a product of the political environment, e.g., politics, judiciary, and bureaucracy. The laws featured at this level are predominantly regarding property rights. Moreover, policies are also situated here. The carbon policy and RES support schemes are the most commonly studied institutions in energy system models.

The third level depicts the play of the games. While the second level mainly contains the formal rules of the games, this level deals with the relationships between the actors, i.e., the governance structures. The governance structures address the forms of decision-making like centralized, collective, or market-based. They are closely tied to the allocation of ownership and property rights. Topics such as market design, self-governance, and contracts belong to this level.

The last level describes the process of resource allocation. In energy system planning, it represents the instantaneous flow of energy associated with quantity and prices between economic actors.

Actors Although actors are not characterized by any of the institutions, they play a central role in studying them because the institutions are set to regulate the actors both formally and informally. In this section, we continue to deepen the understanding of the institutions by introducing the most important actors in energy system planning.

Firstly, there are governments at different levels. There are mainly three energy goals for the power system from a governmental viewpoint: reliability, affordability, and sustainability. In addition, the national government recognizes the spatial challenges and aims to solve them with lower-tier governments in the Netherlands [7]. In practice, the provincial government allocates land and permits to RES projects. From the property rights perspective, the governments used to play a central role instead of a supporting role before the unbundling of the power system in the 1990s, when the power system was vertically-integrated. This indicates that the infrastructure, namely the generation and network assets, was built and operated by a centralized entity, such as a state-owned utility company.

Secondly, there are generation companies, consumers, and network companies, who are connected through the electricity markets. Producers such as large generation companies invest in generation capacities and sell electricity on the electricity market to maximize their profits, while the transmission system operators and the distribution system operators make transmission and distribution network investments, respectively. Besides capacity expansion, the responsibility of the network operators is also to transmit energy and ensure the reliability of the networks.

The rest of the representative actors are residents, energy communities, and landowners. Public acceptance for residents is a critical issue when it comes to wind turbines [28], [29]. Some non-profit organizations also have similar interests. Energy communities are playing an increasingly prominent role in RES investments [30]. They would like to invest in RES but also maximize the profits [31], which aligns with the goal of generation companies. The construction of RES requires land. The interest of landowners is also financial. According to [32], landowners are positive towards wind energy if they are involved and receive financial compensation.

2.3. Model fundamentals

2.3.1. Single-objective optimization

In energy system planning, energy system optimization models (ESOM) are the most widely used single-objective optimization models. ESOM refer to optimization models that aim to find the optimal capacity expansion of generation and networks [33]. The objective is to minimize the total system cost while satisfying several constraints such as energy balance, generation limits, and network limits. The resulting system optimal is equivalent to the outcome of a perfect market. Policy-makers often use such models as a benchmark to help them make decisions on potential policy changes.

A generic mathematical formulation of an energy system optimization model is presented now, where its simplest form is:

2

$$\min_{\mathbf{x_n},\mathbf{y_n},\mathbf{z},\mathbf{u}} \sum_{n\in N} c^I(\mathbf{x_n},\mathbf{y_n}) + c^{II}(\mathbf{z},\mathbf{u}) \tag{2.1a}$$

$$\text{s.t. } h^I(\mathbf{y_n},\mathbf{u}) = 0, \quad \forall n \in N \tag{2.1b}$$

$$\mathbf{g^I}(\mathbf{x_n},\mathbf{y_n}) \leq 0, \quad \forall n \in N \tag{2.1c}$$

$$h^{II}(\mathbf{u}) = 0, \tag{2.1d}$$

$$\mathbf{g^{II}}(\mathbf{u},\mathbf{z}) \leq 0 \tag{2.1e}$$

In principle, there are location and time dependencies for the vectorial decision variables. However, the generic formulations presented in this chapter only differentiate the location dependency.

This optimization problem aims to find the best location, sizing, and utilization of generation and network assets. Let $n \in N$ denote the location of the generation assets. $\mathbf{x_n}$ represents the sizing of generation assets at location n, i.e., the investment variables. $\mathbf{y_n}$ is the utilization of generation assets at location n, i.e., the operational variables. $\mathbf{z}$ represents the sizing of the networks, and $\mathbf{u}$ represents the flow variables.

The objective function to be minimized is the system cost that consists of two components: generation-related costs $\sum_{n\in N} c^I(\mathbf{x_n},\mathbf{y_n})$ and network-related costs $c^{II}(\mathbf{z},\mathbf{u})$. The model is subject to a number of constraints. Constraints $h^I(\mathbf{y_n},\mathbf{u}) = 0$ indicate that supply matches demand at location n, i.e., Kirchhoff's current law is satisfied. Constraints $g^1_n(\mathbf{x_n},\mathbf{y_n}) \leq 0$ are used to ensure that the energy production respects the capacity limits that are to be optimized. Constraints $h^{II}(\mathbf{u}) = 0$ specify that the flows must obey Kirchhoff's voltage law or an approximation thereof. Inequality constraints $\mathbf{g^{II}}(\mathbf{u},\mathbf{z}) \leq 0$ limit the flow variables $\mathbf{u}$ within the bounds of the network capacities $\mathbf{z}$.

2.3.2. Multi-objective optimization

When multiple objectives are considered, two approaches can be used. On the one hand, the objectives can be modeled as constraints or with weights in the objective function of a single-objective optimization problem. On the other hand, the objectives can be optimized simultaneously. A set of mathematically equivalent solutions, the so-called Pareto-optimal solutions, is derived. Compared to a single optimal solution derived from single-objective optimization models, the solution set, which consists of alternatives, provides room for discussions among the actors, making it ideal for collective decision-making.

The mathematical formulation for the latter approach of multi-objective optimization (MOO) in its simplest form is written as follows.

Assuming $f_1(\mathbf{x_n},\mathbf{y_n},\mathbf{z},\mathbf{u})$ is the 1st goal and $f_k(\mathbf{x_n},\mathbf{y_n},\mathbf{z},\mathbf{u})$ is the kth goal. When cost is the objective, e.g., as the kth goal, then $f_k(\mathbf{x_n},\mathbf{y_n},\mathbf{z},\mathbf{u}) = \sum_{n\in N} c^I(\mathbf{x_n},\mathbf{y_n}) + c^{II}(\mathbf{z},\mathbf{u})$.

$$\min_{\mathbf{x_n},\mathbf{y_n},\mathbf{z},\mathbf{u}} (f_1(\mathbf{x_n},\mathbf{y_n},\mathbf{z},\mathbf{u}),...,f_k(\mathbf{x_n},\mathbf{y_n},\mathbf{z},\mathbf{u})) \tag{2.2a}$$

$$\text{s.t. } h^I(\mathbf{y_n},\mathbf{u}) = 0, \quad \forall n \in N \tag{2.2b}$$

$$\mathbf{g^I}(\mathbf{x_n},\mathbf{y_n}) \le 0, \quad \forall n \in N \tag{2.2c}$$

$$h^{II}(\mathbf{u}) = 0, \tag{2.2d}$$

$$\mathbf{g^{II}}(\mathbf{u},\mathbf{z}) \le 0 \tag{2.2e}$$

The objective is to minimize the considered objectives $f_1(\mathbf{x_n},\mathbf{y_n},\mathbf{z},\mathbf{u})$ to $f_k(\mathbf{x_n},\mathbf{y_n},\mathbf{z},\mathbf{u})$ simultaneously. Accordingly, the optimization problem concerns a multi-dimensional space corresponding to the objective function's vector. The constraints stay the same as those in ESOM.

Although this generic formulation *merely* adds more objectives to ESOM, the implementation needs further deliberation. In ESOM, once the optimization problem is formulated, it is ready to be solved by an optimization algorithm. However, solving a MOO problem in a multi-dimensional space requires an evolutionary method and becomes a simulation problem. For energy system planning, the evolutionary method usually starts with a random set of values for the investment capacities $\mathbf{x_n}$. Then, the values of the operational variables $\mathbf{y_n}$ need to be fixed, and afterward, the constraints will be checked, and only the ones that satisfy the constraints will be left. Depending on the dispatch sequence, $\mathbf{y_n}$ may be different following the same values of $\mathbf{x_n}$. When there are flexibility options such as network, storage, controllable generation, and demand-side management, the sequence on which one to utilize first usually depends on the modeler's way of implementation. This feature indicates a strong assumption and judgment from the modelers, making the solution to MOO problems a blend of art and science.

2.3.3. Equilibrium formulation

From the decision-making perspective, the aforementioned two problems take the form of centralized decision-making, i.e., there is one problem and thus one problem owner. Decentralized decision-making indicates that different actors make investment decisions according to their own wishes, resulting in a number of optimization problems. In reality, it is often coordinated through an electricity market. In the simplest form of a market, three types of actors, i.e., a producer, a network operator, and a market operator, are involved. We provide the simplest form of the three types of optimization problems under a perfect market below.

A producer's problem takes the investment variables $\mathbf{x_n}$ and the operational variables $\mathbf{y_n}$ as decision variables. The objective is to maximize the profit or minimize the related costs as cast in this problem. The income of the producer is a function of the energy price in the pool λ_n. Note that here, a perfectly competitive market is assumed, and thus λ_n is exogenous to this problem. However, λ_n is not always exogenous. More explanations are given after the formulation.

$$\min_{\mathbf{x_n},\mathbf{y_n}} \sum_{n\in N} c^I(\mathbf{x_n},\mathbf{y_n},\lambda_n) \tag{2.3a}$$

$$\text{s.t. } \mathbf{g^I}(\mathbf{x_n},\mathbf{y_n}) \leq 0, \quad \forall n \in N \tag{2.3b}$$

The network operator's problem aims to minimize network-related costs. The energy price λ_n also plays a role here since the network operator harvests congestion rent.

$$\min_{\mathbf{z},\mathbf{u}} c^{II}(\mathbf{z},\mathbf{u},\mathbf{y_n},\lambda_n) \tag{2.4a}$$

$$\text{s.t. } h^{II}(\mathbf{u}) = 0, \tag{2.4b}$$

$$\mathbf{g^{II}}(\mathbf{u},\mathbf{z}) \leq 0 \tag{2.4c}$$

The pool-based market operator gathers the market information and makes sure that supply matches demand and generates the energy price at equilibrium.

$$h^I(\mathbf{y_n},\mathbf{u}) = 0 : \lambda_n, \quad \forall n \in N \tag{2.5a}$$

We would like to make two remarks regarding this formulation and its implementation. First, the different optimization problems are interconnected by the price λ_n. This means that the problems can not be solved separately and have to be solved together. This price is an equilibrium price, and therefore, this formulation is referred to as equilibrium models (EM) in this thesis. Second, this generic formulation is only readily used under certain assumptions. We assume a perfect market here, and therefore, EM are equivalent to ESOM. In addition, this formulation indicates concurrent decision-making for generation and network planning because the generation and network investment variables are independent of each other. However, when studying strategic behaviors in the market, it is common to assume that λ_n is a decision variable for the producer and/or the network operator and that the decision-making for two actors is sequential, making the implementation a multi-level optimization problem instead of single-level one.

2.4. Literature review

A literature review has been performed to assess the state-of-the-art on how institutions are included in optimization models for energy system planning. The reviewed papers are summarized in Table 2.1, Table 2.2, and Table 2.3. Following this literature review, research trends and gaps are captured and summarized. Based on those, sub-questions 2 - 4 are motivated.

2.4.1. Decision-support for policy-making

Policies are the most commonly modeled institutions in the existing literature. In this subsection, we examine the relevant papers (shown in Table 2.1) from the following three perspectives: Which modeling typologies are used? What are the policies? How are they modeled?

Table 2.1: Summary of the papers that focus on modeling policies.

Institutions (what)					Optimization models (how)		Paper
Level				Description of the institutions	Typology	Modeling of the institutions	
1	2	3	4				
X	X	X		Conflicting and non-commensurate policies	MOO	MOO	[34]
	X	X	X	Energy management policies (demand projections, population growth, end-use consumption reductions, and solar energy adoptions)	ESOM	Parameter-based scenario analysis	[35]
X	X	X		National energy strategies (energy efficiency measures, different technologies, and carbon taxes)	ESOM	Constraint-based and parameter-based scenario analysis	[36]
	X	X	X	Electrification policies and carbon policies	ESOM	Explicit constraints and sensitivity analysis	[37]
	X	X	X	Policy measures such as energy taxes and constraints for the amounts of emissions or energy resources	ESOM	Constraint-based scenario analysis	[38]
	X	X	X	Subsidy policies	ESOM	Parameter-based scenario analysis	[39]
	X	X	X	Carbon and local pollutant emission taxes	ESOM	Objective-based and parameter-based scenario analysis	[40]
	X	X	X	Policy uncertainties of carbon taxes and power substitution policies	ESOM	Constraint-based and parameter-based scenario analysis	[41]
X	X	X	X	Carbon subsidies and risk preferences	ESOM	Objective function and parameter-based scenario analysis	[42]
	X	X	X	Emission trading system	ESOM	Parameter-based scenario analysis	[43]
		X	X	Green certificate market	ESOM	Parameter-based scenario analysis	[44]
	X	X	X	Carbon emissions trading and renewable energy quota mechanisms	ESOM	Objective-based scenario analysis	[45]
	X	X	X	Carbon mitigation policies	ESOM	Constraint-based scenario analysis	[46]
	X	X	X	RES policies	ESOM	Constraint-based scenario analysis	[17]
X	X	X	X	Carbon policies and public acceptance of onshore wind	ESOM	Sensitivity analysis related to carbon constraint and onshore wind potential constraint	[47]
	X	X	X	Policy goals (renewable portfolio standards and carbon caps)	ESOM	Constraint-based scenario analysis	[48]
	X	X	X	Policy constraints such as carbon cap, carbon price, and renewable portfolio standards	ESOM	Sensitivity analysis	[49]
X	X	X	X	Sustainability regulations and policies (carbon emissions, social acceptance policy, , and noise emissions policy)	ESOM	Objective function and parameter-based scenario analysis	[50]

From the typology perspective, most of the policies are modeled using ESOM. Nevertheless, MOO is sometimes used as well. Oliveira and Antunes (2011) presented a multi-objective linear programming model to evaluate distinct and non-commensurate policies for energy, environmental, economic, and social issues [34].

The modeled policies include general energy management policies, renewable energy targets, carbon taxes, RES subsidies, and market instruments. Furthermore, certain types of policies are often modeled in a specific way, i.e., as parameters, constraints, or objective functions.

When a policy is modeled as a parameter, it means that the model's input data is a result of a policy instrument. An illustrative example would be a national policy on building energy efficiency that declines future energy demands, which are parameters of the model. Such general energy management policies are found in [35]–[37], which are related to demand growth, population growth, efficiency, electrification, promotion of RES technologies, etc. In addition, the effects of carbon taxes or RES subsidies are often evaluated as parameters of the optimization as well, see [36], [38]–[42]. In [43]–[45], topics such as emission trading, and renewable or green certificate market have been studied. Moreover, policies can also be modeled as constraints. On the one hand, the majority of the papers use an exogenous parameter in the constraints, e.g., a RES target or a carbon cap as in [17], [46]–[49]. On the other hand, an explicit constraint is sometimes used. This means that the constraint represents a particular policy instead of a parameter in the constraint. Musselman et al. (2021) analyzed the impacts of various electrification policies on the power system expansion in Sub-Saharan Africa by explicitly modeling the policies as constraints [37]. The above approaches of modeling policies as either constraints or parameters often require a combination of scenario analysis and sensitivity studies. Another way to consider policies is to model them in the objective function, see [40], [42], [45], [50]. Quiroga, Sauma, and Pozo (2019) analyzed carbon and pollutant taxes under five policy-relevant scenarios where global and local pollutant emissions were considered. The objective functions and the taxes were modified in each scenario to reflect different policies [40]. Ju et al. (2016) proposed a planning model for the Chinese power system taking into account two policy instruments, carbon emissions trading, and the renewable energy quota mechanism. Different objective functions were constructed to include these policies whose effects were evaluated in the case studies [45].

In summary, to align with the three perspectives posed at the beginning, we found research potential in the following aspects. First, other modeling typologies than ESOM should be further investigated, e.g., using MOO models. Second, although parameters and constraints are commonly used to evaluate policies, it is not common to model them in objective functions and even as decision variables, and thus, doing so might open up new research possibilities. Meanwhile, research efforts are needed from the policy side, which is practically relevant. In particular, spatial issues are high on the public agenda since wind turbines take up land, which causes both land-use conflicts and social acceptance issues [50], leading to delays in the energy transition. The study of Schlachtberger et al. (2017) gives a good starting point to delve into this issue, where they studied the pan-European power system investment and modeled public acceptance for onshore wind by its energy potentials [47]. Nevertheless, the spatial issues are still largely underexposed in existing studies, especially in the way that renewable energy potentials are related to spatial policies. In Chapter 3, we will deal with the spatial issue with sub-question 2: "*How can renewable energy potentials that consider physical constraints and spatial policies be included in energy system optimization models?*".

2.4.2. Towards multi-actor multi-objective decision-making: combination of methods

All models are ultimately used by people, in our case, to support investment decision-making. While cost is often considered the only objective to simplify the model, there are other objectives for various actors that are modeled by the following approaches.

The first and the most straightforward approach is to include more objectives (also referred to as preferences, interests, or indicators in the literature) in optimization models. For this purpose, MOO is often used as in [51]–[53]. In addition, ESOM can also be utilized by constructing and evaluating different single-objective functions. Rodgers et al. (2018) used a simulation-based optimization approach for optimal energy system planning. Health damages were quantified by using a surrogate cost function in the objective as well as the minimization of social damages of emissions was considered [54]. Tash, Ahanchian, and Fahl (2019) addressed the heterogeneity in the investment decisions of actors using an energy system optimization model [55]. The actors were represented by their main economic features regarding wind and solar PV.

In addition to optimizing for different objectives, these objectives need to be associated with stakeholders' perceptions. Due to different weighing of the objectives in people's minds, the optimal energy system planning may vary for different actors given the same outcome objectives. Multi-criteria decision-making (MCDM) is a decision-making technique that is commonly combined with optimization models. The principle is that after optimal results have been generated, MCDM is used to evaluate the results based on the stakeholders' interests. Both ESOM [56]–[58] and MOO models [59] can be used as long as alternative solutions are generated so that afterward, MCDM can be used to rank the alternatives.

Another line of research to generate alternatives is the modeling to generate alternatives (MGA) approach. Sometimes the optimal solutions are not desired, whereas a sub-optimal solution may be preferred due to e.g., social acceptance or reliability considerations. MGA is a powerful tool for producing near-optimal solutions in the decision space. Nacken et al. (2019) highlighted the need for the near-optimal decision space generated by an ESOM. They illustrated and explained the transmission expansions to carry out the generation and the visualization of such a space to support the decision-making for stakeholders [60]. Jing et al. (2019) combined two optimization methods for energy system design. One is a portfolio constraint-based approach which is inspired by MGA. The other is an eps-constraint method for MOO. This holistic approach was able to provide alternatives in the decision space for decision-makers [61]. Furthermore, game theory can also be combined with ESOM to derive near-optimal solutions. Huang et al. (2018) tackled the stakeholders' decision-making problem by presenting a game analysis combined with an energy system optimization model. The study featured a Nash equilibrium of the stakeholders and simulated their negotiation process [62].

Finally, we recognized another way of modeling in which a participatory approach is used to complement the MCDM technique. An MCDM technique is a mathematical tool

Table 2.2: Summary of the papers that focus on modeling multiple objectives.

Institutions (what)					Optimization models (how)		Paper
Level				Description of the institutions	Typology	Modeling of the institutions	
1	2	3	4				
X		X		Techno-economic-social factors	MOO	Various objectives were considered simultaneously.	[51]
X	X	X		Costs, emissions, and the diversification of the generation mix	MOO	Various objectives were considered simutaneously.	[52]
X		X		Socio-techno-economic design (six objectives)	MOO	Various objectives were considered simutaneously.	[53]
X		X		Health and societal damages	ESOM	Various objectives were evaluated by modifying the objective function.	[54]
X	X	X		Heterogeneity of the investment decisions of actors and carbon taxes and RES targets	ESOM	Actors were represented by their main economic features regarding wind and solar PV.	[55]
X		X		Stakeholders' preferences	ESOM	MCDM was used.	[56]
X		X		Total annualized cost, CO2 emissions, and grid dependence	ESOM	Multi-criteria optimization strategy was used.	[57]
X		X		Several technological, economic, and environmental criteria	MOO	MCDM was used.	[58]
X		X		Conflicting objectives with fuzzy weights of stakeholders	MOO	MCDM was used.	[59]
X		X		Possible energy system designs favored by different stakeholders	ESOM	Near-optimal decision space was explored using MGA.	[60]
X		X		Decision-makers' preferences on certain technology	MOO	A portfolio constraint-based approach and a MOO model was combined.	[61]
X		X		Different interests of stakeholders and their interactive decision-making behaviors	ESOM, EM	An optimization model was combined with a game analysis.	[62]
X		X		Economic sustainability, environmental sustainability, and local energy autonomy	ESOM	MCDM was complemented by a participatory approach.	[63]
X		X		Stakeholder inputs that define scenarios and review results	ESOM	MCDM was combined with a participatory approach.	[64]
X		X		Citizens' values	MOO	A participatory approach was used.	[65]

to formalize the decision-making, which, eventually, needs to be verified and conducted by humans. A participatory approach focuses on human involvement in the planning process with the support of mathematical tools. Workshops, surveys, and interviews are usually used to ensure that the results generated from the mathematical tools are understandable and acceptable to the stakeholders. McKenna et al. (2018) presented an integrated participatory approach for local energy planning. One of the novelties of this study lies in the combination of methods to highlight different values in the energy system, including economic sustainability, environmental sustainability, and local energy autonomy. An energy system model with MCDM was used in stakeholder workshops to provide alternatives for energy system planning [63]. Simoes et al. (2019) presented an approach for holistic decision-support of energy system modeling. An energy system model was combined with stakeholder input using MCDM to critically select scenarios and review results [64]. Hori et al. (2020) presented a co-creative design method to support energy systems planning. This method includes a participatory development of the local energy vision, a MOO, and an optimization process to account for the preferences of residents [65].

Based on the above-reviewed papers, we found that for the decision-support in real life, studies with different levels of complexity were conducted, which were often supported by combining optimization models with different methods. In terms of the used optimization models, both ESOM and MOO have accounted for stakeholders' preferences, while MOO is the mainstream in the reviewed literature. Apart from the alternatives generated directly from these two models, MGA is also used to provide near-optimal solutions. Afterward, MCDM is the dominant decision-making approach supported by a qualitative participatory approach for citizen engagements.

Besides these general trends, different application areas need different approaches. The existing studies shed light on the importance and usefulness of combining these methods, and therefore, future studies can merge from new user cases following these directions. For example, when a near-optimal solution is desired for different stakeholders, MOO could complement MGA to explore the near-optimal space. Another promising direction is the combination of MOO with MCDM. Various MCDM techniques are suitable for different applications, e.g., fuzzy techniques when the decision-makers are unsure about the weights of the preferences or other techniques for collective decision-making. In Chapter 4, we present an approach for collective decision-making in energy system planning which motivates sub-question 3: *"How can collective energy system planning be modeled using multi-objective optimization?"*.

2.4.3. The need for reflections and innovations beyond market equilibrium

Table 2.3 summarizes the papers that focus on modeling the electricity markets. This subsection and the next one will discuss these papers.

The methods adopted by the reviewed literature heavily rely on the assumptions regarding the sequence of generation and network investments. The planning of transmission networks has traditionally followed the logic of "generation first" as in [67]–[69]. However, other sequences of decision-making might prevail in some cases, e.g., see [70], [71]. Especially because of the rapid development of RES, the transmission network needs to be planned more proactively compared to the past taking into account the possible

Table 2.3: Summary of the papers that focus on modeling the electricity market.

Institutions (what)					Optimization models (how)		Paper
Level 1	Level 2	Level 3	Level 4	Description of the institutions	Typology	Modeling of the institutions	
		X	X	Market-based coordination of generation expansion and transmission expansion	EM	Cournot model	[66]
		X	X	Market-based coordination of generation expansion and transmission expansion	EM and ESOM	Bi-level optimization and integrated planning	[67]
		X	X	Market-based coordination of transmission expansion considering generation expansion	EM	Multi-level optimization	[68]
		X	X	Market-based coordination of generation expansion and transmission expansion	EM	Bi-level optimization	[69]
		X	X	Market-based coordination of generation expansion and transmission expansion	EM	Iterations to reach the equilibrium	[70]
		X	X	Market-based coordination of generation expansion and transmission expansion	ESOM	Integrated planning	[71]
X		X	X	Separate planning models of different stakeholders	EM	Multi-agent game	[72]
X		X	X	Market-based coordination in investment decision-making and different preferences of agents	EM	Multi-agent system and multi-level optimization	[73]
X		X	X	Market-based coordination of generation expansion and transmission expansion with multiple objectives for transmission expansion	EM	Multi-level optimization and MOO	[74]
		X	X	Market-based coordination of generation expansion and transmission expansion	EM	Simulation of the decision-making behaviors of individual market participants and the ISO	[75]
		X	X	Market-based coordination of generation expansion	EM	Bi-level optimization	[76]
		X	X	Energy system features such as estimation of the rated power of a particular power generating unit, grid constraints, detailed economic analyses, and consideration of rules of electricity market and power system operation	ESOM	Three formulations of binary variables	[77]
		X	X	Power pricing	ESOM	Power flow model	[78]
		X	X	Commerical bilateral energy trades	ESOM	Flow-based market coupling	[79]
	X	X	X	Market options and efficiency and sustainability policies	ESOM	Decision variables and constraints	[80]

increases in capacity and locations. As an example, the Netherlands plans to invest heavily in RES, and the transmission system operator is actively involved. A co-planning process would ensure the least-cost outcome to the largest extent. Future studies on different sequences of investment decision-making, i.e., concurrent, generation first, or network first, will undoubtedly contribute to the optimal co-investments for the future energy system.

In addition to the sequence of decision-making, modeling electricity markets also concern a variety of optimization-based methods and solution techniques. The reviewed papers feature multi-agent systems, multi-level optimization, MOO, simulation-based optimization, decomposition techniques, and co-evolutionary algorithms, as briefly discussed below.

In a multi-agent system, various stakeholders are described as agents and exchange information. Lei et al. (2021) considered different stakeholders, including distributed generation investment operators, power grid investment operators, and power users, in their work and analyzed their game behaviors in a planning model [72]. Multi-level optimization highlights the order of decision-making when the timing matters. Mishra et al. (2019) [73] proposed a generation and transmission co-planning approach for coordinated investment decision-making using a multi-agent system. A multi-level optimization method was used, where the Nash equilibrium was modeled for the market-clearing on the operational level. MOO models often capture the interests of actors. Javadi and Saniei (2012) [74] used a game theory-based model to determine the generation and transmission expansion planning. A mixed-integer non-linear programming optimization determined the Nash equilibrium. Moreover, the independent system operator considered multiple objectives, including cost, social welfare, and reliability. Simulation-based optimization is used when the investment timing is to be considered or when there is a stopping criterion for simulation. Decomposition and co-evolutionary algorithms are both solution techniques for large-scale optimization problems when the problems are computationally hard to solve or even non-tractable. Roh, Shahidehpour, and Wu (2009) presented a coordinated expansion planning model for generation and transmission under a competitive market environment. The decision-making behavior of individual market participants and the ISO was simulated. The equilibrium state was determined when the ISO terminated the iterative simulation process. Decomposition techniques were deployed to solve the problem [75]. Wang et al. (2009) proposed a co-evolutionary algorithm for the Nash equilibrium among individual generating companies by an incomplete information game model. The equilibrium was obtained based on the market-clearing conditions of the ISO [76]. Co-evolutionary algorithms can ensure fast solutions. However, the global optimum cannot be guaranteed.

2.4.4. Lack of studies on operational details

Traditional optimization-based investment modeling has a long time horizon from years to decades, and therefore, large amounts of operational details are ignored. These operational details cover the real-time allocation of resources that happens within seconds and include the market-clearing process, which often has a time interval of one hour.

Nevertheless, some papers studied the details of the markets, from technical details to economic considerations. Lyzwa, Wierzbowski, and Olek (2015) derived an optimal energy mix that is based on three formulations of binary variables using mixed-integer linear programming [77]. This paper presented detailed mathematical formulations to account for sophisticated energy system features such as estimation of the rated power of a particular power generating unit, grid constraints, detailed economic analyses, and consideration of electricity market rules and power system operation. López-Ramos, Nasini, and Sayed (2020) proposed a planning model for power pricing and grid investment [78]. This model went beyond the literature on power flow optimization by investigating the substitutability pattern between pricing and expansion. An extended power flow model was linearized, and the bounds to the optimal operator profit were developed and used in a mixed-integer linear programming model. Hagspiel et al. (2014) presented a method for the joint optimization of generation and transmission investment [79]. Flow-based market coupling was considered by an algorithm based on the linear representation of the physical flow laws. Power transfer distribution factors were iteratively updated to ensure the correctness of the physics regarding grids.

Despite some papers like those reviewed, the operational details, including power flow calculation, power pricing, and inclusion of different markets, are often not modeled in planning models. The reason might be two-fold. On the one hand, studying these details is often out of the scope of investment models since investment models feature long-term horizons. On the other hand, on a practical note, including these would make the model size even larger and thus harder to solve. Consequently, there is a lack of references on how to integrate those aspects in investment models and their effects. However, studies in this direction are relevant both from a modeling perspective and a policy-making perspective.

It is important to find a balance between computational tractability and the level of detail. Different market options, as well as efficiency and sustainability policies, were investigated using an ESOM in [80]. However, there is no existing work focusing on integrating multiple markets into investment models. In particular, the role of bilateral trading is often overlooked. To deal with this problem, we model bilateral trading in Chapter 5 with sub-question 4: *"How can decentralized planning processes considering bilateral trading be modeled?"*.

2.5. Conclusions

The energy system is a socio-technical system that consists of several intertwined subsystems. The realization of techno-economic optimal energy system design is inevitably hindered by the social aspects that co-exist. While optimization models are widely used for energy system planning from the technical subsystem viewpoint, their interlink with the institutional subsystem is largely underexposed in the existing literature. Improved optimization models incorporating institutions would be more relevant than techno-economic optimization models alone.

In this chapter, we started with a socio-technical system description of the energy system. Williamson's four-level institutional analysis framework has been used to assess the relevant institutions systematically. We also presented three optimization models in their basic forms. These optimization models will be enriched with institutions in the following chapters.

By performing a literature review and scrutinizing the existing literature, we highlighted the following research gaps which motivate our sub-questions:

- The spatial issues of renewables received insufficient research interest in existing studies. Sub-question 2 *"How can renewable energy potentials that consider physical constraints and spatial policies be included in energy system optimization models"* deals with this issue and is answered in Chapter 3.
- MOO can help with actors' decision-making for energy system planning. However, there is not yet a method for collective decision-making. Sub-question 3 *"How can collective energy system planning be modeled using multi-objective optimization?"* addresses this research gap which is then answered in Chapter 4.
- The integration of different market designs in investment models, especially when considering bilateral trading, is necessary. Sub-question 4 *"How can decentralized planning processes considering bilateral trading be modeled?"* discusses this problem, and Chapter 5 provides an answer.

3

Spatially explicit model

3.1. Introduction

3.1.1. Background

The utilization of variable renewable energy sources (VRES) is growing rapidly. Compared to traditional sources of electricity generation, several factors make them difficult to integrate into the power system. First of all, the production of wind energy and solar energy is variable and location-specific because it is driven by weather conditions. Secondly, wind turbines and solar panels are characterized by more intensive land-use compared to conventional power plants. As the share of renewable energy sources is expected to grow significantly in the coming decades, it becomes more important to consider spatial-temporal details of VRES, such as land-use and location-specific production profiles, as emphasized by Pfenninger, Hawkes, and Keirstead (2014) [18] and DeCarolis et al. (2017) [81]. This holds especially for densely populated areas like the Netherlands or areas with abundant nature reserves.

Although wind turbine monopiles do not occupy much land themselves, the areas between the turbines are also affected. Such indirect land-use, i.e., the land-use that does not compete with the primary use of land, causes problems for people. In particular, due to aesthetic reasons or noise pollution, social resistance is a problem for the development of VRES all across the world and indeed, the scientific community has paid attention to it. For example, the public resistance against new energy developments in Canada was investigated by Shaw et al. (2015) [82]. Enevoldsen and Sovacool (2016) [83] studied the methods to increase the social acceptance of wind energy in France. Similarly, utility-scale solar parks cause problems in direct land-use, i.e., the land-use that competes with other usages of land. These barriers hinder the development of VRES, and thus the importance of land-use is emphasized in the following literature. For example, Van Haaren and

This chapter was published as N. Wang, R. A. Verzijlbergh, P. W. Heijnen, and P. M. Herder, "A spatially explicit planning approach for power systems with a high share of renewable energy sources", *Applied Energy*, vol.260, 2020. The first author of the paper, also the author of this thesis, conceptualized and conducted the research. The other authors performed an advisory role.

Fthenakis (2011) [84] performed a study on the locations of wind farms based on land examination. Shmelev and Van Den Bergh (2016) [85] conducted a literature review on the optimal diversity of renewable energy alternatives, where land-use is argued as a key dimension. Rauner, Eichhorn, and Thrän (2016) [86] did a land-use analysis for the German power system. Furthermore, a multi-criteria analysis with a focus on land-use to identify the high-priority locations for VRES was given for the case of Bangladesh [87].

In recent years, a large body of scientific literature on the modeling of power systems with high shares of renewable energy sources (RES) has emerged, see e.g., the review of [88]. Optimization models with a focus on investment form a significant part of the available tools. In such models, it is usually the objective to find a minimum-cost power system, given time-series of wind and solar production. These optimization models often use location-specific VRES profiles, but most of them implicitly assume unlimited land availability. As discussed, the land-use of VRES is crucial. However, this unlimited land assumption neglects it and would lead to more optimistic results than what is feasible in reality. Nevertheless, there exists literature that discusses the land-use of VRES and the location-specific VRES production profiles as limiting factors in the optimization problem.

An optimization model for a regional energy system was proposed by Arnette and Zobel (2012) [89]. As data inputs for their model, they pre-selected suitable site locations for wind and solar energy using an existing geographic information system model that examines land cover characteristics. Hong, Bradshaw, and Brook (2015) [90] considered land-use as a surrogate for environmental impacts and minimized global land-use for future energy scenarios. Pfenninger and Keirstead (2015) [91] used an optimization model to study the power system scenarios of Great Britain. In this model, they provided a spatially explicit way to deal with the location-specific VRES data. Similarly, an Australian case study used location-specific VRES data and location-specific maximum VRES capacities as data inputs [92]. In addition, the maximum RES capacities for European countries based on land cover characteristics were used in the European power system optimization model PyPSA-Eur [93].

In the studies mentioned above, the land-use and the production profiles of VRES were considered either location-specifically or in an aggregated way. The location-specific data was either obtained from existing studies or was made for the specific case study, which makes it irrelevant for new cases. These are understandable choices since these studies focused on optimization modeling and therefore left the detailed assessments of the land-use of VRES and the necessary steps to obtain location-specific data out of scope.

Based on our literature review, we conclude that the land-use aspects of VRES in optimization models are still not fully appreciated. The comprehensive approach that considers land-use of VRES by assessing land cover data to obtain location-specific VRES potentials is often seen in other fields of research than optimization studies and is usually country-specific. For example, some studies use geographic information systems to assess the land-use of VRES to estimate the VRES potentials, see the case of Spain [94], Turkey [95], Germany [96], Switzerland [97], Finland [98] and India [99]. These studies focus on the detailed assessment of land-use of VRES. Similarly, another line of research concentrates on various metrics of VRES potentials such as capacity factor, maximum possible capacity, annual potential generated energy, and spatial-temporal correlation. Case studies are seen for China [100], and for the globe [101].

This literature review shows that although spatial aspects of VRES are drawing attention in scientific communities, very few studies performed detailed assessments of land-use to obtain the VRES potential in optimization models for power systems with a high share of RES. Since this type of work often belongs to different fields (land cover assessment, VRES potential estimation, and high-RES power system planning models), the workflow that links those fields is desired but is rarely seen [102]. In other words, we find that an integrated and spatially explicit approach is needed on how the location-specific land-use of VRES should be assessed, how that is matched to the location-specific VRES data, and how those are related to the optimization model.

3.1.2. Contribution and audience of the chapter

This chapter proposes a spatially explicit planning approach in optimization models for power systems with a high share of RES. Its objective is to incorporate the location-specific land-use of VRES and the location-specific VRES production profiles in high-RES power system planning models in a systematic way. The contributions of this chapter and the possible use of the approach are as follows:

1. The chapter links three different scientific bodies of knowledge: data-driven land cover assessment, VRES potential estimation, and power system planning models. This approach allows to improve the traditional way of energy system planning modeling by considering actual location-specific VRES potential as a constraint. With our integrated and generally applicable method, energy system planning researchers can exploit the strength of the other two fields instead of resorting to simplistic constraints or neglecting land-use altogether.

2. The approach entails all the necessary steps to systematically consider the location-specific land-use and the location-specific production profiles of VRES in the optimization model. The approach starts from the raw data, including geographical boundary data, land cover data, and VRES data, to the transformation of these data to the inputs of the optimization model, and then to the formulation and the results of the model.

   The approach would be valuable for optimization studies where the published location-specific data on the land-use and the production profile of VRES is not available and where case-specific data has to be compiled.

3. This data-driven approach keeps the spatial explicitness that is in line with the used database. It means that the approach gives full exposure of the land cover characteristics and control of the corresponding area to the user, i.e., the user can identify the land cover in the resolution of the database explicitly, and thus is able to include/exclude the area in various ways. Consequently, the location-specific VRES potential constraints can be changed depending on the desired level of spatial details.

4. Our approach helps to reveal the role of the land-use of VRES on the results of the

power system planning optimization models. This provides a novel way to inspect the sensitivity of the optimization results to location-specific land-use constraints.

This way of sensitivity analysis would give insights to power system modelers and policy-makers. For modelers, the impact of land-use could be quantified by the change in results such as generation mix, the spatial distribution of generation technologies, and the total cost of the system. For example, what is the spatial distribution of the optimized wind turbine locations if a certain type of land cannot be used to build the turbines? For policy-makers, in addition to those results, this method quantifies the geographical distribution of the land-use of VRES, which helps to evaluate the effect of possible spatial policies ex-ante. For instance, where will wind turbines be located, and how much land will they occupy given the policy that they have to be placed at least 2 km from the residents in order to mitigate social resistance? And what are the extra system costs associated with those constraints? These kinds of analyses would not be possible without the spatially explicit planning approach, even for studies where the data has been published.

5. The case study presents the future high-RES energy system scenario for the Netherlands, which gives practical insights to policy-makers and adds to the literature in energy system planning.

3.1.3. Background of the case of the Netherlands

In the Netherlands, policy-makers put the climate agreement into practice by formulating a target amount of RES capacity that needs to be integrated into the current power system. This is done by implementing a country-wide program (Regional Energy Strategies) [103], which divides the country into 30 regions (Figure 3.1) that need to coordinate where to locate the required RES capacity. However, the Netherlands is a densely populated country which makes the placement of wind turbines and solar plants difficult. Therefore, the Netherlands will be used as a case study to show the feasibility and usefulness of our integrated, tripartite approach.

3.1.4. Structure of the chapter

The chapter is organized in the following way. Firstly, Section 3.2 describes the proposed approach which includes the modeling of spatially explicit data and the formulation of the optimization model. Next, Section 4.5 presents the scope and the input data of the case study. In Section 3.4, the land cover assessment is elaborated and the VRES potentials are calculated. Then, Section 3.5 presents and discusses the optimization results. In Section 5.6, conclusions are drawn.

3.2. Proposed approach

Figure 3.2 shows a schematic depiction of our approach. In the following sections, we describe the details of the spatially explicit data modeling and how this is used in the optimization model.

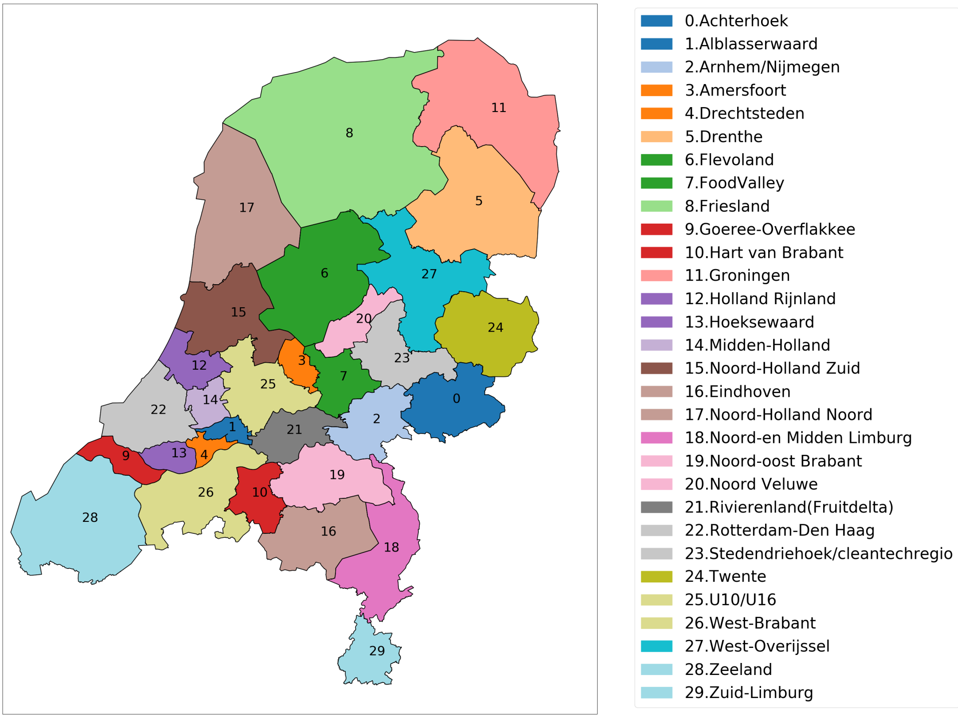

Figure 3.1: 30 regions in the Netherlands.

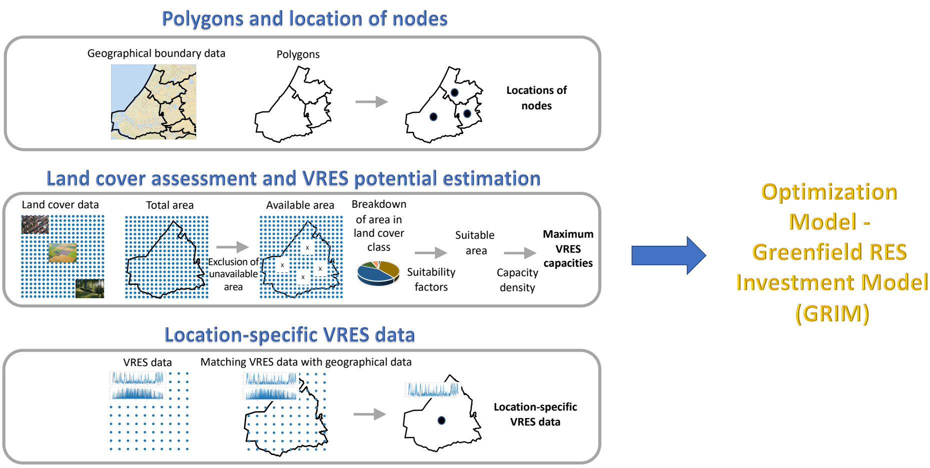

Figure 3.2: Schematic of the approach.

3

3.2.1. Spatially explicit data modeling

The spatially explicit data includes geographical boundary data, land cover data, and VRES data.

Polygons and location of nodes The starting point is a data set of coordinates that represents the geographical boundaries of the interested nodes to be modeled. The data set forms polygons that define the spatial granularity of the model, which can be, for example, an entire country or group of countries in a European power system model, or a municipality or a neighborhood in a local power system model. The centroids of the polygons are the locations of the nodes n in the optimization model.

Starting from polygons is usually applicable to optimization studies where the results (e.g., the optimized generation capacities) at the nodes n are the focus of the chapter. The OpenStreetMap project [104] is a commonly-used source to find the polygons, when, for example, only the names of the municipalities are available.

Land cover assessment and VRES potential estimation After obtaining the polygons, the land inside the polygon needs to be assessed in order to check how much land is available and suitable for VRES development. This is done by performing a land cover assessment.

The land cover assessment is an indispensable step in this approach since doing the assessment essentially implies that each area with a certain land cover (see the definition of land cover and the database introduced in the following paragraph) is explicitly identified. Hence, any means of inclusion/exclusion of the identified areas is possible, e.g., full exclusion, partial exclusion, exclusion in radius, etc. Several exemplary exclusions are explained below and will be illustrated in Section 3.4.1.

The land cover represents the physical material on the surface of the land, which is classified into five major categories in Corine Land Cover (CLC) database [105]. These are artificial surfaces, agricultural areas, forest and semi-natural areas, wetlands, and water bodies. Those categories are further divided into a total of 44 classes. The CLC database has a grid size of 100 m by 100 m. Not all the land cover is suitable for VRES development, so two steps will be taken in order to find suitable land.

The first step is to exclude the land that is not available for VRES development physically, which is an example of fully excluding. For instance, for onshore wind turbines, the CLC classes that are considered unavailable are urban fabrics, airports, rice fields, water bodies, etc. On the other hand, national parks also need to be excluded. However, nature reserves are not a class in CLC, but they can sometimes be found in the form of polygons. These polygons, together with the area in unavailable land cover classes, are excluded. This exclusion process can be done using e.g., Python NumPy masked arrays.

Next, the remaining land is considered suitable to some degree and will thus be partially excluded based on its land cover classes. Since the resolution of the land cover data is not fine enough to assess the land cover on the scale of individual wind turbines and solar panels, it is common in the literature to assign suitability factors $\alpha_{i,c}$ to each land cover class [96]. The value of the suitability factor depends on technology i and Corine Land Cover class c. After the assignment of suitability factors, the suitable areas for technology i at location n for CLC class c are obtained (see (3.1)).

$$S_{i,n,c} = S_{\text{unit}} B_{n,c} \alpha_{i,c}, \forall i \in \text{VRES}, \forall n \in N, \forall c \in \text{CLC} \quad (3.1)$$

where i is either wind or solar energy, $B_{n,c}$ is the number of grid cells (100 m*100 m) at node n for CLC class c, S_{unit} is the area of a grid cell, $S_{\text{unit}} = 0.01\,\text{km}^2$.

Since some of the unavailable lands are selected based on the CLC classes, in principle, in the first step, a suitability factor of zero could be assigned. However, the separation of the two selection steps will explicitly give two different ways to adapt the approach to specific cases. In the first step, the exclusion of unavailable land can be based on any land cover, e.g., residential areas with social resistance to VRES technologies can be excluded, or even a settlement area in the radius of certain CLC classes can be excluded as well (see an example in Section 3.4.1). In the second step, suitability factors can be changed depending on the local surface conditions, e.g., if the trees in the forest area are high, or the slope of the ground is large, these conditions would make the suitability factors even lower. In this way, by changing the exclusion criteria and the suitability factors, the approach provides a flexible way to use VRES potential constraints based on location-specific conditions, such as local surface conditions, social acceptance, and local spatial policies.

To quantify the land requirement of VRES technologies, capacity density, defined as the maximum potential installed capacity per unit area, needs to be incorporated into the calculation. The maximum VRES capacity is calculated according to Equation (3.2):

$$K_{i,n}^{\max} = \sum_{c \in \text{CLC}} S_{i,n,c} \beta_i, \forall i \in \text{VRES}, \forall n \in N \quad (3.2)$$

where β_i is capacity density, which is $5\,\text{MW/km}^2$ for wind [106], and $30\,\text{MW/km}^2$ for solar [107] in this chapter.

Location-specific VRES data After specifying the location of nodes (polygons), the VRES data that determines wind and solar energy production at the same spatial resolution needs to be obtained. This location-specific VRES data is defined as the normalized VRES energy output for VRES technology i at node n at time step t, which lies in the range of 0 to 1, and will be referred to as capacity factors $\eta_{i,n,t}$ in Equation (3.5) of the optimization model.

The available VRES data is usually wind speed at hub height and solar irradiation data from meteorological measurements or reanalysis data sets, then the data will be transformed into VRES capacity factors $\eta_{i,n,t}$ [108].

The location of the VRES data either corresponds to the location of the meteorological stations or at the grid points of the reanalysis data that is being used. In the next steps of the proposed approach, we resolve the geographical inconsistency between the VRES data and the polygons n.

The first step is to find all the VRES data points inside the polygon. If there is at least one data point inside the polygon, we then take the mean of the data at those points to be the VRES data for the node n. However, if there are no data points inside the polygon, the VRES data at node n will be the linear interpolation of the data at the surrounding points.

In theory, it is possible to obtain the VRES data sets at each node n, e.g., in the work of [108]. However, it is important to understand that the VRES generation can be anywhere in the polygon other than at node n. For wind and solar energy, the data at node n is most of the time different from the averaged data in the polygon. Therefore, we estimate the VRES data in the whole polygon instead of only at the centroid.

3.2.2. Optimization modeling

In the next section, we present our optimization model, which we labeled the Greenfield Renewables Investment Model (GRIM). This model is a linear programming model that minimizes the total annualized cost of investment and operation. This optimization model has a set of hypotheses, and hence it is important to clarify the scope and the usage of this model before presenting the detailed formulations.

Scope and usage of the model The main contribution of the approach is to systematically find the location-specific maximum potential VRES capacities and then consider them in the power system planning optimization model. In this way, the effects of the location-specific land-use limit of VRES on power system planning can be revealed. In order to focus the reader on this main contribution, the formulation of the maximum VRES potential constraints will be discussed in detail. Instrumentally, the rest of the power system planning model will be simplified.

The presented model aims to include only the essential components of the state-of-the-art power system investment optimization models (e.g., spatial-temporal RES production profiles, energy storage, and network flows), and it is meant to showcase how the maximum VRES potential constraints can be linked to this family of optimization models.

For instance, GRIM assumes there is no existing power generation, no storage, and no networks. This assumption is referred to in the word greenfield in the acronym. In addition, real network topology, alternative current network flow formulation, comprehensive inclusion of different generation and storage technologies, ancillary services, power system stabilities, etc. are not taken into account. These aspects have been extensively discussed in power system models and are thus not the focus of this work. Nevertheless, it is straightforward to apply the proposed method and fine-tune the optimization model to other detailed models of readers' interest. Furthermore, the model disregards carbon pricing and does not take into account opportunity cost or loss of revenues when certain land areas are re-purposed, e.g., when agricultural land is changed into solar parks or wind farms.

Objective function The objective function is to minimize total annualized cost consisting of capital expenditure (CapEx) cost of generation and storage technologies C_i, CapEx cost of networks $C_{n,m}$, fixed operation & maintenance (FOM) costs a_i and variable operation & maintenance (VOM) costs b_i. All costs are annualized by an annuity factor A_i (for generation and storage technologies) or $A_{n,m}$ (for networks). The network cost depends on the length $\delta_{n,m}$, the capacity $K_{n,m}$ of the line, and the factor f which will be explained in Section 3.2.2.

$$\text{Min.} \sum_{i\in(G+SC+S)}\sum_{n\in N}\frac{C_iK_{i,n}}{A_i}+\sum_{(n,m)\in E}\frac{f\delta_{n,m}C_{n,m}K_{n,m}}{A_{n,m}}+\sum_{i\in(G+SC)}\sum_{n\in N}a_iK_{i,n} + \sum_{t\in T}\sum_{i\in G}\sum_{n\in N}b_iP_{i,n,t} \tag{3.3}$$

The decision variables are the capacity of generation and storage units $K_{i,n}$ of technology i at node n, the network capacity $K_{n,m}$ of line (n,m), the energy production $P_{i,n,t}$ of generation technology i at node n at time t, the energy charging of storage $CP_{i,n,t}$ and the energy discharging of storage $DP_{i,n,t}$ of storage technology i at node n at time t, the energy export $P^{\text{export}}_{n,m}$ and the energy import $P^{\text{import}}_{n,m}$ from node n to node m at time t.

The optimization model has a set of constraints, as described below.

Energy balance constraints The energy supply has to match the demand at every time step. This means the energy that comes into the node, is equal to the energy that flows out of the node at all time steps. Therefore, at every time step, the sum of the demand, the energy export, and the energy charging of storage are equal to the sum of the energy production, the energy import, and the energy discharging of storage. $\tau_{n,m}$ is used to account for the power loss in the lines. More discussions of network modeling are given in Section 3.2.2.

$$\begin{aligned} &D_{n,t}+\sum_{(n,m)\in E}P^{\text{export}}_{n,m,t}+\sum_{i\in SC}CP_{i,n,t} \\ &=\sum_{i\in G}P_{i,n,t}+\sum_{(n,m)\in E}(1-\tau_{n,m})P^{\text{import}}_{n,m,t}+\sum_{i\in SC}DP_{i,n,t}, \forall n\in N, \forall t\in T \end{aligned} \tag{3.4}$$

Energy production constraints For conventional generation and biomass plants, the energy production per time step cannot exceed the installed capacity, thus $\eta_{i,n,t}=1$. For wind and solar energy, the energy output per time step depends on the installed capacity and the capacity factor $\eta_{i,n,t}$ that reflects the meteorological conditions (see Section 3.2.1 for modeling of the capacity factor).

$$P_{i,n,t}\le\eta_{i,n,t}K_{i,n}, \forall i\in G, \forall n\in N, \forall t\in T \tag{3.5}$$

VRES potential constraints The upper bound of the installed capacities $K^{\max}_{i,n}$ for wind turbines and solar panels are given.

$$K_{i,n}\le K^{\max}_{i,n}, \forall n\in N, \forall i\in \text{VRES} \tag{3.6}$$

$K^{\max}_{i,n}$ is derived using Equation (3.2) and the process of obtaining $K^{\max}_{i,n}$ is described in Section 3.2.1.

For conventional generation technologies and biomass, the maximum potential installed capacity is not considered as they are not as land-intensive as wind and solar energy.

Network constraints The network is modeled as a fully-controllable direct current network [47], and thus only active power is modeled. The energy import and export cannot exceed the thermal limits of the line.

$$0 \leq P_{n,m,t}^{\text{import}}, P_{n,m,t}^{\text{export}} \leq K_{n,m}, \forall (n,m) \in E, \forall t \in T \tag{3.7}$$

In this way, energy conservation is preserved, however, interested modelers could add other constraints by ensuring e.g., voltage conservation.

This chapter follows the modeling approach of [47] by firstly increasing the line capacity to 1.5 times to fulfill the $n-1$ security requirements. This increase in line capacity will influence the network cost in the objective function and the optimized network capacity. Secondly, in reality, the network length $\delta_{n,m}$ may not be the shortest length between nodes, due to physical barriers such as buildings, protected areas. The land cover assessment does not take into account the possible detour of the network, hence a factor of 25% is added to the line length between two nodes. These effects are modeled by adding a factor f ($f = 1.5 * 1.25$) to the objective function.

Storage constraints The stored energy at time t is equal to the sum of the stored energy at time $t-1$ and the net charging energy. While charging/discharging, losses are included by incorporating the efficiency coefficients.

$$SP_{i,n,t} = SP_{i,n,t-1} + \eta_i^{in} CP_{i,n,t} - \frac{1}{\eta_i^{\text{out}}} DP_{i,n,t}, \forall i \in S, \forall n \in N, \forall t \in T \tag{3.8}$$

The energy charging/discharging per time step cannot exceed the capacity of the storage conversion, and the stored energy per time step cannot exceed the energy content of the storage unit.

$$SP_{i,n,t} \leq K_{i,n}, \forall i \in S, \forall n \in N, \forall t \in T \tag{3.9}$$

$$DP_{i,n,t}, CP_{i,n,t} \leq K_{i,n}, \forall i \in SC, \forall n \in N, \forall t \in T \tag{3.10}$$

Besides, since only one year is modeled, the storage is considered to be cyclic. This means, that when t is the first step of the year, $t-1$ becomes the last time step of the year, i.e., Equation (3.8) becomes

$$SP_{i,n,0} = SP_{i,n,t_{\text{end}}} + \eta_i^{\text{in}} CP_{i,n,0} - \frac{1}{\eta_i^{\text{out}}} DP_{i,n,0}, \forall i \in S, \forall n \in N \tag{3.11}$$

RES target constraint A RES target constraint is added to indicate the minimum percentage of RES in total energy production. This RES target is specified by ω, ranging between 0 and 1.

$$\omega \sum_{i \in G} \sum_{n \in N} \sum_{t \in T} P_{i,n,t} \leq \sum_{i \in \text{RES}} \sum_{n \in N} \sum_{t \in T} P_{i,n,t} \tag{3.12}$$

Non-negativity constraints At last, all the decision variables must be equal to or larger than zero.

$$0 \leq K_{i,n}, K_{n,m}, \forall i \in (G + SC), \forall n \in N, \forall (n,m) \in E \tag{3.13}$$

$$0 \leq K_{i,n}, SP_{i,n,t}, CP_{i,n,t}, DP_{i,n,t},, \forall i \in S, \forall n \in N, \forall t \in T \tag{3.14}$$

$$0 \leq P_{i,n,t}, \forall i \in G, \forall n \in N, \forall t \in T \tag{3.15}$$

3.3. Scope and data inputs of the case study

The background of the case study was explained in Section 3.1. This section presents the scope of the case study, the corresponding input data, and how they were modeled as inputs to the optimization model.

3.3.1. Scope of the case study

As explained in Section 3.2.2, the presented model intends to only include the essential components that are typically considered in this family of optimization models. Therefore, the results of this example are meant to illustrate the usage of the approach and to reveal the role of land-use constraints in the power system planning models, given the context of the Netherlands.

3.3.2. Data inputs

The data modeling and the optimization modeling were done using Python. The most used packages in this chapter are NumPy, Pandas, netCDF4, shapely, NetworkX, and Pyomo.

Polygon data The geographical granularity is the 30 regions in the Netherlands. In this case, the regions are not administrative units (e.g., provinces), hence their polygons are not directly available in databases. Therefore, all the municipality polygons were first downloaded from the OpenStreetMap project and were then merged into the desired regions. The result is a Python dictionary with region names as the keys and polygons as the values including longitude and latitude coordinates.

Land cover data The land cover data was obtained from the Corine Land Cover database [105] which has coverage for all the European countries. The suitable areas and the maximum potential installed capacities in each polygon were obtained. This land cover assessment and the calculation of maximum potential installed capacity will be elaborated in Section 3.4.

VRES data The hourly wind speed was taken from the data set downloaded from Royal Netherlands Meteorological Institute [109]. The wind data of CLC classes belonging to water bodies are excluded, as only onshore wind turbines are considered in this chapter (see Section 3.3.2). The wind speed data set contains data for different heights covering the whole of the Netherlands with 2.5 km horizontal resolution. The power curve of Vestas V90 3MW wind turbine was used to convert the wind speed to hourly wind capacity factor, and the wind speed at 80 m was used to match the hub height. Ideally, wind and solar data from the same data source are used. Unfortunately, this data set only has wind speed, so solar data was taken from another data set [108]. The solar data was extracted for each node n (i.e., the centroid of the polygon). The weather data in 2015 was used. In Figure 3.3, the time-series for the region Rotterdam-Den Haag are illustrated.

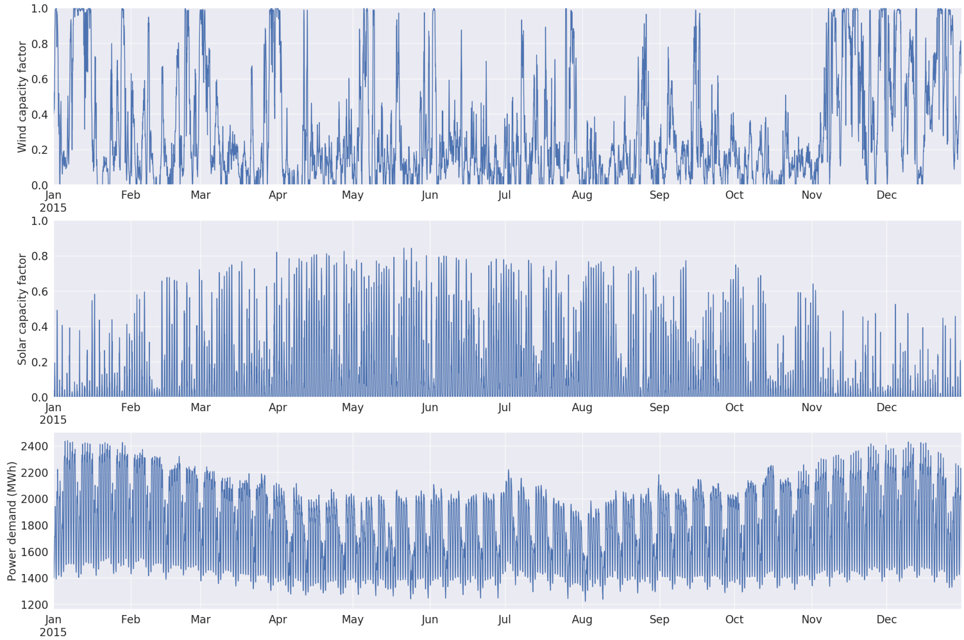

Figure 3.3: Time-series of wind capacity factor, solar capacity factor, and power demand for the region Rotterdam-Den Haag.

Network topology As mentioned in Section 3.2.1, the detailed modeling of the power network is out of the scope of this work. For the purpose of the case study, we assume a meshed network where adjacent polygons are connected.

Demand data The data of hourly power demand for the Netherlands in 2015 (113 TWh) was derived from the European Network of Transmission System Operators for Electricity (ENTSO-E) [110]. The hourly power demands for the 30 regions were scaled according to the population in each region (see Figure 3.6) obtained from the OpenStreetMap project that includes population information. The time-series of power demand in the region Rotterdam-Den Haag is illustrated in Figure 3.3.

Cost parameters The chosen generation technologies are onshore wind turbines, solar PV, biomass plants, coal plants, and CCGT plants. The land and feedstock requirements for biomass are not included. Offshore wind is not included (see discussions in Section

3.5.5). The storage technologies are hydrogen storage and flow battery storage. Pumped hydro storage is not considered due to non-availability in the Netherlands. The discount rate is 5%. The cost parameters are summarized in Table 4.2.

Technology	CapEx (€/kW)	FOM (€/kW/yr)	VOM (€/kWh)	Lifetime(yr)
Onshore wind	1205	45	0.002	25
Solar PV	925	21	0.001	25
Biomass	2640	90	0.0845	33
Coal	1600	28	0.03	42.5
CCGT	800	20	0.046	30
Hydrogen conversion	2400	0,04		
Hydrogen storage	0,06 €/kWh	62% (in/out efficiency)		
Flow battery conversion	650	0.9		
Flow battery storage	450 €/kWh	90% (in/out efficiency)		
Network	10000 €/MW/km	5% 100km (power loss factor)		

Table 3.1: 2050 estimation of cost parameters (based on [111], [112], [113], [114], [47], except for the network cost and power loss factor).

Wind and solar curtailment costs are essentially taken into account because by curtailing, the same investment cost would lead to lower production and hence a higher cost of electricity.

The network cost in our study is relatively high compared to other studies (see e.g., [47], [111], [113], and [114]) due to two reasons. Firstly, according to the 2019 data [115] from network operators in the Netherlands, the network cable cost is 3000 €/MW/km - 50000 €/MW/km. Secondly, the costs related to substations and the distribution network cost are often not included in existing studies. Therefore, the chosen network cost is considered reasonable and even conservative for the Netherlands.

According to [116], for the Netherlands, the transmission and distribution loss factor is 4.77% in 2014. In addition, considering the fact that the lengths of all the network connections in this chapter are less than 100 km, 5%/100 km is used as a typical number representative of the Dutch power networks.

3.4. Modeling of VRES potentials

In this section, the land cover characteristics in the Netherlands will be assessed and the maximum potential installed capacities and the annual capacity factors of wind and solar energy will be calculated.

3.4.1. Land cover assessment

Table 3.2 gives the detailed land cover assessment for the Netherlands: CLC classes available for VRES development, available areas for each available CLC class, percentages of them in terms of the total area of the country, suitability factor for each available CLC class, suitable areas and percentages of them in terms of the total area of the country. Each column is further elaborated on below.

First of all, unavailable land cover and nature reserves are excluded from the total area. In the Netherlands, existing wind turbines are to a large extent built along roads or highways and at the construction sites such as the Rotterdam Port area. Therefore, the transport area is not excluded. Some of the urban areas are considered available as well (see Table 3.2 for the CLC classes that are considered available). Next, since most of the nature reserves in the Netherlands are small monuments, we excluded only the two largest reservations, Veluwe and Waddenzee. After those exclusions, the rest is considered available for VRES development. These criteria are based on physical conditions and this is considered a moderate exclusion.

In addition, a stricter exclusion on land-use for wind energy is given. The rationale behind this is that if social resistance against wind energy is taken into account, the land will be even more limited. In this case, the land is constrained in addition to the moderate exclusion. This stricter exclusion assumes that all the land in the built environment, i.e., all the CLC classes of Artificial Surface, is excluded. Furthermore, the area in their 2 km radius is excluded as well. In this way, the social resistance and spatial policies of wind energy are operationalized and thus the feasible wind energy potential is quantified.

Figure 3.4 shows all the land, the available land after moderate exclusion, and after strict exclusion in the Netherlands.

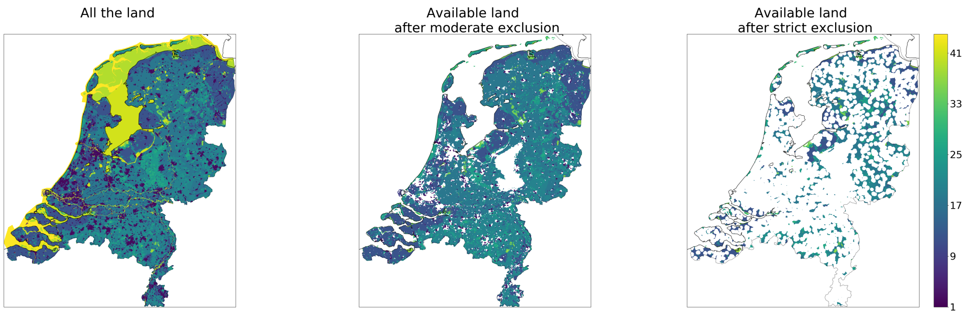

Figure 3.4: Land in the Netherlands (the colored area represents different CLC classes, the white area is either not in the Netherlands or is excluded). Left to right: all the land, the available land after moderate exclusion, and the available land after strict exclusion.

The moderate exclusion will be the baseline case to be elaborated on in this section, but the optimization results of both cases will be discussed in Section 3.5.

The land that is available for VRES development in the Netherlands is 77.35% of the total land. This means that, in the baseline case, around 80% of the land can be used for the installation of wind turbines and solar panels. However, different local conditions such as spatial policies could be implemented, which will change the exclusion criteria and the suitability factors. This would reduce the amount of suitable land in the end.

Then, the suitability factors are applied on the available area resulting in the suitable areas. The suitability factors for wind turbines and for solar panels are similar for most of the land use classes. The only difference is that solar panels are allowed to be put on building rooftops, hence, a suitability factor of 0.3 is given to discontinuous urban fabric

CLC class	Available area (km^2)	Percentage	Suitability factor	Suitable area(km^2)	Percentage
2 Discontinuous urban fabric	3288.10	7.91%	0.3	986.43	2.37%
3 Industrial or commercial units	807.18	1.94%	0.8	645.74	1.55%
7 Mineral extraction sites	46.25	0.11%	0.5	23.13	0.06%
8 Dump sites	21.49	0.05%	0.5	10.75	0.03%
9 Construction sites	153.67	0.37%	0.3	46.10	0.11%
12 Non-irrigated arable land	7366.88	17.72%	0.4	2946.75	7.09%
15 Vineyards	0	0	0.1	0	0
16 Fruit trees and berry plantations	71.63	0.17%	0.1	7.16	0.02%
18 Pastures	10089.93	24.28%	0.6	6053.96	14.57%
20 Complex cultivation patterns	5304.71	12.76%	0.1	530.47	1.28%
21 Land principally occupied by agriculture, with significant areas of natural vegetation	1136.94	2.74%	0.1	113.69	0.27%
23 Broad-leaved forest	568.16	1.37%	0.3	170.45	0.41%
24 Coniferous forest	1146.76	2,76%	0.3	344.03	0.83%
25 Mixed forest	725.17	1.74%	0.3	217.55	0.52%
26 Natural grasslands	475.29	1.14%	0.6	285.17	0.69%
27 Moors and heathland	246.85	0.59%	0.6	148.11	0.36%
29 Transitional woodland-shrub	13.62	0.03%	0.5	6.81	0.02%
30 Beaches, dunes, sands	143.04	0.34%	0.3	42.91	0.10%
32 Sparsely vegetated areas	0	0	0.8	0	0
35 Inland marshes	364.74	0.88%	0.1	36.47	0.08%
36 Peat bogs	80.21	0.19%	0.1	8.02	0.02%
37 Salt marshes	96.69	0.23%	0.1	9.67	0.02%
Sum	32147.31	77.35%	n.a.	12633.38	30.40%

Table 3.2: The land cover characteristics of the available and suitable land for VRES development in the Netherlands. Suitability factors are based on own compilation and the work of [96].

for solar panels. This land cover assessment aims to give a general understanding of the available land and suitable land for VRES development in the Netherlands.

The total suitable area is 12 633.38 km^2, which is 30.40% of the land in the Netherlands. The regional distribution of the suitable areas of the available CLC classes was calculated as well. The four CLC classes with the largest areas in Table 3.2 are illustrated in Figure 3.5.

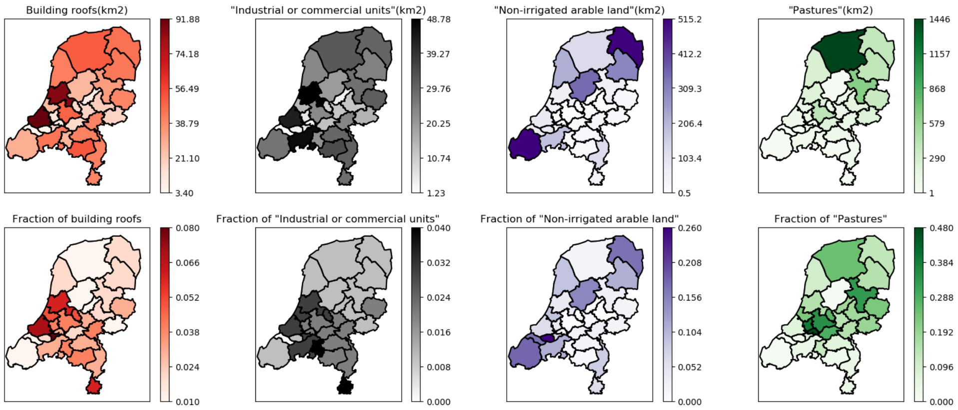

Figure 3.5: Selected land cover characteristics for the 30 regions in the Netherlands

In summary, the CLC class of pastures is the most suitable land cover class for VRES development in the Netherlands, occupying 14.57% of the total area. Non-irrigated arable land also plays an important role with a percentage of 7.09%. Other CLC classes are not prominent, but among all, discontinuous urban fabric and industrial or commercial units are the most significant for solar panels and for wind turbines, respectively.

3.4.2. Maximum VRES capacities and annual capacity factors

Maximum VRES capacities at all regions are calculated based on Equation (3.2). The suitable areas for wind and solar energy in the Netherlands are 11 646 km^2 and 12 633 km^2, respectively, occupying 28.02% and 30.40% of the total land of the Netherlands. This leads to 58.23 GW of potential wind capacity and 379 GW of potential solar capacity. Figure 3.6 illustrates the geographical distribution of the maximum potential capacities.

Furthermore, the annual capacity factors are shown in this figure as well. For wind energy, the western and northern coastal regions have more favorable wind conditions than those of other regions. The annual capacity factors range between 0.20 and 0.36. With regard to solar energy, this range is smaller, which is 0.11 to 0.14. Moreover, unlike wind, solar annual capacity factors do not show a strong geographical pattern and are distributed rather evenly across the country.

3.5. Optimization results and discussions

This section presents the results from the optimization model in terms of the generation mix, the spatial distribution of the generation capacity, and the total cost of the system.

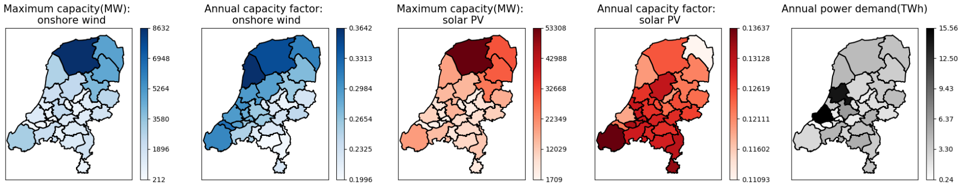

Figure 3.6: The geographical distribution of five figures in the Netherlands. Left to right: the maximum potential installed capacity (MW) and the annual capacity factor for onshore wind turbines, the maximum potential installed capacity (MW) and the annual capacity factor for solar PV, and the annual power demand (TWh).

It starts with the scenario with the baseline VRES potential constraints obtained from Section 3.4.2. Afterward, the scenario concerning strict VRES constraints based on the strict exclusion criteria on land-use (described in Section 3.4.1) will be used to check the sensitivity of the model outcomes to this constraint. Lastly, the scenario without the constraints on the land-use of VRES is briefly presented, which imitates the existing studies.

3.5.1. Baseline scenario with moderate VRES potential constraints

Generation mix Figure 3.7 shows the generation mix for five RES targets for different scenarios.

At the 0% RES target, coal plants comprise most of the capacity to supply base demand, whereas the capacity of CCGT is 25% of that of coal and it supplies the peak demand. At the 20% RES target, wind comes into the generation mix by bringing in an extra capacity compared to the first target. Then, starting from the 50% target, solar PV appears. Regarding fossil fuels, the capacity of CCGT is equal to coal at this target and it surpasses coal when RES share is above 50%. In other words, when the RES share is below 50%, coal represents the majority of the fossil fuel capacity. Moreover, going from 20% to 50% RES, the total capacity doubles, which is mainly due to the investment in solar and wind energy. At the 80% RES target, biomass for the first time appears in the generation mix to replace some of the coal capacity. However, coal and CCGT are still in the generation mix to provide controllable power production.

The fossil fuels are gone at the 100% RES target, in which they are replaced by more biomass. Hydrogen storage is being deployed to cover periods of little VRES production. Storage only appears at the 100% RES target, while for other targets, fossil fuel plants can cover those periods. In addition, out of the two storage options in the model, hydrogen storage seems to be more cost-effective than flow battery storage under the existing cost parameters of both technologies.

With respect to the RES capacities for all the targets, wind capacity stays almost the same at the 50%, 80%, and 100% RES targets, solar capacity has reached its peak deployment at the 80% target. Nevertheless, the total wind capacity is higher than the total solar capacity for all the targets. Apparently, wind is more cost-effective than solar power. Hence, wind energy plays a dominant role with solar energy and biomass complementing its variable production.

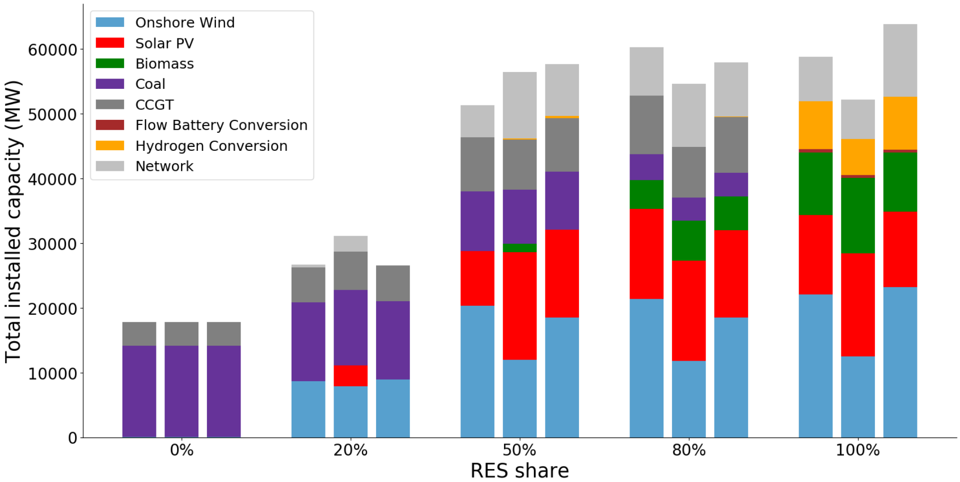

Figure 3.7: Total installed capacity (MW) for different RES targets for the three scenarios. At each RES target, left to right: baseline scenario, new policy scenario and unlimited land scenario.

Spatial distribution of the generation capacities Figure 3.8 shows the generation capacities in the 30 regions in the Netherlands and the land-use for onshore wind and solar PV represented by the fraction between the used land and the suitable land.

At the 0% RES target, coal and CCGT plants are located mainly in Noord-Holland Zuid and in Rotterdam-Den Haag regions (these are the regions in the densely populated west of the country). This result is plausible since these regions are also demand centers in the Netherlands (see Figure 3.6). Besides, there is 22 MW of onshore wind, which is negligible compared to the capacities of coal and CCGT.

At the 20% RES target, wind energy is installed mainly in these two demand centers. However, due to their limited size, wind energy also has to be installed in the neighboring regions to supply the two demand centers. Results show that the Rotterdam-Den Haag region is fully occupied by wind turbines, and two of its neighboring regions Goeree-Overflakkee and Holland-Rijnland provide additional wind energy capacity. The other demand center, Noord-Holland Zuid, nevertheless, still has land for wind turbines.

From the 50% to the 100% RES target, wind capacities continue to expand from the two demand centers to their neighboring regions as well as to the northern regions where the wind conditions are good, e.g., Noord-Holland Noord and Friesland. However, due to their large maximum potential capacity and relatively long distance to the demand centers, they are not heavily occupied by wind turbines. By contrast, most of the neighboring regions of the demand centers are fully occupied. At the 100% RES target, 7 out of the 30 regions are fully used for wind turbines which correspond to 38% of the total suitable land and 11% of the total land of the Netherlands.

Total cost The total cost of the system is divided by the total power demand (113) to represent the cost of electricity (Figure 3.9). Most of the cost is proportional to the installed capacity in Figure 3.7 except for the operation cost. This operation cost, however,

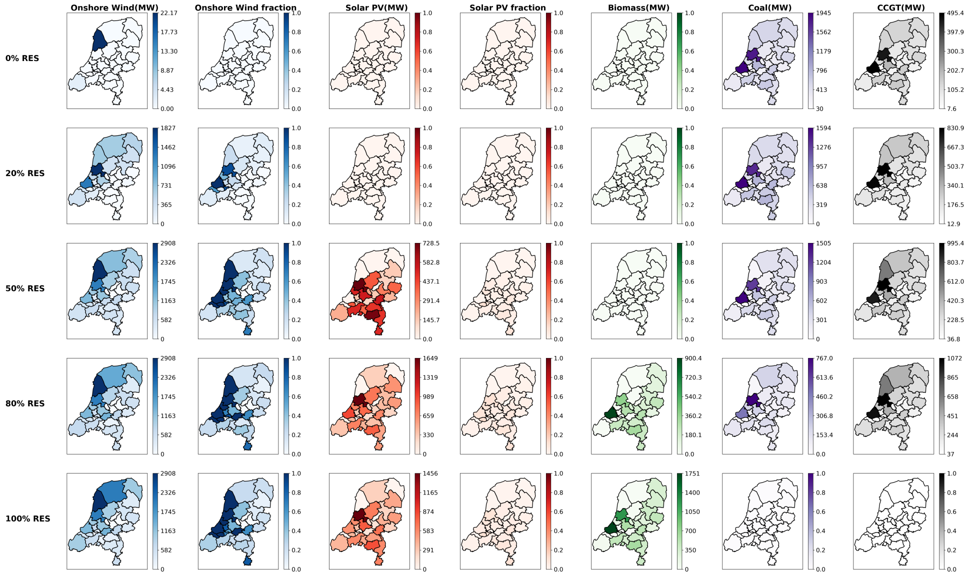

Figure 3.8: Generation distribution for the 30 regions for different RES targets. Left to right: onshore wind (MW), onshore wind fraction, solar PV (MW), solar PV fraction, biomass (MW), coal (MW), CCGT (MW).

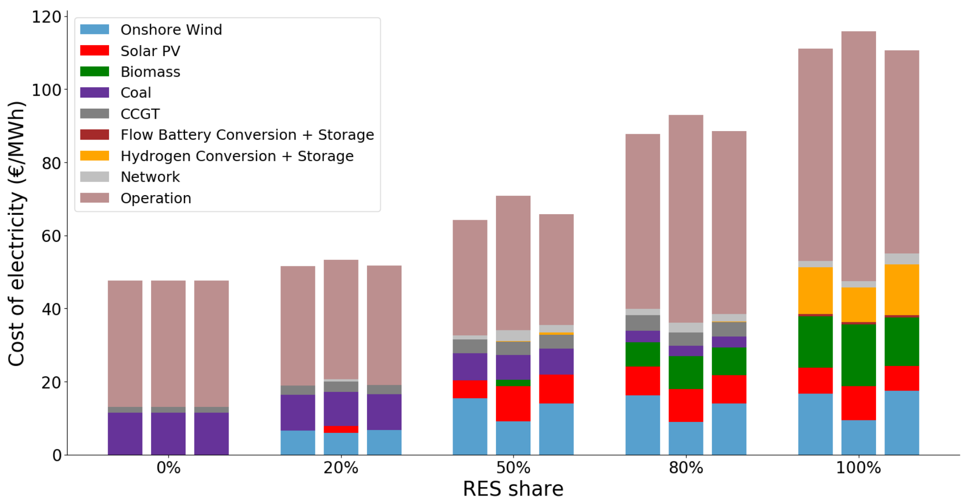

Figure 3.9: Cost of electricity (€/MWh) for different RES targets for the three scenarios. At each RES target, left to right: baseline scenario, new policy scenario, and unlimited land scenario.

accounts for a significant part of the total cost. It includes the FOM cost and the VOM cost. Here the VOM cost, i.e., the fuel cost is the main differentiator of the total costs for the different RES targets. From the 0% to the 50% RES target, although the cost of electricity increases, the operation cost actually decreases because of the lower capacity for coal and CCGT. However, instead of decreasing, the operation cost increases for the 80% RES target, which is due to the introduction of biomass in the generation mix. The incremental increases in cost for the five RES targets are 4 €/MWh, 12 €/kWh, 24 €/MWh and 23 €/MWh. Another important finding is that the cost of the network is at a maximum of 1.5% of the cost of electricity which is at the 100% RES target. This small contribution implies that the assumptions we made for the cost and topology of the network do not have a significant influence on the key performance indicators of the overall system, i.e., the generation mix and the system's total cost.

3.5.2. New policy scenario with strict constraints on the land-use of VRES

The merit of our approach is that it assesses the land cover in a spatially explicit way such that the VRES potential constraint can be adapted based on any selection of the allowed land cover as described in Section 3.2.1. To give an example of the usage and the relevance, apart from the baseline scenario, a 2 km exclusion scenario that reflects social resistance and spatial policy was proposed in Section 3.4.1. The results of this scenario are discussed in this section.

Spatial distribution of wind capacity In Figure 3.10, the geographical distribution of the land-use of wind turbines represented by the fraction between the used land and the suitable land is shown.

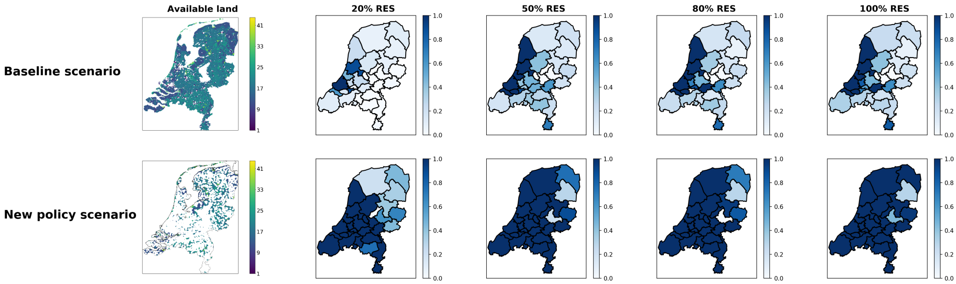

Figure 3.10: The fraction of the used land over the suitable land of wind turbines under the two scenarios: baseline scenario and new policy scenario.

Under the 2 km policy, only 7% of the total area in the Netherlands is suitable for wind turbines, instead of the 30% in the baseline case. Compared to the baseline case, this strict VRES constraint on land-use has a larger impact on the occupied land. At the 20% RES target, 70% of the regions are fully occupied by wind turbines, whereas only one region is entirely used in the baseline case. At the 100% RES target, 93% of the regions are wholly possessed, which corresponds to 92% of the total suitable land and 6% of the total land of the Netherlands.

Generation mix Figure 3.7 shows the total installed capacity for the new policy scenario. First of all, due to the strict wind energy constraints on land-use, there is a decrease in wind capacity for all the RES targets and the wind capacity is almost reaching its maximum potential. Secondly, there is a capacity increase in solar energy and in biomass. Moreover, compared to the baseline case, these two technologies both come earlier into the generation mix as the RES share increases. Solar energy first appears at the 20% RES target, and biomass appears at the 50% RES target at the earliest. This indicates that solar energy and biomass compensate for the decrease in wind capacity compared to the baseline scenario. Thirdly, there is an indispensable rise in the network capacity at the 20%, 50%, and 80% RES target, because wind power is now produced in larger quantities at larger distances from the demand centers. Storage, again, is only present at the 100% RES target.

Total cost Next, the costs of electricity are compared as well. There is not a significant cost rise for all the RES targets, which varies between 2 €/MWh to 5 €/MWh. This implies that the extra cost of extra solar and biomass energy is almost equal to the cost reduction in wind energy.

3.5.3. Unlimited land scenario with no constraints on the land-use of VRES

As mentioned in Section 3.1, most of the existing optimization studies do not include the constraints on the land-use of VRES. Therefore, the effects of this simplification on the optimization results are unknown. In this scenario, we assess the model results without the VRES potential constraints (Equation (3.6)). In this way, the drawbacks of the existing models will be unveiled, and hence the advantage of our approach will be further elaborated.

Spatial distribution of wind capacity In Figure 3.11, the geographical distribution of the wind capacity and the fraction between the used land and the suitable land are shown. The left two columns present results from the baseline scenario, the right two columns show results from this scenario.

At the 20% RES target, due to the land-use constraints, the baseline scenario results in capacities mostly in the two demand centers and their surroundings. In the unlimited land scenario, the results are similar but the capacities are more concentrated. This trend becomes clearer at the 50%, 80%, and 100% RES targets. At the 50% and 80% target, in the baseline scenario, the coastal regions around the demand centers are fully occupied by wind turbines. However, in this scenario, only three regions are wholly packed with wind turbines. These three regions have the best wind conditions in the neighborhood, and thus wind turbines are preferred to be placed there. This tendency to place the wind turbines in the model without land-use limits of VRES results in unrealistic land occupation. Goeree-Overflakkee region has to install 4.64 - 4.91 times its maximum allowable capacity, and Rotterdam-Den Haag region has to install 1.31 - 1.35 times its maximum allowable capacity. At the 100% RES target, the numbers are even higher. In the baseline scenario, the coastal regions are already fully occupied and the capacities have to be built in the north or in the south. And the maximum installed capacity is 2908 MW in Noord-Holland Noord region. In the current scenario, this pattern of capacity expanding

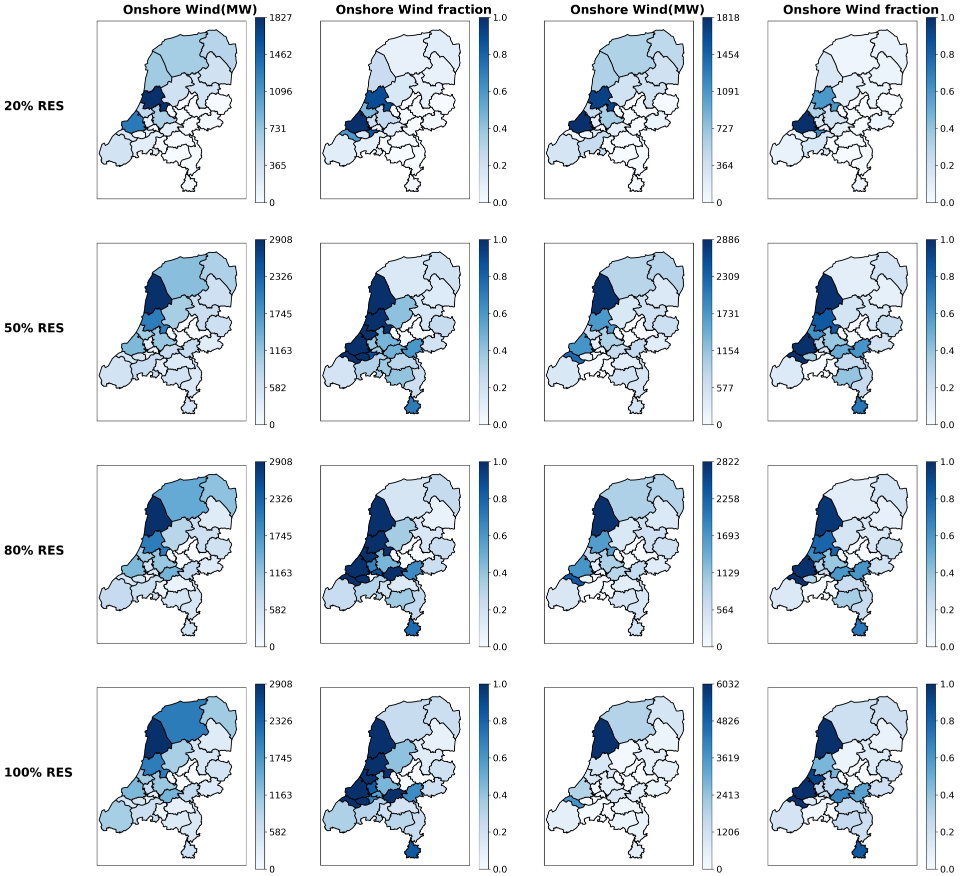

Figure 3.11: Wind capacity and the fraction between the used land and the suitable land. Left two columns: baseline scenario. Right two column: unlimited land scenario.

to the neighboring regions does not appear. Instead, the model prefers to install capacities in the three regions with favorable wind conditions, of which the maximum capacity is 6032 MW. Consequently, the capacities in these three regions are beyond the physical limits of the land. Compared to their maximum allowed capacities, Goeree-Overflakkee region has to install 7.63 times, Noord-Holland Noord region has to install 2.07 times and Rotterdam-Den Haag region has to install 1.42 times.

Generation mix Compared to the results in the baseline scenario, in this scenario, there are two main differences. Firstly, the total capacity is higher at 50%, 80%, and 100% RES target. This is due to the increase in network capacity in all three targets. And there is a major difference in solar capacity at 50% RES target. Secondly, storage comes into the generation mix much earlier in this scenario, although its capacity is not high.

Total cost Due to the difference in the generation mix, the cost breakdown is also different which corresponds to the generation mix. However, the difference in total cost is not significant. Because in this scenario, the total wind capacity does not change much, whereas the spatial distribution shows a different pattern.

3.5.4. Discussions of the results

In this case study, three scenarios are analyzed to show how the proposed approach can be used. It must be emphasized that the role of the land-use constraints deduced from the results (e.g., in cost, and capacity) are case-specific, given the situation in the Netherlands. For other cases with either unique land suitability (e.g., prohibited zones), or different distribution of demand or meteorological profiles, the results might not be comparable to the Dutch case. Nevertheless, the obtained results from the three scenarios will be further compared. This is in order to give an example of what key results can be analyzed and what conclusions can be drawn.

In Section 3.5.1, the baseline scenario is based on the realistic assessment of the land cover, and thus this scenario takes the actual location-specific land-use limit of placing VRES technologies into account. Next, in Section 3.5.2, a stricter constraint on the land-use of VRES is applied. If a spatial policy to mitigate the social resistance of VRES is designed (e.g., the 2 km policy in this case), this scenario shows the effects on the optimization results and the land-use coverage of such a policy. At 100% RES target, 92% of the suitable land in the Netherlands will be fully occupied. At 50%, 80%, and 100% RES target, the wind capacity is reduced by 9182 MW or 43% on average, compared to the baseline scenario.

Then, Section 3.5.3 shows the optimization results without any constraints on the land-use of VRES. The total capacity and the cost of the system are similar to those of the baseline scenario. This is because for this specific Dutch case, on the one hand, the favorable VRES locations are not excluded much (by e.g., nature reserves). This means that the VRES capacity constraints play a less significant role compared to the case where the favorable VRES locations are excluded more. On the other hand, the VRES land-use constraints will essentially change the optimal spatial distribution of the VRES capacity, and thus more network is needed. However, in this model, since the cost of the network is not a significant component of the total cost of the system, the total cost is similar to that of the baseline scenario.

Nevertheless, Section 3.5.3 indicates that without the constraints on land-use, the optimal capacities in some regions would be infeasible in reality. Our approach gives a unique kind of realistic result that would be needed for planning purposes, and that would not be obtained using existing approaches. In addition, for other cases, other insights, such as the changes in total capacity and total cost between the baseline scenario and the unlimited land scenario, might be seen.

To give an indication of how the results could be used directly for real-life purposes, they are first validated by comparing the cost of electricity to the Dutch electricity price, and then the generation mix is compared to the literature. In 2015, the electricity consumption from RES in the Netherlands is 2%. According to TenneT [117], the 2015 average Dutch wholesale price is 40 €/MWh. In Figure 3.9, for 2% RES, the cost of electricity is between 47 €/MWh and 52 €/MWh. However, the wholesale price does not include capital costs. The operational part of the cost of electricity is between 32 €/MWh and 35 €/MWh. This cost is comparable but lower than the real-world electricity price, which is reasonable since other costs such as taxes are not calculated. Although different production profiles of VRES were used, the generation mix of 100% RES scenario for other case studies, such as Australia [118], Portugal [119], islands across the globe [120], Europe [47], shows that wind dominates in the generation mix of RES. This trend is consistent with our results.

Because the 100% RES scenarios have not materialized in the real world yet, it is impossible to validate those results using real-world data. Furthermore, uncertainties in the input data are also unavoidable. In such cases, a sensitivity study adds additional insights into the robustness of the results. We, therefore, performed sensitivity experiments by varying the CapEx of the technologies and the capacity densities to + 30% and - 30% compared to their original values and evaluate the effects on total installed capacity (Figure 3.12) and the cost of electricity (Figure 3.13) at 100% RES target of the baseline scenario. The results show that the CapEx has a stronger influence on the installed capacities than the capacity densities. A change in solar PV CapEx has the highest effect on the installed capacities. Overall effects on the costs are more limited, ranging from roughly 105 €/MWh to 115 €/MWh. In summary, the trend still holds that wind plays the most important role, biomass serves as a controllable generation, and hydrogen is the main storage source, given our assumptions.

3.5.5. Discussions of the approach and future work

Our approach shows useful and promising results, but every work, ours also, has some possible extensions that warrant further research. Firstly, we provided detailed VRES potential constraints based on the land-use of VRES, but the planning of networks will also be influenced by land cover characteristics (e.g., no-go zones), which were ignored in our approach. The next step is to investigate the sensitivity of the outcomes when there are constraints on land-use for networks. Secondly, different technologies (e.g., offshore wind) will be considered in the future. These two possibilities are not included in the current approach, as they feature different methodologies. For instance, in order to apply this approach to offshore wind, data sets other than the CLC database that show

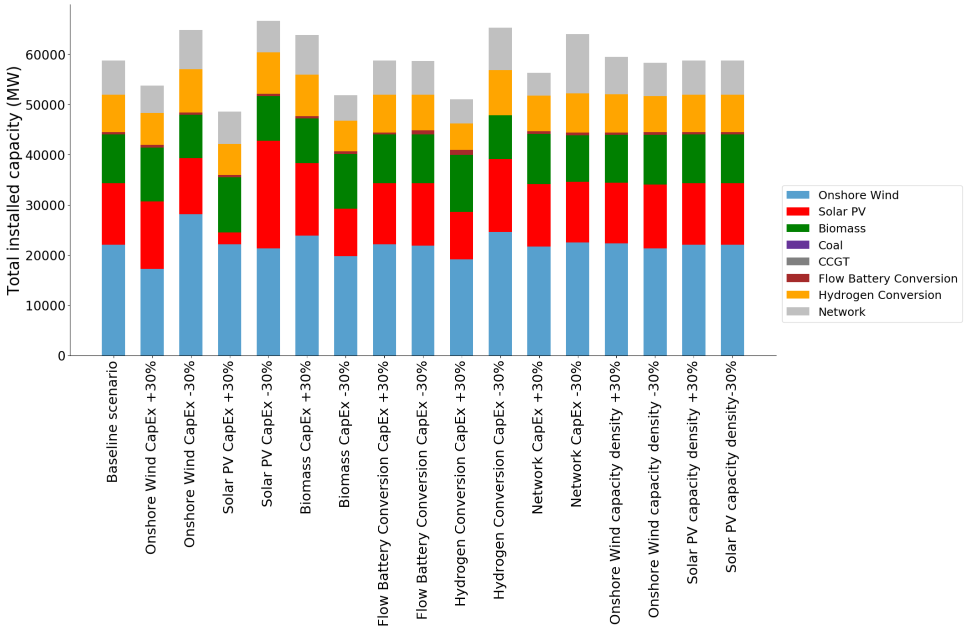

Figure 3.12: Sensitivity study for the total installed capacity at 100% RES target of the baseline scenario.

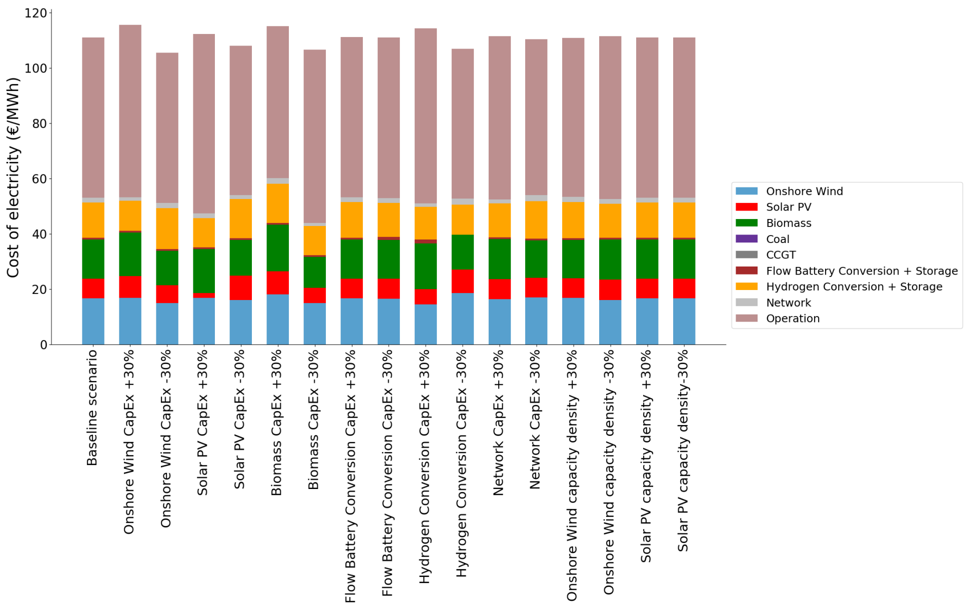

Figure 3.13: Sensitivity study for the cost of electricity at 100% RES target of the baseline scenario.

the suitability of installing offshore wind turbines would be required.

3.6. Conclusions

We provided a spatially explicit planning approach for power systems that integrates the location-specific land-use of VRES into the optimization model. Instead of relying on land-use data from other studies, this data-driven approach is a first-of-a-kind study in the literature on power system optimization modeling that bridges three fields of study: land cover assessment, VRES potential estimation, and energy system planning models. It considers location-specific VRES potential constraints which can be adapted to local conditions (e.g., social resistance, spatial policy, and physical conditions) regarding land-use and reveals the role of the land-use of VRES on the results of such planning models.

A case study for a densely populated area, in our case the Netherlands, has been done to show the strength of the approach and to give policy-relevant results. We found that under moderate VRES potential constraints (the baseline scenario), wind energy will be the primary energy source in the generation mix for scenarios for high-RES targets. Storage only plays a role at the 100% RES target. At this target, wind turbines would cover 38% of the suitable land in the Netherlands.

In addition, we applied a stricter spatial policy (the 2 km policy as described in Section 3.4.1) on wind energy. The results showed that 92% of the suitable land in the country then has to be used for wind turbine installations to achieve the 100% RES target with minimum cost. However, the total cost of the system under this policy has not increased much compared to the baseline scenario, since solar energy and biomass can compensate for wind energy at just a slightly higher system cost. Besides, due to the reduction in wind capacity, solar energy and biomass both come into the generation mix earlier compared to the baseline scenario, whereas storage still only appears at the 100% RES target.

At last, the results of the scenario with no land-use constraints on VRES were analyzed. The optimal capacities are infeasible considering the land limits, making the results not instructive for planning purposes in reality.

We conclude that, for new spatial policies that address the social resistance of VRES, the VRES potential constraints considering land-use have a significant influence on the optimization results and would thus require drastically different policy measures. Therefore, our integrated approach is a necessary next step in creating more policy-relevant models for large-scale deployment of RES in densely populated areas or areas with abundant nature reserves. The proposed approach elaborates the essential steps to operationalize land-use in the constraints after which its impacts on the optimization results will be revealed.

4

Multi-objective multi-actor model

4.1. Introduction

4.1.1. Background and motivation

Renewable energy sources (RES) can help reduce carbon emissions and have been the pillar in the energy transition. Although facing uncertainties in the future, RES investment is arguably a robust energy planning approach under the concern of energy independence [121]. However, the projection from McKinsey & Company (2019) [122] states that currently, in 2020, only 27% of the global power generation comes from RES. This fact indicates that, despite the effort made for a carbon-free future energy system, there is still a long way to go to construct a system with a high-RES penetration. Many people are taking part in this transition. Amongst others, researchers in the field of future energy system design aim to identify what the best RES investment plans would be.

Different categorizations of energy system planning models exist that focus on RES integration ([123] and [124], such as optimization models and simulation models (see the recent reviews of [125], and [126], respectively). Optimization models, being the most common approach in generation investment problems [124], are especially suitable for studies on long-term RES investment [127], as they are able to find the theoretical optimal solution that maximizes or minimizes the objective function (such as cost or emissions). On the other hand, simulation models, such as agent-based models and system dynamics models, are powerful in solving other problems since they rather look for system patterns taking into account the interactions between agents or other system components. This chapter focuses on the optimal future energy system designs and will therefore focus on optimization models instead of simulation models.

In most optimization models, the objective is usually to minimize total cost [123] to find the optimal RES generation mix. The cost-optimal models have been extensively

---

This chapter was published as N. Wang, P. W. Heijnen, and P. J. Imhof, "A multi-actor perspective on multi-objective regional energy system planning", *Energy Policy*, vol.143, 2020. The first author of the paper, also the author of this thesis, conceptualized and conducted the research together with the last author. The other author performed an advisory role.

discussed in the literature, e.g., see the recent review of [88]. However, according to [128], RES are already cost-competitive with their fossil-fuels counterparts. Especially, onshore wind turbines are (one of) the cheapest generation sources among all sources, including conventional generation. Despite the low cost, the global installed capacity of onshore wind turbines is only 309 GW, which is less than half of the installed capacity of solar PV [129]. This implies that, for the RES investment in practice, the cost is not the only criterion. In fact, the energy system is strongly interconnected with society. In addition to economic factors (such as cost), the decision-making in energy system planning also depends on environmental, technical, and social aspects and is usually complex [130]. These factors need to be emphasized in research in order to help the stakeholders [1] understand the barriers that hinder the progress in RES implementation, to contribute to the discussion with all the actors and thus further assist their decision-making [131]. Optimization models that can handle all these factors (provided they can be quantified) are multi-objective optimization (MOO) models.

4.1.2. Literature review

Multi-objective optimization in energy system planning MOO models generate solutions to achieve predefined objectives such as cost and emissions, where the decision variables are subject to a set of constraints. According to [132], and [133], there are two types of MOO models. In the first type, the different objectives are merged into a single-objective function - the so-called scalarization. Weights have to be allocated to each objective. In this way, one optimal solution will be found, just as for single-objective optimization. In the second type, no weights are given, but a set of Pareto-optimal solutions for all objectives will be found. These solutions are non-dominated, i.e., solutions for which other solutions that are better regarding each objective do not exist. It is important to know that these solutions are mathematically equally good [134], and thus the ranking of the solutions totally depends on the decision-maker. Compared to the scalarization method, the Pareto-optimal solutions present a better picture of the trade-offs between the objectives, and more insights would be obtained when the preferences of the actors are taken into account afterward (a posteriori). Using Pareto-optimal solutions is more methodical and less subjective [135] and allows to analyze the correlation between the objectives [132]. In fact, the comprehensive review of [132] concludes that most MOO studies in energy system planning generate a set of Pareto-optimal solutions instead of using scalarization.

The reviews of [132], [133] and [136] give good overviews of earlier studies on MOO literature that provides Pareto-optimal solutions. To avoid repetition, the relevant literature in the recent ten years is briefly reviewed here. Tekiner, Coit, and Felder (2010) [137] proposed a multi-period multi-objective generation expansion approach to minimize total cost and emissions simultaneously. A model to design a RES-based energy system was presented by Zou et al. (2010) [138], where it accounts for total cost and system reliability. Perera et al. (2013) [139] and Clarke, Al-Abdeli, and Kothapalli (2015) [140] designed standalone hybrid energy systems to minimize cost and emissions. The model of [141] minimized total cost and emissions as well and is applied to a town in Germany. A long-term energy system planning of the Croatian energy system was done by Prebeg

[1] Note that in this chapter, the terms stakeholders, actors, and decision-makers are used interchangeably.

et al. (2016) [142], where the objectives are minimizing cost and maximizing the RES contribution. Mahbub et al. (2017) [143] investigated the future energy scenarios in an Italian region to minimize cost and emissions. A MOO model for expansion with high-RES shares was developed by Luz, Moura, and de Almeida (2018) [144], which was applied to a Brazilian case to give advice on the RES targets posed by the government. Furthermore, minimizing cost and emissions were also found in the studies of [89], [145]–[147] for energy system planning with various focuses such as stochastic planning or seasonal storage. In addition, in studies focusing on system integration options [148] such as community microgrids, virtual power plants, energy hubs, and Integrated Community Energy Systems [149], Pareto-optimal solutions were also searched for. For example, Gui et al. (2014) [150] selected the type and capacity of distributed generation units as the decision variables. A case study for a microgrid system is carried out. In [151], the solutions were generated randomly for Integrated Community Energy Systems to minimize cost and emissions.

In summary, various MOO studies generate Pareto-optimal solutions where minimizing cost and emissions are considered the most commonly used objectives. Although the Pareto-optimal solutions are useful in revealing the bounds of the solution space, they need to be further analyzed to help the final decision-making by stakeholders with different preferences. The post-processing of the results requires other techniques than only MOO. Actually, the decision-aiding for multiple actors is often discussed in another field of study, multi-criteria decision-making (MCDM) [132]. Therefore, multi-actor decision-making in energy system planning will be introduced in the next section.

Multi-actor decision-making in energy system planning Given the complex nature of the energy system planning problem, decision-making is not possible without considering the various interests and preferences of multiple actors [152]. The multi-actor perspective can be considered using various methods, such as the value case method [153] which identifies and aligns the values of multiple stakeholders by means of workshops and interviews for large innovation projects. According to [130], the most frequently used decision-making models in RES investment are life cycle assessment, cost-benefit analysis, and MCDM. While life cycle assessment mainly focuses on the environmental impacts of RES and cost-benefit analysis is used to account for the monetary aspects, MCDM inherently considers the conflicting objectives of the stakeholders and is able to include aspects with different units [125].

MCDM is an evaluation method that considers criteria from different aspects simultaneously, such as technical, economic, and environmental aspects [152]. In this method, a set of alternatives are evaluated against those criteria, and the output is usually a ranking of the alternatives. MCDM methods in energy system planning have been reviewed comprehensively by [136], [154]–[156]. Besides, the studies of [157], [158] also provide reviews on MCDM with various focuses. Generally, three types of methods are discussed in the literature, which are value measurement methods, goal programming, and outranking methods [155]. This paragraph will now briefly introduce these methods and outline some studies from the recent ten years. The value measurement methods give a numerical score to the criteria based on the relative importance and rank the alternatives. These methods usually include an analytical hierarchy process ([158]–[168]). Goal programming uses mathematical equations to select the alternatives that are closest to the ideal points that have been defined beforehand with regard to the objectives. The most popular method belonging to this category is the Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) ([162], [166], [169]–[174]). Outranking methods apply a different methodology compared to the previous two. Instead of obtaining a merit order of the alternatives like the previous methods do, the alternatives are compared pair-wise. Examples of these methods are preference ranking organization method for enrichment of evaluations ([171]) and elimination et choix traduisant la realité ([175] and [176]).

Among those MCDM methods, TOPSIS offers a simple way of combining the preferences of multiple actors to allow for group decision-making [177], which is most relevant to this research. It has been used in other fields such as IT personnel selection [178], smart medical device selection [179], and stock exchange [180]. The applications of TOPSIS in energy system planning are now reviewed, by elaborating on the aforementioned studies in the previous paragraph. Kaya and Kahraman (2011) [169] proposed a modified fuzzy TOPSIS methodology and applied it to an energy decision-making problem. Wind energy was found to be the best RES alternative. Similarly, Streimikiene et al. (2012) [170] developed a framework to prioritize energy generation technologies. Alsayed et al. (2013) [171] found the optimal size of a wind turbine-PV energy system by comparing scenarios of different installed capacities. A Turkish case study was done by Brand and Missaoui (2014) [172]. They use inputs from stakeholders and evaluate five power mix scenarios. Also, for Turkey, Şengül et al. (2015) [173] developed a framework to support the ranking of RES, and they find that hydropower is the best option. However, the study of [166] showed that wind energy is the best alternative for Turkey by using a combination of fuzzy analytical hierarchy process and TOPSIS. Another modified fuzzy TOPSIS framework is proposed by Afsordegan et al. (2016) [162] to rank seven energy alternatives under nine criteria. European Union energy development scenarios are evaluated by Baležentis and Streimikiene (2017) [174]. The evaluations are based on the policy priorities such as energy efficiency measures and the increasing use of RES.

These studies focus on either the ranking of the RES alternatives or evaluating the scenarios consisting of energy mix options. The former, although being able to give advice on the best RES, lacks detailed and quantitative insights on the investment capacity taking into account realistic data such as demand profiles and the generation profiles of wind and solar energy. The evaluations of future energy scenarios overcome part of the problem as they are able to choose a specific energy mix. However, the scenarios are often given and may be far from optimal. Furthermore, the decision-making for a group of actors has not yet been studied using TOPSIS in the field of energy system planning.

Combination of MOO and MCDM Regardless of the sector, decision-making is always a complex task. Depending on the goal of the study, it usually involves the combination of methodologies, where the merits of both would be utilized conjointly. For instance, in supply chain management, it is essential to optimize the purchase process, while considering multiple criteria to evaluate different suppliers. Kannan et al. (2013) [181] used MOO and MCDM to rate and select the best green suppliers. The performance of the energy supply chain was assessed thoroughly with the help of combining various methods in [182].

Model combinations are also studied in the field of energy system planning. For example, when criteria such as benefit and opportunity are crucial, strategic planning and MCDM can be jointly used to provide decision-support in prioritizing RES for policy-makers [157]. The need for using MOO and MCDM was recognized by Antunes and Henriques (2016) [136]. MOO is able to provide a large set of optimal solutions showing trade-offs between different objectives. Starting from the Pareto-optimal solutions, MCDM further enables a richer critical evaluation and analysis of the solutions. Hajibandeh et al. (2018) [183] combined MOO and MCDM to identify efficient strategies for system operators with a focus on demand response programs.

Our literature review shows that although the RES investment problem has been studied extensively, the combination of MOO and MCDM to find the optimal generation mix has not often been addressed. The holistic approach that combines both methodologies will be able to give a comprehensive understanding of the optimal future energy system designs to various stakeholders, including but not limited to policy-makers. Before further stating the research gap and our contributions, two studies that combine MOO and MCDM in energy system planning will first be discussed.

For the design of a standalone energy system, Perera et al. (2013) [59] used fuzzy TOPSIS, which is capable of handling the ambiguity associated with the relative weights of the objectives to analyze the Pareto-optimal solutions. Their approach would be useful for the decision-aiding of a particular decision-maker who has ambiguity on the relative importance of the objectives. Jing et al. (2018) [184] use MOO and MCDM to design a combined cooling, heat, and power energy system with a focus on solid oxide fuel cells. The purpose of their study is to select the best location and building type for such a system with different input data.

These two papers indicate the strength of combining MOO with MCDM, in particular TOPSIS. However, they are not able to cope with multiple actors with different preferences. Perera et al. (2013) [59] focused on dealing with the ambiguity of opinions of a particular decision-maker, while various actors who are simultaneously involved in an energy system planning problem are not addressed, and hence, the optimal decisions for those actors cannot be derived. In the work [184], TOPSIS is used to evaluate two objectives (cost and emissions), but actors are not included at all.

4.1.3. Research gap and contributions of the chapter

We conclude that in the literature on energy system planning, the combination of MOO and MCDM has not drawn enough attention. Two studies that have done so either focus on dealing with the ambiguity of a hypothetical decision-maker or pay attention to the optimal selection of the location of the energy system with different input data. However, the inclusion of multiple stakeholders with diverse preferences and, accordingly, the comparisons and trade-offs of the optimal solutions from the actors' perspectives have not been studied. In other words, no researchers have yet performed energy system planning through the lens of the multi-actor perspective. This perspective is needed in the complex energy system where multiple stakeholders need to reach agreements on RES investment capacity. Therefore, it is crucial to inform the stakeholders about the optimal generation mixes from their perspectives and other stakeholders' perspectives in

RES investment negotiations. This understanding will assist their decision-making and thus accelerate the RES implementation process.

In addition, based on the literature review on MOO, the visual impact of wind turbines [185], and the land-use of RES has not previously been included in MOO studies as separate objectives. The visual impact of wind turbines can be considered as a proxy for acceptance of wind energy, and the land-use of RES is a significant issue [186] regarding spatial policies.

Therefore, we propose a two-stage multi-actor multi-objective regional energy system planning model that is able to consider multiple actors and their preferences. It combines a MOO model with TOPSIS. Figure 4.1 pinpoints the positioning of our study with regard to the existing studies in the field of energy system planning.

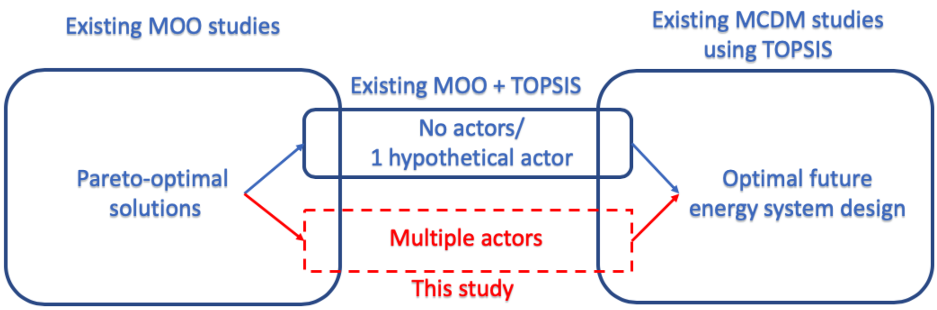

Figure 4.1: Positioning of the chapter in the literature on energy system planning.

The major contributions of the chapter are the following:

- The proposed method simultaneously considers several actors that are often involved in the RES investment process, which addresses the multi-actor environment in the real world. It will be particularly useful for energy system designers, policy-makers, investors, and residents that participate in energy system planning. Furthermore, the approach is generic, indicating that other than the exemplary actors and the objectives which are considered in this chapter, the integrated method is able to include other actors and their preferences with minor adjustments on a case-by-case basis.
- Optimal energy mix for each actor can be derived using our quantitative method. The preferred technologies and the optimal investment capacity for each actor can now be compared, which was previously largely discussed qualitatively.
- Due to the two-stage approach, a set of Pareto-optimal solutions will be obtained using MOO at first. Then, the degrees of optimality of all the obtained Pareto-optimal solutions can be derived for each actor. Therefore, in addition to the optimal solution for each actor, our approach enables the possibility to find solutions that are sub-optimal for each actor yet e.g., most satisfying for all the actors.
- Researchers can now use our approach directly or with minor adjustments, to explore and reveal the impacts of various policy options (e.g., RES subsidies, emission

targets, and spatial policies) on the optimal investment decisions from the multi-actor perspective, which was in the past mostly evaluated without the attention on the various actors.

- The land-use of RES and the visual impact of wind turbines which is considered as a proxy for acceptance will be modeled separately as two objectives.

4.1.4. Overview of the proposed approach

In order to guide the readers, the scope of the models in this chapter and a brief introduction to our approach are given.

Scope of the models in this chapter The main contribution of the chapter is to present a two-stage multi-actor multi-objective regional energy system planning approach that is able to give investment decisions with various degrees of optimality from a multi-actor perspective. This will be done by generating a set of Pareto-optimal solutions using a MOO model, which is then evaluated using TOPSIS to consider the actors and their preferences.

Considering the goal of the study, therefore, in this chapter, the scope of the MOO model, the considered actors, and their preferences are limited and simplified. They are mainly used to perform an illustrative case study that will later be conducted to demonstrate the usage and strength of the approach. However, as stated in the first major contribution of the work, they can be adapted for any specific case where the approach is still applicable and useful.

Introduction of the approach The model focuses on a standalone regional energy system that requires investment in RES, including wind energy, solar energy, and biomass, as well as storage. The investments are further divided into six technologies, which are Vestas V66 wind turbines, Vestas V110 wind turbines, residential PV, utility-scale PV, biomass, and hydrogen storage. Vestas V66 and Vestas V110 are turbines of different sizes, resulting in different land-use and visually impacted area (VIA). A simulation model is constructed to model the energy flow based on the six technologies.

To find the optimal investment decisions on the number of wind turbines and the capacities of the other technologies, a MOO algorithm, the genetic algorithm (see Section 4.3.4 for details), will be used. In this chapter, the involved actors in energy system planning are simplified into three main actor groups (see Section 4.4.1 for details), who are governments, funders, and local residents. They have four common interests, which will be the objectives to be minimized. These objectives are total capital expenditure (CapEx), total operation & maintenance (O & M) costs, land-use, and VIA. Using a genetic algorithm, the Pareto-optimal solutions will be obtained regarding the four objectives. Within the common interests, they also have their major preferences (see Table 4.1). Subsequently, based on the major preferences of the actors, TOPSIS is used to find the optimal solution for each actor.

An overview of the approach is shown in Figure 4.2.

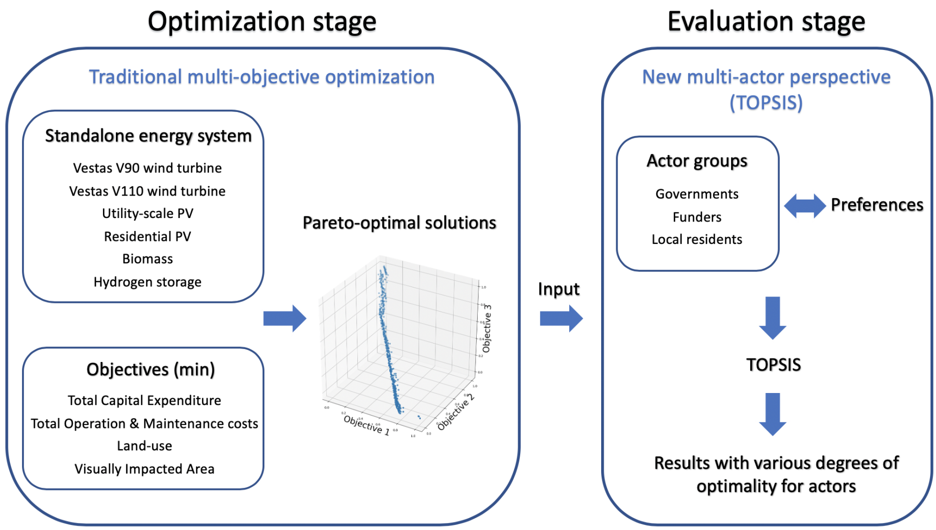

Figure 4.2: Overview of the approach.

4.1.5. Structure of the chapter

The chapter is organized as follows. Firstly, Section 4.2 describes the simulation model that simulates the energy flow. Then, the optimization model and the algorithm are discussed in Section 4.3. Next, the actors and their preferences are described, and TOPSIS is formulated in Section 4.4. Section 4.5 introduces the case study and summarizes the input data. Later, results and discussions are presented and elaborated in Section 5.5. At last, conclusions are drawn, and policy implications are given.

4.2. Simulation model

The simulation model for energy system planning consists of a number of individual models to simulate energy generation and storage.

4.2.1. Considered technologies

As mentioned in Section 4.1.4, in this chapter, the modeling of the energy flow starts with the six considered technologies. They are Vestas V66 wind turbines, Vestas V110 wind turbines, residential PV, utility-scale PV, biomass, and hydrogen storage technology. Moreover, hydrogen storage technology consists of storage conversion and storage. Accordingly, the decision variables are the numbers of the wind turbines ($\mathrm{WT}_i, \forall i \in \{\mathrm{V66}, \mathrm{V110}\}$) and the installed capacities of the other technologies ($K_i, \forall i \in \{\mathrm{PV\text{-}residential}, \mathrm{PV\text{-}utility}, \mathrm{biomass}, \mathrm{storage}, \mathrm{storage\text{-}conversion}\}$).

The proposed simulation model includes state-of-the-art components in regional energy planning models, such as RES generation profiles and storage technology. A general model of storage is used. Although hydrogen storage is specified, other forms of storage, such as flow battery storage, can also be used subject to the choice of the chapter.

In addition, biomass is included to provide controllable generation. It is noted that this model is used to illustrate the usage of the proposed method. Therefore, an exhaustive inclusion of generation technologies and the detailed modeling of hydrogen storage are considered out of scope.

4.2.2. Energy production from intermittent sources

Energy generated from variable renewable energy sources (VRES), i.e., solar and wind, is affected by meteorological conditions, which are included in the model using capacity factors. Therefore, their generated energy ($P_{i,t}$) at all time steps depends on the installed capacity of each technology (K_i) and the capacity factor ($\eta_{i,t}$) of each technology ($i, \forall i \in$ VRES). The installed capacity of the wind turbines (K_i) is calculated as the sum of the rated power (P_i^{rated}) and the number of the turbines (WT_i).

4

$$K_i = P_i^{\text{rated}} \text{WT}_i \quad \forall i \in \{\text{V66, V110}\} \tag{4.1}$$

$$P_{i,t} = \eta_{i,t} K_i \quad \forall i \in \text{VRES}, \forall t \in \{1, 2, \ldots, T\} \tag{4.2}$$

where VRES = {V66, V110, PV-utility, PV-residential}.

However, the generated energy ($P_{i,t}$) may not be enough to fulfill the energy demand (D_t) at all time steps. In other words, there may be a deficit in the required energy supply, which is calculated by:

$$P_t^{\text{deficit}} = D_t - \sum_{i \in \text{VRES}} P_{i,t} \quad \forall t \in \{1, 2, \ldots, T\} \tag{4.3}$$

4.2.3. Energy storage

If there is a shortage in energy supply (i.e., $P_t^{\text{deficit}} \geq 0$), the storage can be used to supply stored energy to the demand (storage discharging) if there is enough stored energy. If the solar PV and the wind turbines produce more energy than is required (i.e., $P_t^{\text{deficit}} < 0$), the excess energy can be stored (storage charging) in the storage technology if the storage is not full. The efficiency of charging and discharging is denoted by η. The energy that is stored ($P_{\text{storage},t}$) at all time steps is calculated by:

$$P_{\text{storage},t} = \begin{cases} P_{\text{storage},t-1} - \frac{1}{\eta} P_t^{\text{deficit}} & \forall t \in \{1, 2, \ldots, T\} & \text{if } P_t^{\text{deficit}} \geq 0 \text{ and} \\ & & P_{\text{storage},t-1} \geq \frac{1}{\eta} P_t^{\text{deficit}} \\ 0 & & \text{if } P_t^{\text{deficit}} \geq 0 \text{ and} \\ & & P_{\text{storage},t-1} < \frac{1}{\eta} P_t^{\text{deficit}} \\ P_{\text{storage},t-1} - \eta P_t^{\text{deficit}} & \forall t \in \{1, 2, \ldots, T\} & \text{if } P_t^{\text{deficit}} < 0 \end{cases} \tag{4.4}$$

We define two extra variables for discharging ($P_t^{\text{discharging}}$) and charging (P_t^{charging}), respectively. They are defined in the following way as non-negative variables:

$$P_t^{\text{discharging}} = \begin{cases} \eta (P_{\text{storage},t-1} - P_{\text{storage},t}) & \forall t \in \{1, 2, \ldots, T\} & \text{if } P_t^{\text{deficit}} \geq 0 \\ 0 & & \text{if } P_t^{\text{deficit}} < 0 \end{cases} \tag{4.5}$$

$$P_t^{\text{charging}} = \begin{cases} 0 & \text{if } P_t^{\text{deficit}} \geq 0 \\ \frac{1}{\eta}(P_{\text{storage},t} - P_{\text{storage},t-1}) \quad \forall t \in \{1,2,...,T\} & \text{if } P_t^{\text{deficit}} < 0 \end{cases} \tag{4.6}$$

The model is initialized with the energy storage empty:

$$P_{\text{storage},0} = 0 \tag{4.7}$$

The charging and discharging happen in the storage conversion, whose capacity ($K_{\text{storage-conversion}}$) is proportional to the storage capacity (K_{storage}), i.e.,

$$K_{\text{storage-conversion}} = \gamma K_{\text{storage}} \tag{4.8}$$

where γ is taken as 0.167 [47] in this chapter.

The constraints regarding the bounds of the storage will be given in Section 4.3.3.

4

4.2.4. Energy from biomass

The energy generated by biomass ($P_{\text{biomass},t}$) at all time steps is used to fulfill the remaining deficits in supply. It is only deployed when energy from VRES is not enough, and the storage has been emptied after discharging. The amount of energy generated by biomass is calculated as follows.

$$P_{\text{biomass},t} = \begin{cases} P_t^{\text{deficit}} - \eta P_{\text{storage},t-1} \quad \forall t \in \{1,2,...,T\} & \text{if } P_t^{\text{deficit}} \geq 0 \\ & \text{and } P_{\text{storage},t} = 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.9}$$

The constraints regarding the bounds of the energy generated by biomass will be given in Section 4.3.3.

4.3. Multi-objective optimization Model

In order to find the Pareto-optimal solutions for the generation mixes, in this chapter, a MOO problem is formulated, and a genetic algorithm is used to solve the model. This section introduces the objectives and constraints of the optimization problem as well as the optimization technique that is used.

4.3.1. Choice of objectives

The four objectives that will be minimized are total CapEx, total O & M costs, land-use, and VIA. CO_2 emissions are often used as an objective in MOO studies, however, in this chapter, they are treated as an implicit constraint that CO_2 emissions are considered to be reduced by 100% since only RES are used.

As stated in Section 4.1.4, in order to convey the main message which is an improved energy planning method by adding the multi-actor perspective to MOO, some modeling choices are made. Without increasing the computational burden, the four most important objectives that are related to the preferences of the actors are chosen, where land-use is crucial for a region with limited land. The model is considered to be used directly for the design of a carbon-free future energy system. However, if a new study is to be conducted that focuses on the different emission targets, our model can always be fine-tuned on a case-by-case basis.

4.3.2. Objectives

Total CapEx The total CapEx of the six technologies is the first objective to be minimized. C_i represents the CapEx for every unit capacity of each technology (i). The total annualized CapEx is calculated as:

$$C^{\text{CapEx}} = \sum_{i \in \text{G}} \frac{r C_i K_i}{1 - \frac{1}{(1+r)^{L_i}}} \tag{4.10}$$

where G = {V66, V110, PV-utility, PV-residential, biomass, storage, storage conversion}, r is the discount rate, which is taken as 5% in this chapter [10], L_i is the lifetime of the technology (i).

Total O & M costs The total O & M costs are the second objective to be minimized. For each technology (i), the operation and maintenance costs consist of the fixed operation & maintenance (FOM) costs per unit capacity per year (a_i) and the variable operation & maintenance (VOM) costs per unit energy generated (b_i). The total annualized operation and maintenance costs are calculated as:

$$C^{\text{O\&M}} = \sum_{i \in \text{G}} (a_i K_i + b_i \sum_{t \in \{1,2,\ldots,T\}} P_{i,t}) \tag{4.11}$$

Land-use The total land-use of RES indicates the used land by RES technologies. It is quantified using the land-use factor (ϕ_i) of each technology (i), which is defined as the area of used land per unit capacity. The assumption in this research is that wind turbines and utility-scale PV take up land since they are land-intensive compared to other technologies. Residential PV is placed on rooftops and does not occupy any land, but it will be constrained by the available rooftop surfaces (see Section 4.3.3).

$$\text{LU} = \sum_{i \in \{\text{V66,V110,PV-utility}\}} \phi_i K_i \tag{4.12}$$

VIA The VIA caused by the energy system is calculated in a similar way. An assumption is made that only wind turbines have a specific visual impact $(v_i, \forall i \in \{\text{V66, V110}\})$, measured in the area of impacted land per wind turbine. Solar PV and biomass are not assumed to have any effects on visual impact.

$$\text{VIA} = \sum_{i \in \{\text{V66, V110}\}} v_i \text{WT}_i \tag{4.13}$$

4.3.3. Constraints

The optimization model has to satisfy a set of constraints. They are now discussed.

Energy balance constraint The first constraint concerns the energy balance. The energy demand has to be met all the time.

$$\sum_{i \in \text{VRES} \cup \{\text{Biomass}\}} P_{i,t} + P_t^{\text{discharging}} \geq D_t + P_t^{\text{charging}} \quad \forall t \in \{1,2,\ldots,T\} \tag{4.14}$$

Energy storage constraints The energy stored (P_t^{stored}) needs to be between zero and the installed storage capacity (K_{storage}). The amount of charging and discharging (P_t^{deficit}) is limited by the storage conversion capacity. The relevant constraints are:

$$0 \leq P_{\text{storage},t} \leq K_{\text{storage}} \quad \forall t \in \{1, 2, ..., T\} \tag{4.15}$$

$$0 \leq P_t^{\text{deficit}} \leq K_{\text{storage-conversion}} \quad \forall t \in \{1, 2, ..., T\} \tag{4.16}$$

Energy from biomass constraint The energy generated from biomass $P_{\text{biomass},t}$ cannot be negative or exceed its capacity (K_{biomass}). Therefore, the energy generation from biomass adheres to the following constraint:

$$0 \leq P_{\text{biomass},t} \leq K_{\text{biomass}} \quad \forall t \in \{1, 2, ..., T\} \tag{4.17}$$

Land-use constraint The next constraint is a constraint on land-use. The energy system cannot use more land than is available and suitable for RES development in the system. The suitable land (LU^{max}) for wind turbines and utility-scale PV energy can be calculated following the approach in [10].

$$\sum_{i \in \{\text{V66,V110,PV-utility}\}} \phi_i K_i \leq \text{LU}^{\text{max}} \tag{4.18}$$

Residential PV constraint The last constraint is about the available rooftop surface. Residential PV are solar panels that are placed on rooftops. The total area occupied by the residential PV has to be less than the total roof surface, represented by the parameter TRS. Same as suitable land for wind turbines and utility-scale PV, this total roof surface can also be estimated following the approach in [10].

$$\phi_{\text{PV-residential}} K_{\text{PV-residential}} \leq \text{TRS} \tag{4.19}$$

4.3.4. Optimization algorithm

In this research, the Non-dominated Sorting Genetic Algorithm II (NSGA-II), which is one of the most widely used genetic algorithms [187], is used to find the set of Pareto-optimal solutions.

A genetic algorithm is an artificial intelligence technique that is widely used to solve MOO problems. It offers a high degree of flexibility and can handle non-linear functions. A genetic algorithm is specifically efficient for finding the Pareto-optimal solutions in a MOO problem because it evaluates multiple solutions in a single iteration.

The NSGA-II algorithm works based on an evolutionary process. A simplified flowchart of the NSGA-II algorithm used in this research is presented in Figure 4.3. It starts with an initial population that is made up of a random set of individuals, i.e., the installed capacities of the six technologies. Then, the defined objectives and constraints are evaluated. The population is selected if the values of the objectives are low and the constraints are met. Next, subsequent generations are generated by combining different individuals and by random changes to a single individual, i.e., crossover and mutation process. The algorithm keeps creating new generations until a certain number of generations have been reached. The final generation of the population is the output of the algorithm. In this research, the population size is 200, and the generation is 500. These values are set based on the work [53] and are made larger to ensure convergence.

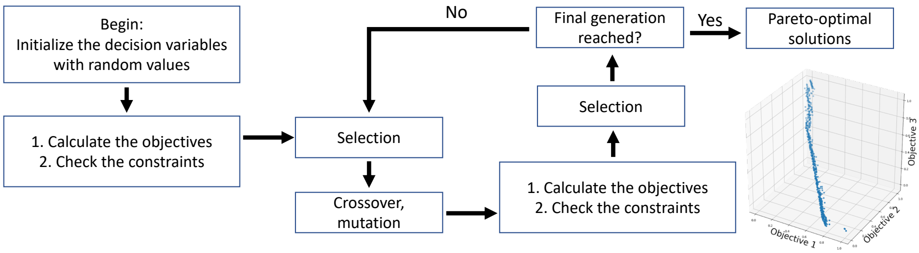

Figure 4.3: Flowchart of the NSGA-II algorithm.

4

4.4. Multi-actor perspective

After obtaining the Pareto-optimal solutions, the trade-offs between the different objectives can be obtained. However, it remains unclear what the optimal solutions will be for the actors with unique (combination of) preferences. To be able to take these preferences into account, the results will be evaluated using TOPSIS from a multi-actor perspective. First, the involved actors and their preferences will be discussed. Then, the process of TOPSIS will be elaborated.

4.4.1. Involved actors and their preferences

The involved actors and their preferences are inputs for the model. Since the focus and the contribution of this chapter are to provide an integrated energy planning approach to take the actors' preferences into account, simplified choices are made for the chosen actor groups and their preferences. For detailed discussions in those aspects, interested readers could refer to [136], [148] and [188]. If different groups of actors and their preferences are to be used, the formulations of the objectives will need to be changed accordingly, but our proposed method will still be valid. In this work, the involved actors are simplified to three actor groups: governments, funders, and local residents. We consider that the overarching preference of all these actors is to plan a regional energy system consisting solely of RES. Therefore, 100% carbon emission reduction or solely using RES is considered to be their joint objective which will be treated as a given and is not included in their preference list. The rest of their preferences are shown in Table 4.1.

It has to be noted that, as mentioned in Section 4.1.4, total CapEx, total O & M costs, land-use, and VIA will be the objectives in the optimization model. These objectives are all considered preferences for all the actors. In Table 4.1, only the major preferences of the actors are marked. The other preferences are included in the optimization as objectives but play a less important role compared to the major preferences. Therefore, in TOPSIS, the solutions will be evaluated based on their major preferences. The three actor groups and their major preferences are now discussed further.

All levels of government are aligned in their preferences to minimize total CapEx, total O & M costs, land-use, and VIA. Governments make up the first composite actor. The landowners have identical preferences to the governments. Therefore, they are also represented by this actor group.

RES projects need to be funded. Examples of funders are energy cooperatives, producers, or investors. They are primarily concerned with minimizing total CapEx and total O & M costs. This actor group is referred to as the funders.

The local residents that want to prevent visual impact from wind turbines are unique in their major preferences: they mainly care about minimizing VIA. Therefore, local residents acting against wind turbines are categorized as another actor group.

Table 4.1: The major preferences of the three actor groups.

Objectives / Actors groups	Total O & M costs	Total CapEx	Land-use	VIA
	min	min	min	min
Governments	✓	✓	✓	✓
Funders	✓	✓		
Local residents				✓

4.4.2. Multi-Criteria Decision-Making model (TOPSIS)

After obtaining the Pareto-optimal solutions from MOO, the solutions will be evaluated based on their desirability to different actors, and then the final optimal solution for each actor will be obtained, which results from a ranking of the outcomes using TOPSIS method. [177] presents an extension of TOPSIS that is able to combine the preferences of multiple actors to allow for group decision-making, which will be used in this research. The process for TOPSIS will be described as follows, where steps 1 - 5 are illustrated in Figure 4.4.

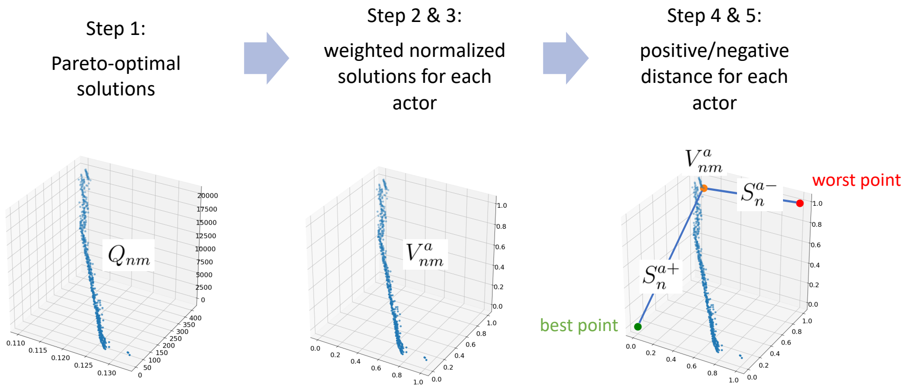

Figure 4.4: Illustration of steps 1 - 5 of the TOPSIS method, where only three objectives are visualized.

Step 1 is to construct the decision matrix consisting of the values (Q_{nm}) for each of the four preferences $m, \forall m \in$ M for each solution $n, \forall n \in$ N, where M = {total CapEx, total O & M costs, land-use, VIA}, and N is the set of Pareto-optimal solutions.

Step 2 is to create a normalized decision matrix with the normalized values (R_{nm}). A simple linear normalization is applied. In the equation below, $Q_{\max,m}$ represents the maximum value for preference m out of the complete set of solutions. $Q_{\min,m}$ represents the minimum value for preference m:

$$R_{nm} = \frac{Q_{nm} - Q_{\min,m}}{Q_{\max,m} - Q_{\min,m}} \quad \forall n \in \mathrm{N}, \forall m \in \mathrm{M} \tag{4.20}$$

Step 3 is to define the weighted normalized decision matrix (V^a_{nm}) for each actor $a, \forall a \in \mathrm{A}$, where $\mathrm{A} = \{$governments, funders, local residents$\}$. Major preferences for one actor group are awarded a weight of 1. If a preference is not the major preference for a specific actor group, the weight is 0.

4

$$V^a_{nm} = w^a_m R_{nm} \quad \forall n \in \mathrm{N}, \forall m \in \mathrm{M}, \forall a \in \mathrm{A} \tag{4.21}$$

Step 4 is to find the best point (I^{a+}_m) regarding each preference m for each actor a and the worst point (I^{a-}_m) regarding each preference m for each actor a. In this research, all preferences are minimized.

$$I^{a+}_m = \min_{\forall n \in \mathrm{N}} V^a_{nm} \quad \forall m \in \mathrm{M}, \forall a \in \mathrm{A} \tag{4.22}$$

$$I^{a-}_m = \max_{\forall n \in \mathrm{N}} V^a_{nm} \quad \forall m \in \mathrm{M}, \forall a \in \mathrm{A} \tag{4.23}$$

Step 5 is to derive the positive distance (S^{a+}_n) and the negative distance (S^{a-}_n) for each solution n for each actor a. These are calculated using the Euclidean distance between each solution and the best/worst points. If the positive distance (S^{a+}_n) is large, it means that this solution is far from the best point, i.e., it is not a good solution. Similarly, a good solution will entail a large negative distance and a small positive distance.

$$S^{a+}_n = (\sum_{m \in \mathrm{M}} (I^{a+}_m - V^a_{nm})^2)^{\frac{1}{2}} \quad \forall n \in \mathrm{N}, \forall a \in \mathrm{A} \tag{4.24}$$

$$S^{a-}_n = (\sum_{m \in \mathrm{M}} (I^{a-}_m - V^a_{nm})^2)^{\frac{1}{2}} \quad \forall n \in \mathrm{N}, \forall a \in \mathrm{A} \tag{4.25}$$

Step 6 is to determine the so-called normalized coefficient of closeness (CC) (CC^a_n) for each solution n for each actor a. To do this, first, the absolute CC (CoCl^a_n) for each solution n for each actor a is calculated.

$$\mathrm{CoCl}^a_n = \frac{S^{a-}_n}{S^{a+}_n + S^{a-}_n} \quad \forall n \in \mathrm{N}, \forall a \in \mathrm{A} \tag{4.26}$$

Then, CoCl^a_n are normalized to CC^a_n. CC^a_n represents the degree of optimality of solution n for actor a, which will be referred to as CC score in the rest of the chapter. A CC score of 1 means that the solution is the closest to the best solution and the furthest to the worst solution for the specified actor.

$$\mathrm{CC}^a_n = \frac{\mathrm{CoCl}^a_n - \mathrm{CoCl}^a_{\min}}{\mathrm{CoCl}^a_{\max} - \mathrm{CoCl}^a_{\min}} \quad \forall n \in \mathrm{N}, \forall a \in \mathrm{A} \tag{4.27}$$

Step 7 is the final step. Each solution now has a CC score for each actor. To combine the preferences of the actors, the method proposed by [177] is used. The geometric mean of the CC scores for all actors is calculated to define an average CC score ($CC_n^{average}$). In the equations below, |A| represents the size of the set of actors A.

$$CC_n^{average} = (\prod_{a \in A} CC_{n,a})^{\frac{1}{|A|}} \quad \forall n \in N \tag{4.28}$$

Two more values are defined: maximin and minimax. For each solution, the minimum CC score of all the actors is taken, and then the solution that has the highest minimum CC score is defined as the maximin. It indicates the solution that achieves the highest least satisfaction for all the actors. Similarly, for each solution, the maximum CC score of all the actors is used, and subsequently, the solution with the lowest maximum CC score is defined as the minimax. It usually represents the decision of a risk-neutral decision-maker.

$$\text{maximin} = \max_{\forall n \in N} (\min_{\forall a \in A} CC_n^a) \tag{4.29}$$

$$\text{minimax} = \min_{\forall n \in N} (\max_{\forall a \in A} CC_n^a) \tag{4.30}$$

4.5. Case study set-up

To illustrate the usage of the approach, a case study will be done. This section introduces the background of the case study and the data inputs.

4.5.1. Background

To combat climate change, in 2019, the Dutch government concluded the National Climate Agreement to reduce the Netherlands' emissions by 49% by 2030, compared to 1990 levels, and by 95% by 2050 [7]. One of the measures is to promote RES investment on the regional level. For that purpose, the country has been divided into 30 energy regions [189], where each region is asked to come up with its plan for the RES investment capacity. Amsterdam is located in the region Noord-Holland Zuid (see Figure 4.5). The region is currently working closely with the local and regional stakeholders, and the governments [190] to propose their RES investment plan. The multi-actor nature of the complex regional energy planning process fits perfectly the scope of our chapter. Therefore, this region is chosen as the case to show the usage and strength of our method and to give policy-relevant results.

Following the approach in [10], in this region, the total suitable land for RES development (LU^{max}) is 409 km^2 and total roof surface is 86 km^2.

4.5.2. Hourly energy demand

The hourly Dutch national electricity demand is used to scale the demand for this region based on population. The national energy demand has been retrieved from the European Network of Transmission System Operators for Electricity (ENTSO-E) Transparency Platform [191]. In this research, the ENTSO-E data from 2015 is used.

Figure 4.5: The region Noord-Holland Zuid in the Netherlands [190].

4.5.3. Hourly wind and solar PV power output

The outputs of solar PV and wind turbines depend on their specific capacity factor (see Equation (4.2)). In this research, the data is derived following the approach in [10]. The data from 2015 is used.

Two wind turbines are considered: the Vestas V66 turbine with a rated power of 1750 kW and a rotor diameter of 66 meters (which is sometimes referred to as small wind turbines in this research), and the Vestas V110 turbine with a rated power of 2000 kW and a rotor diameter of 110 meters (which is sometimes referred to as big wind turbines in this research). These turbines have separate input data for capacity factors.

In total, three time-series are used in this chapter as the inputs for wind and solar energy.

4.5.4. Techno-economic parameters

Table 4.2 shows the techno-economic parameters that are used in this research. For each technology, the parameters regarding cost, lifetime, land-use factors, and VIA are given.

4.6. Results and discussions

The MOO model generates a set of Pareto-optimal solutions, they have then been processed with the MCDM technique (TOPSIS) from a multi-actor perspective. In this section, the results will be presented.

4.6.1. Aggregation and interpretation of the results

After applying the TOPSIS method to the Pareto-optimal solutions, for each solution, a unique CC score will be obtained for each actor based on their preferences. In principle,

Table 4.2: 2050 estimations of the techno-economic parameters.

Parameter / Technology	CapEx (€/kW)	FOM costs (€/kW/yr)	VOM costs (€/kWh)	Lifetime (yr)	Land-use factor (km^2/kW)	VIA per turbine (km^2)	Source
Residential PV	1250	17	0	25	0.00003	/	[192]
Utility-scale PV	850	27	0	25	0.00003	/	[186], [192]
Vestas V66 wind turbine	1205	45	0	25	0.00014	12.2	[10]
Vestas V110 wind turbine	1205	45	0	25	0.00034	32.7	[10]
Biomass	2640	90	0.0845	33	/	/	[10]
Hydrogen storage conversion	2400	0.04	0	5	/	/	[10], [193]
Hydrogen storage	0.06(€/kWh)	62% (in/out efficiency η)	0	5		/	[10], [193]

the solution with the highest CC score should be the optimal solution for the particular actor. However, in this chapter, for each actor, the solutions that have the top 2% CC scores are taken first, and then the mean of these solutions is regarded as the final optimal solution for each actor. The same process is applied for all the results that will be presented later, except for the cost-optimal result, which is not an averaged result.

The reasons are two-fold. Firstly, as mentioned in Section 4.1.2, TOPSIS, as one of the goal programming methods, evaluates the solutions based on their distances to the ideal points. This indicates that, among the Pareto-optimal solutions, there might be several solutions that have similar CC scores but feature different generation mixes. Only taking the solution with the highest CC score will completely ignore the near-optimal solutions. By averaging, the near-optimal solutions are taken into account, and thus the robustness of the optimal solutions is enhanced. Secondly, the nature of MOO and genetic algorithms indicates that only a finite number of Pareto-optimal solutions can be generated. For this reason, the results only represent a part of the Pareto-optimal solutions. This understanding helps to interpret the results in Section 4.6.2 concerning the optimal solution for the local residents.

Before discussing the results, it is crucial to emphasize that the case study results have to be used carefully since they are subject to the assumptions and the model set-up used in this research. The main aim of the case study is to showcase the kind of problem the proposed method is able to solve as well as its applicability, highlighting its added value and uniqueness compared to existing methods such as those of [59], [184]. Nevertheless, the general trend in the optimal solutions is captured.

4.6.2. Optimal solutions for the actors

Figure 4.6 shows the optimal solutions for the governments, the funders, and the local residents, and they will now be discussed. The cost-optimal solution, the average-optimal solution, the maximin solution, and the minimax solution will be discussed in Section 4.6.3.

For the governments-optimal solution, the generation mix mainly consists of biomass and residential PV. Each of them contributes around half of the total capacity. The levelized cost of electricity (LCOE) is 129 €/MWh, which is the highest among those of the three actors and is the same as the LCOE of the local residents-optimal solution. Since there are hardly any wind turbines in the generation mix, the land-use and VIA are negligible. Moreover, biomass is the largest component in the total CapEx and the total O & M costs. In general, since all four objectives are considered the major preferences of the governments, none of the objectives is the highest or the lowest among the optimal solutions of the three actors.

For the funders, their major preferences are the total CapEx and the total O & M costs. Compared to the governments, the optimal solution for the funders features more wind turbine installations. Biomass is still an important generation source, but now the small wind turbines replace residential PV, becoming the second-largest generation source in capacity. Furthermore, thanks to the wind turbines, which produce cheap energy, the LCOE drops to 115 €/MWh. The penalty for more wind turbines is increased land-use and VIA. The land-use is now 88% of the total suitable area, which is also around a quarter of the total area in the region. The VIA is even more astonishing, which is 12 times the

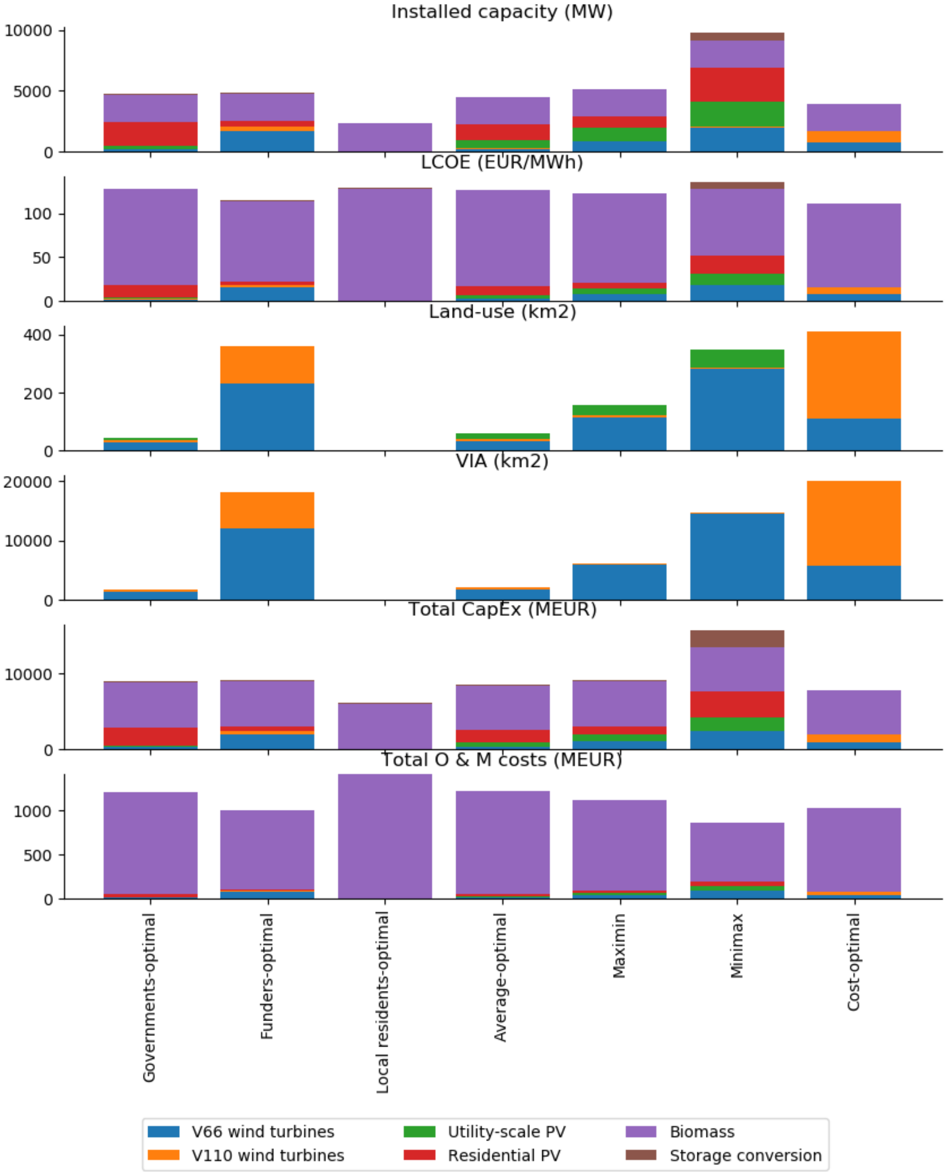

Figure 4.6: The governments-optimal solution, the funders-optimal solution, the local residents-optimal solution, the average-optimal solution, the maximin solution, the minimax solution, and the cost-optimal solution.

total regional area. However, it has to be noted that, the exact number of VIA is not instructive since a detailed study regarding the VIA has to be conducted depending on the layout of the wind farm in reality. Hence, the values of VIA should be interpreted relatively. As for the funders' major preferences, the total CapEx is comparable to that of the governments-optimal solution, but the total O & M costs are much lower and are the lowest among the three optimal solutions.

The only major preference of the local residents is VIA. Unlike the major preferences of the governments and the funders, which are related to all the considered technologies, the major preference of local residents is only affected by wind turbines. Therefore, in the evaluation stage, they are indifferent to other technologies. This observation indicates that for the local residents-optimal solution, solar PV and biomass may both appear with certain capacities. However, as mentioned in Section 4.6.1, only a part of the Pareto-optimal solutions will be generated from the MOO model in each model run. In this case, only biomass is present in the generation mix, leading to low total CapEx and high total O & M costs. Its LCOE is the same as the governments-optimal solution - 129 €/MWh.

In summary, for such a standalone energy system with only RES, different actors all favor biomass in the generation mix. Wind turbines sometimes play a role, but only for actors who consider cost more crucial than other criteria. In addition to biomass, residential PV serves as the other main generation source if more criteria are taken into account.

4.6.3. Comparison to the cost-optimal solution

The MOO model provides solutions that optimize four objectives. A cost-optimal solution, which is a single-objective solution, does not belong to the Pareto-optimal solutions. In this chapter, nevertheless, it is of utmost interest, since it is often the proposed solution from existing literature. Therefore, it will be discussed and compared with other solutions to highlight the added value of our multi-actor approach.

In order to minimize cost, wind turbines contribute to 43% of the generation mix in the cost-optimal solution. The LCOE is 111 €/MWh, which is comparable to the funders-optimal solution. It is noticeable that the land-use has already reached its upper bound according to Equation (4.18). Because of this constraint, wind turbines cannot be installed more, and thus the LCOE cannot be lower. With regard to VIA, the effect of big turbines has increased compared to the funders-optimal solution.

In practice, only one solution is required. Therefore, besides the optimal solutions for all the actors and the cost-optimal solution, it is important to come to a solution that considers all the actors. In this chapter, this single solution is quantified using the average-optimal solution, the maximin solution, and the minimax solution.

The average-optimal solution is calculated based on Equation (4.28), which shows the solution combining all the major preferences of the actors. The solution with the highest average CC score is discussed. This solution is comparable with the governments-optimal solution, but with more capacities in utility-scale PV.

The maximin solution is a solution that may not be optimal but is acceptable or satisfying for everyone. It is calculated based on Equation (4.29). An acceptable solution is here interpreted as the solution that has the highest least satisfaction for the actors. Compared with the average-optimal solution, an extra capacity of small wind turbines comes into the generation mix. The land-use is 38% of the total suitable area, and the VIA is four times the area in the region.

The minimax solution, also known as the least regret solution, is the solution that all the actors will have the least regret after making the decision. It features risk-neutral decision-makers and is calculated based on Equation (4.30). This solution has the highest total capacity, which includes all the considered technologies. Storage is present for the first time. Biomass, residential PV, utility-scale PV, and small wind turbines have similar installed capacities. The LCOE and the total CapEx are the highest among all the solutions. However, despite the large capacity of wind energy, the land-use, and the VIA are not as high as those in the funders-optimal solutions, since the contribution of big wind turbines is small.

4.6.4. Alignment of the optimal solutions for the actors

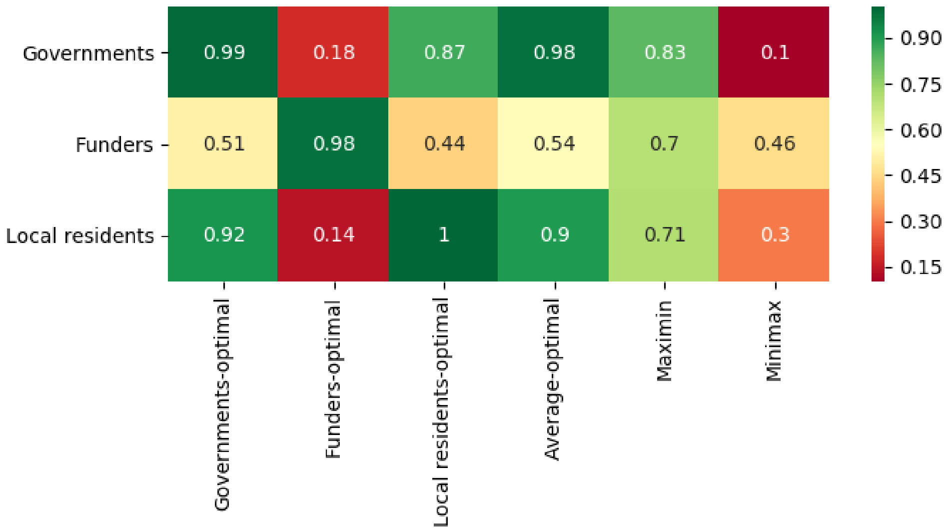

Figure 4.7: The alignment of the solutions in terms of CC scores for the actors.

In the previous sections, the optimal results in terms of installed capacity, LCOE, land-use, VIA, total CapEx, and total O & M costs are discussed. In this section, the solutions are further analyzed by looking at the alignment of these solutions, or in other words, how well each solution performs for other actors. For the optimal solution for each actor, the CC scores of other actors are obtained. Figure 4.7 shows such an alignment matrix. The cells show the CC scores for each actor for the six solutions. It is noted that the CC scores for a particular actor (i.e., row-wise) are the normalized values using the best and the worst values of their own (see Equation (4.27)). In other words, a score of zero does not indicate that all the major preferences are the lowest for this actor. It is only undesirable based on the overall evaluation of these major preferences among all its Pareto-optimal solutions.

Several observations are gained from this table. The main observation is that the governments and the local residents are well aligned, while the funders often have diverging views with them. In addition, the funders-optimal solution is considered a bad solution for the government (with a CC score of 0.18) and also for the local residents (with a CC score of 0.14). This is because, with wind energy being the cheapest energy, funders are prone to more capacity in wind energy which, in turn, increases the land-use and the VIA. Furthermore, the maximin solution seems to be the most acceptable solution for all the actors, since the least satisfied actor still has a score of 0.7.

4.6.5. Discussion of the results

The presented results are based on certain data assumptions. Therefore, sensitivity studies add more insights into the understanding of the results. This section will first present the sensitivity studies on the input parameters, and then the influence of the weights of the actors will be elaborated. Next, the impacts of the changes in demand data are discussed. At last, the results are compared with other studies.

Sensitivity experiments are performed, where the CapEx of all the technologies, the VOM of biomass, and the land-use factors of the wind turbines and solar PV are changed to the + 30% and - 30% of the corresponding values. Out of all the optimal solutions, the results of the average-optimal solutions are given in Figure 4.8. It can be seen that all the input parameters have a significant but reasonable influence on the results. For example, the drop in the CapEx of utility-scale PV will cause an increase in its capacity and a decrease in the capacity of residential PV. Furthermore, if the VOM of biomass becomes lower by 30%, the capacity of biomass will have a considerable rise. Nevertheless, for the average-optimal solution that considers the major preferences of all the actors, the overall trend still holds. Biomass is the backbone of the generation mix, solar PV is the second largest contributor, and wind turbines play a less important role, which is mainly due to the major preferences in land-use and VIA from the governments and the local residents.

To calculate the average results, in this chapter, it is assumed that the weights of all the actors are equal (see Step 7 in Section 4.4.2). This assumption is made because the focus of this work is only to showcase the usage of the proposed approach. However, the changes in the weights of the actors may have effects on the results and therefore, their influences are investigated.

Table 4.3: Scenarios with different weights allocated to the actors.

Scenario \ Actor group	Governments	Funders	Local residents	Mean method
Reference	1	1	1	Geometric
Mean	1	1	1	Arithmetic
Mean-govt2x	2	1	1	Arithmetic
Mean-funders2x	1	2	1	Arithmetic
Mean-residents2x	1	1	2	Arithmetic

Four scenarios with different weights of the actor groups are introduced in Table 4.3. To be able to allocate different weights to the actors, the geometric mean cannot be used, because it multiplies all elements together (see Equation (4.28)). Therefore, the arithmetic

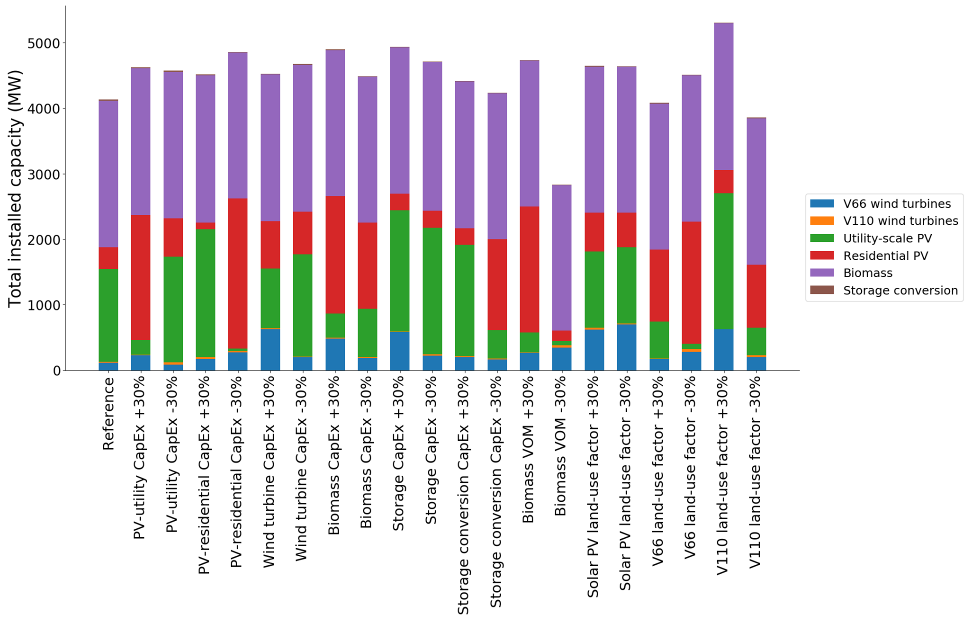

Figure 4.8: Sensitivity studies for CapEx, VOM of biomass and land-use factors.

mean or simple mean is used for these scenarios. The average-optimal solutions are shown in Figure 4.9. The use of arithmetic mean already changes the results, more residential PV is preferred, and utility-scale PV becomes less favorable. If governments are given more weight, the percentage of residential PV even increases. However, when the funders are provided with more decision rights, wind turbines will play a more important role. Similarly, given the major preference for VIA, local residents will try to minimize the use of wind turbines.

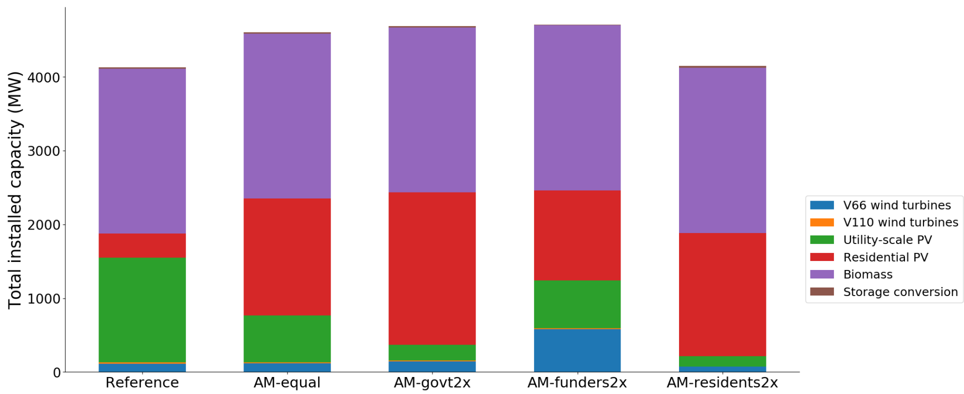

Figure 4.9: Sensitivity studies for different weights allocated to the actors.

In this chapter, the demand data of 2015 is used, and the scaling of national demand to regional demand is based on population. The change in demand data in the future, especially in view of the scenarios such as high electrification, and other scaling methods, might have an impact on the results. The data from [191] shows that between 2010 and 2018, the national demand varies between - 2% and + 5% compared to the 2015 data. To explore the influences of other scaling methods, we scaled the 2015 demand based on the annual regional demand data from [194], which shows that our scaling method based on population only underestimates the demand by 8%. Nevertheless, [195] indicates that in the Netherlands, the demand will increase by 50% in a high electrification scenario in 2050. We, therefore, conducted a sensitivity study for demand data. The results show that the average-optimal generation capacities are changed proportionally to the demand change. For example, for the high electrification scenario where the demand is expected to grow by 50%, biomass capacity also increases by 50%. The capacity of solar PV grows more than 50% since capacity factors have to be taken into account.

Since the multi-actor perspective for energy system planning is new and has not been studied before in literature, the cost-optimal results presented in Figure 4.6 are now compared to existing studies. The LCOE from our study is 111 €/MWh, which is comparable to the optimization study for the Netherlands [10]. In terms of the generation mix, [10] shows wind energy has the largest contribution. Our model results indicate that the optimal share of wind energy is 46%. This is because, in [10], the total land-use constraints are not met. In our case, the total land-use constraint is met so that the wind capacity cannot increase anymore.

4.7. Conclusions and Policy Implications

In the field of energy system planning, MOO is used to take various design criteria (such as cost and emissions) into account. Existing studies focus on the trade-offs between those criteria that are often visualized by a set of Pareto-optimal solutions. However, the energy system is a complex system where different actors need to reach agreements on the final investment, and the actors have their own, sometimes conflicting, interests. Their conflicts of interest are one of the major reasons that hinder the energy transition. Therefore, adding actors' perspectives to the MOO studies is of utmost importance to the successful design and implementation of a future energy system, which is not yet done in the literature. This chapter proposes the first-of-a-kind multi-actor perspective in multi-objective regional energy system planning studies. It is based on a combination of models: MOO and MCDM. The key advantages of our approach are: firstly, it is able to consider various actors in an energy system planning problem simultaneously; secondly, it assigns a degree of optimality to every obtained Pareto-optimal generation mix, i.e., the generation mix that is optimal for each actor and the sub-optimal generation mix for all the actors can now be quantified. Besides, the land-use of RES and the visual impact of wind turbines are now modeled separately as two objectives.

A simplified case study for the greater Amsterdam region in the Netherlands has been done to illustrate the usage of the approach and to show promising policy-relevant results. The optimal generation mixes of different actor groups for a standalone RES-based energy system are obtained. Given our model and data assumptions, governments would prefer a generation mix consisting of mainly solar PV and biomass with similar capacities. Local residents are only concerned about minimizing the use of wind turbines, and thus solar PV and biomass are both favored by them. By conducting an alignment check for all the actors with respect to the optimal solution of each actor, we find that the governments and the local residents are well-aligned in the generation mix. On the other hand, the investors (or the so-called funders in this chapter) prefer a generation mix with more wind turbines, since that leads to the lowest LCOE. In addition, a least-cost optimization, which is the most common method in energy system planning, is carried out. It is found that the cost-optimal solution entails biomass and wind turbines in the generation mix, which is only similar to the funders-optimal solution in our study.

Our results reveal, in a measurable way, a core fact in energy system planning that delays the energy transition process that different stakeholders would shape the future energy system in the way they opt for. The market, at the hands of investors, will likely converge to large shares of low-cost energy, such as wind energy in our model. However, this scenario will deploy all the land in a highly-populated region (as in our case) to place wind turbines and will also cause high public resistance. It will be vastly undesirable for other actors, such as the governments and the local residents. Therefore, policy-makers should, on the one hand, incentivize other technologies (such as residential PV) than the cheapest energy (such as wind energy). On the other hand, they should ensure the inclusion of all stakeholders and look for a plan that all actors find most satisfying in the decision-making process of RES investment. This can be done by proposing an acceptable solution for all actors. Our study suggests that, given our model assumptions, an adequately diversified generation portfolio featuring similar capacities in utility-scale PV and residential PV with sufficient biomass, would increase the satisfaction of all the actors. Using this generation mix, investors are the least satisfied but the degree of optimality is still high. This compromise of optimality can serve as a common ground for negotiations in regional energy system planning.

Another key contribution of our proposed approach is that, for the first time in the literature, it opens up the possibility of investigating the impacts of various policies on quantitative and optimal investment decisions from the stakeholders' perspectives. For example, the impact of spatial policy on the land-use of RES and the impact of RES subsidies could be investigated, and the effects of different emission targets could be explored. Using our approach, the impacts of these policy options on actors' optimal investment decisions can now be revealed, which will generate valuable policy implications for the energy system planning process.

Our study proposes a novel and promising approach and shows useful results. However, the same as every work, it has some possible extensions that are recommended for future research. Firstly, our model considers the explicit preferences of the actors in TOPSIS, but in reality, their preferences might be ambiguous. Future research could deploy e.g., fuzzy TOPSIS to account for this ambiguity. Secondly, although our approach is still valid when the objectives are changed, it is computationally non-trivial to include more objectives in the MOO model. In fact, adding every extra objective in any MOO model will largely increase the computational effort, or a good representation of the Pareto-optimal solutions is not obtained. Therefore, we recommend a future research direction that investigates the trade-offs between the number of objectives and the completeness of the Pareto-optimal solutions under various model set-ups.

5

Equilibrium and centralized models with bilateral trading

5.1. Introduction

To mitigate climate change and reduce carbon emissions, renewable energy sources (RES) play a vital role in modern power systems. Countries around the world set ambitious RES targets for the next decades, and the planning of RES generation and transmission is prominent on the agenda.

Energy system optimization models (ESOM) refer to optimization models that aim to find the optimal capacity expansion of generation technologies, and transmission networks [33]. The objective is usually to minimize the total system cost while satisfying a number of constraints such as energy balance, generation limits, and network limits. The results of the models are possible scenarios to achieve certain carbon/RES targets that the energy system might evolve into [18]. Such models are often used by policymakers because they serve as a benchmark to help them make decisions on potential policy changes in view of the modeling outcomes, i.e., optimal capacity expansion and the associated costs. For high-RES energy systems, numerous models are built in recent years, see e.g., reviews of [88], [196] on various tools, and [197] for different countries.

Despite their wide use and policy relevance, existing ESOM have a few characteristics that shift them away from reality. First, uncertainty is often not inherently modeled. Second, the models do not have a comprehensive representation of different electricity markets. ESOM are known to represent the investment equilibrium under a perfectly competitive pool market [198], while other markets are not yet included. Third, externalities beyond the marginal cost of electricity in the market are not commonly addressed. Existing literature has considered emission-based externality, i.e., carbon tax. However,

This chapter is based on the paper N. Wang, R. A. Verzijlbergh, P. W. Heijnen, and P. M. Herder, "An energy system optimization model with bilateral trading and externalities: Application to the Dutch national program Regional Energy Strategies". Submitted, 2022. The first author of the paper, also the author of this thesis, conceptualized and conducted the research. The other authors performed an advisory role.

externalities in planning models are more than that. In this study, we present several externality terms in ESOM and focus on the externalities associated with bilateral trading.

Bilateral trading is generally known as a bilateral market. Since the liberalization of the electricity sector, various bilateral market models were proposed to calculate the market equilibrium under different assumptions. These studies focus on producers and their behaviors in the wholesale market. One of the pioneering works in this field is [199], where Cournot models of the imperfect competition were used to simulate the bilateral market. This model was later modified to study generation investment while different carbon policies were evaluated in [200]. Apart from the equilibrium analysis, research efforts have also been made on individual generators' perspectives to model bilateral contracts. In [201], an optimization model was proposed for the optimal planning for distributed generations under competitive market auctions and fixed bilateral contract scenarios. Other market players than generators such as retailers, prosumers, and energy communities have also been studied. For example, [202] presented a methodology to evaluate bilateral contracts of retailers from a risk perspective. [203] proposed a game-theoretical model to describe the competition for bilateral contracts among generation companies and large consumers. [204] modeled the trilateral interactions among an integrated community energy system, prosumers, and the wholesale electricity market. Bilateral contracts were also modeled in combination with demand response to find the optimal energy storage sizing in [205]. In terms of modeling methods, agent-based modeling is sometimes used to model bilateral contracts. In the review of [206] on electricity systems models, two agent-based modeling platforms that incorporate bilateral contracts, EMCAS and GTMax, are discussed. In addition, [207] evaluated the effects of bilateral markets in England and Wales using an agent-based simulation. [208] addressed the challenge of using software agents for the negotiation of bilateral contracts by presenting a multi-agent energy market. [209] developed utility-based and adaptive agent-tracking strategies for bilateral negotiations. Furthermore, [210] proposed a complex network approach for assessing bilateral trading patterns under physical network constraints. Lastly, in recent years, with the increasing penetration of distributed energy sources, peer-to-peer (P2P) markets have emerged as next-generation market designs. In these markets, bilateral trading is considered one of the most promising P2P market mechanisms [211] and is thus commonly modeled. Particularly, bilateral trades can be associated with the preferences of the trading parties. To represent this feature, terms such as heterogeneous preferences ([212], [213]), product differentiation [214] and energy classes [215] have been used. Among those, product differentiation is a generic mathematical formulation [216] that can be used for various purposes, e.g., [217] used it to account for exogenous network tariffs in P2P markets.

Based on the background information, we found that there remains a research gap in modeling externalities in the bilateral market. The inclusion of externalities would broaden the area of applications for ESOM. In this thesis, we propose an improved energy system model that considers externalities associated with bilateral trading. The contributions of this chapter are summarized as follows:

- This chapter contributes to the state-of-the-art of ESOM and P2P markets. On the one hand, ESOM now include bilateral markets, which were previously only a representation of the long-term equilibrium of the pool market. On the other hand, because this work lies in the intersection of ESOM and market models, it also contributes to the literature on P2P markets by proposing an investment model to reveal the long-term effects of P2P markets.

- Modeling the externalities associated with bilateral trading in ESOM opens up research possibilities beyond a purely economic cost perspective, such as technology preferences, aversions due to social resistance, or trade barriers. These practical implications will be shown in the case study.

- We conduct a case study for the Dutch energy system to reach its RES target in 2030.

The chapter is structured as follows. Firstly, Section 5.2 provides the preliminaries to understand the model by conceptualizing the mixed bilateral and pool markets in this study. Next, the models are presented in Section 5.3. In Section 5.4, a case study of the Netherlands to illustrate the model is introduced. Then, the results are discussed in the next section. At last, Section 5.6 concludes.

5.2. Conceptualizing bilateral trading in the markets

In order to model bilateral trading with external costs, this section introduces the conceptualization of the mixed bilateral and pool markets (see Figure 5.1). This figure is largely built on existing knowledge of electricity markets and used to give background information for the model formulation in Section 5.3.

ESOM are characterized by rich spatio-temporal details of the energy system, and accordingly, some simplifications are made to make the model tractable. One of the common simplifications is to not explicitly model individual generators and/or consumers. Instead, supply and demand that are in proximity are aggregated into geographical nodes. The nodes could be regions in national planning models or countries in continental planning models such as the European planning model. Hence in this study, the nodes are considered as a generic type of actor with an aggregated supply and/or demand, which participates in the market on behalf of the proximity. This way of conceptualizing the problem will be further explained in Section 5.3.1. In addition, the same with the existing ESOM and/or market equilibrium researches such as [218], in this study, the considered actors are limited to a minimal extent while still enough for the functioning of the markets to demonstrate the model. In that regard, some other actors, such as retailers or prosumers, are left out of scope.

The lowest layer in Figure 5.1 is the physical layer, referring to the generation technologies and the transmission networks with their associated actors. The capacity expansions of generation and transmission are done by the nodes and the transmission system operator (TSO), respectively. Regarding energy flows, there are energy exchanges among the nodes, but not between the nodes and the TSO, as the TSO neither produces nor consumes energy.

The middle layer is the market layer. There are two market operators, the energy market operator and the carbon market operator. The energy market operator operates the bilateral market and the pool market together. In the pool market, locational electricity prices are derived by the market operator, at which the buyers and sellers trade energy. The mechanism is different in the bilateral market. We utilize the P2P bilateral

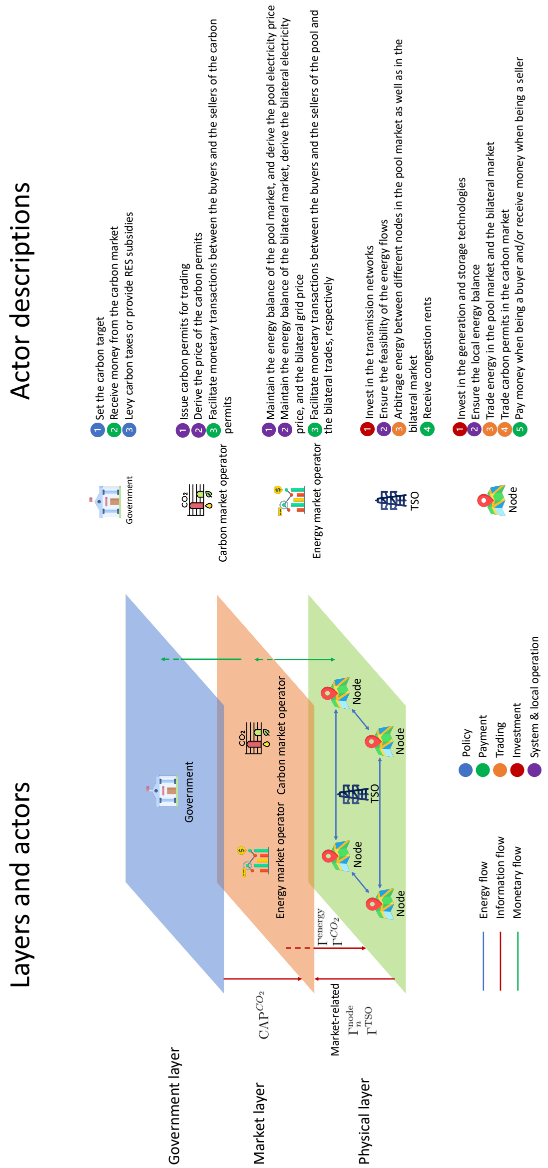

Figure 5.1: Conceptualization of the mixed bilateral and pool markets: layers, actors and their descriptions.

trading mechanism as proposed by [216], where nodes negotiate bilaterally about both the amount and the price of the bilateral energy exchange. The market operator helps to facilitate the transactions when a consensus is reached. More information on the bilateral markets will be given in Section 5.3.1.

Now we turn to the carbon market operator, which will be discussed together with the government level. The role of the government is to set carbon goals for the future, which are facilitated through policies such as a cap-and-trade system and carbon taxes/RES subsidies [200]. The cap-and-trade system is a market-based system where the demands (i.e., the carbon goal) are fixed by the government. In addition, the carbon goals could also be implemented indirectly, i.e., through levying carbon taxes or providing RES subsidies.

Finally, there are information and monetary flows between different layers. To introduce these flows, some mathematical symbols are used in Figure 5.1. The mathematical symbols will only be discussed briefly now since the details will be given in the model formulation in Section 5.3. There is a bi-directional information exchange between the actors at the bottom layer and the market operators during the operational phase of the markets. Γ_n^{node} and Γ_n^{TSO} are the sets of decision variables for node n and the TSO, respectively. The nodes and the TSO provide the information of energy trades (which are parts of their decision variables, denoted by market-related Γ_n^{node} and Γ_n^{TSO} in Figure 5.1) to the market operators. Reversely, the market operators inform them about the prices in the markets, denoted by the set of decision variables of the energy market operator Γ^{energy} and the carbon market operator Γ^{CO_2}, respectively. After the market has been cleared, payments are made, and the process is facilitated through the operators as well. On the contrary, the flows between the upper two layers are unidirectional. The government sets a target CAP^{CO_2} and informs the carbon market operator. The carbon market operator collects the money, which goes reversely to the government.

5.3. Models

In this section, the proposed models are presented, which are divided into an equilibrium model that represents the long-term investment equilibrium under mixed bilateral and pool electricity markets, and an improved energy system optimization model that is equivalent to the equilibrium model for the mixed markets.

We start by formulating the respective optimization problems for the nodes, the TSO, the energy market operator, and the carbon market operator. Here, the same as other ESOM, we assume perfect competition and do not address uncertainties inherently in the model. The problem formulations for different actors give a set of optimization problems. Since these problems are all interconnected, i.e., the parameters in one problem may be the decision variables in others, and vice versa, they should be solved together. Essentially, this set of optimization problems forms an equilibrium problem. After obtaining the necessary and sufficient conditions for the long-term market equilibrium, the equivalent centralized optimization model will be given. This optimization model is the improved energy system model since it endogenously models the mixed bilateral and pool markets. The modeling steps, i.e., from the equilibrium model (the collection of individual optimization problems) to the equivalent centralized optimization model, are commonly seen in market equilibrium studies such as [218] for the pool market and [219] for the P2P market.

In this study, lower case symbols are used for variables, and upper case symbols are used for parameters and sets. Dual variables are expressed using Greek letters and are placed after the colons in the constraints. n is the index for nodes N. i is the index for generation technologies G, and storage technologies S. l is the index for transmission lines in the existing line set L. t represents a time step in the set of total time steps T.

5.3.1. Long-term investment equilibrium model

Each node's optimization problem Let us first introduce this optimization problem conceptually and then give the mathematical formulations. For all the nodes, their optimization problems will be the same. Hence, only one node's problem is discussed here.

A node, representing a market participant, wishes to minimize the net cost or in other words, maximize the net benefit since it can also earn income from sales in the markets. Note that for simplicity, in this study, we assume that a node is a market participant. We are aware that in practice, a node might not always be identical to a market participant. Nevertheless, in the same way as the existing ESOM, this model is ready to be extended in case the generator/consumer level is of interest, where a node should be further split into more market participants (i.e., generators/consumers). In that respect, we will explain how the model should be modified in the formulation later. In this study, the node's optimization problem is cast as a cost-minimization problem. The node could take the following actions: investing in generation and storage capacity, producing energy, consuming energy, trading energy in both the bilateral market and the pool market, and trading carbon permits in the carbon market. In the bilateral market, a communication graph is pre-defined where the edges connect the pair of nodes that might trade energy with each other. The neighboring nodes on this graph negotiate with each other about the trading volume and the bilateral prices, which is facilitated through the energy market operator. Note that the communication graph is most of the time not the same as the physical graph where the nodes are connected by electricity networks since they are different graphs for information exchange and energy exchange, respectively.

Γ_n^{node} is the set of decision variables for node n. It includes the investment capacities $k_{i,n}$ of generation and storage conversion i, the investment capacities $k_{i,n}^{\text{storage}}$ of storage i, the energy production $p_{i,n,t}$ from technology i at time step t, the bilateral trades $p_{n,m,t}^{\text{bilateral}}$ from node n to node m at time step t, the pool trades $p_{n,t}^{\text{pool}}$ for node n at time step t, state-of-charge $soc_{i,n,t}$ of storage i for node n at time step t, storage discharging $p_{i,n,t}^{\text{out}}$ of storage i for node n at time step t, storage charging $p_{i,n,t}^{\text{in}}$ of storage i for node n at time step t and the number of carbon permits $e_n^{CO_2}$ for node n to buy from the carbon market in a year.

The node aims to minimize its total annualized cost related to the investment and operation of its generation and storage technologies. The objective function of the node n is divided into three parts, which are given in (5.1a) - (5.1c).

The first part (5.1a) includes the non-trading-related costs, which are capital expenditure (CapEx) cost of generation and storage technologies, fixed operation & maintenance (FOM) costs, variable operation & maintenance (VOM) costs. These costs are modeled in the same way as in [10]. Here, A_i is the annuity factor for technology i, C_i and CS_i are the

CapEx for generation i and storage i, respectively, and B_i is the VOM cost for technology i.

The second part (5.1b) consists of the trading-related costs, including energy trading costs in the pool, energy trading costs and grid costs in the bilateral market, and carbon trading costs. The node n can trade energy $p^{\text{bilateral}}_{n,m,t}$ at time step t bilaterally with its neighbors $m \in \omega_n$ that are on the communication graph. Trading prices $\lambda^{\text{bilateral}}_{n,m,t}$ and grid prices $\lambda^{\text{grid}}_{n,m,t}$ are associated with the energy trades $p^{\text{bilateral}}_{n,m,t}$ in the bilateral market. In the pool market, the node n trades energy $p^{\text{pool}}_{n,t}$ at the price $\lambda^{\text{pool}}_{n,t}$. In the carbon market, the node n buys a certain amount of carbon permits $e^{CO_2}_n$ that are equivalent to their emissions at the carbon price λ^{CO_2}.

The third part (5.1c) is the external costs, which consist of three parts. The first two parts refer to the external costs that are directly related to the generation capacity or the produced energy. One example is the social costs incurred by the social resistance against wind turbines, then $E^{\text{capacity-ex}}_{i,n}$ refers to the unit social cost of wind turbines at node n. $E^{\text{production-ex}}_{i,n}$ represents either the RES subsidies (resulting in an income) or the carbon taxes (resulting in a cost) for the unit energy produced. From the modeling perspective, these two terms essentially change the CapEx or the VOM of certain technologies by incorporating these externalities. The last external cost is formulated as a product differentiation term for every bilateral trade referred from [214]. It is defined as a general cost term related to bilateral trades because the meaning of the costs depends on the interpretation. On the one hand, it may represent exogenous charges related to the bilateral trades, such as transaction costs, tax payments, and network charges. On the other hand, it could be viewed as an improved utility function, representing the willingness to pay for bilateral trades. These two applications will be further illustrated and discussed in the case study. Further discussions of the product differentiation term can be found in [214].

$$\min_{\Gamma^{\text{node}}_n} \sum_{i\in(G+S)} \frac{C_i k_{i,n}}{A_i} + \sum_{i\in S} \frac{CS_i k^{\text{storage}}_{i,n}}{A_i} + \sum_{t\in T}\sum_{i\in G} B_i p_{i,n,t} \tag{5.1a}$$

$$+ \sum_{t\in T}\sum_{m\in\omega_n} (\lambda^{\text{bilateral}}_{n,m,t} + \lambda^{\text{grid}}_{n,m,t}) p^{\text{bilateral}}_{n,m,t} + \sum_{t\in T} \lambda^{\text{pool}}_{n,t} p^{\text{pool}}_{n,t} + \lambda^{CO_2} e^{CO_2}_n \tag{5.1b}$$

$$+ \sum_{i\in G} E^{\text{capacity-ex}}_{i,n} k_{i,n} + \sum_{i\in G}\sum_{t\in T} E^{\text{production-ex}}_{i,n} p_{i,n,t} + \sum_{t\in T}\sum_{m\in\omega_n} E^{\text{bilateral-ex}}_{n,m} |p^{\text{bilateral}}_{n,m,t}| \tag{5.1c}$$

$$\text{subject to: } \Phi_n\Big(\sum_{i\in G} p_{i,n,t} - D_{n,t} + \sum_{i\in S} p^{\text{out}}_{i,n,t} - \sum_{i\in S} p^{\text{in}}_{i,n,t}\Big) = \sum_{m\in\omega_n} p^{\text{bilateral}}_{n,m,t}, \forall t \in T \tag{5.1d}$$

$$(1-\Phi_n)\Big(\sum_{i\in G} p_{i,n,t} - D_{n,t} + \sum_{i\in S} p^{\text{out}}_{i,n,t} - \sum_{i\in S} p^{\text{in}}_{i,n,t}\Big) = p^{\text{pool}}_{n,t}, \forall t \in T \tag{5.1e}$$

5

$$0 \leq p_{i,n,t} \leq E_{i,n,t}(k_{i,n} + K_{i,n}), \forall i \in G, \forall t \in T \tag{5.1f}$$

$$soc_{i,n,t} = soc_{i,n,t-1} + H_i^{\text{in}} p_{i,n,t}^{\text{in}} - \frac{1}{H_i^{\text{out}}} p_{i,n,t}^{\text{out}}, \forall i \in S, \forall t \in T \tag{5.1g}$$

$$0 \leq soc_{i,n,t} \leq k_{i,n}^{\text{storage}} + K_{i,n}^{\text{storage}}, \forall i \in S, \forall t \in T \tag{5.1h}$$

$$0 \leq p_{i,n,t}^{\text{out}} \leq k_{i,n} + K_{i,n}, \forall i \in S, \forall t \in T \tag{5.1i}$$

$$0 \leq p_{i,n,t}^{\text{in}} \leq k_{i,n} + K_{i,n}, \forall i \in S, \forall t \in T \bar{\mu}_{i,n,t}^{\text{in}} \tag{5.1j}$$

$$e_n^{CO_2} = W_i \sum_{t \in T} \sum_{i \in R} p_{i,n,t} : \lambda_n^{CO_2} \tag{5.1k}$$

(5.1d) and (5.1e) are both the energy balance constraints. The net power injection $\sum_{i \in G} p_{i,n,t} - D_{n,t} + \sum_{i \in S}(p_{i,n,t}^{\text{out}} - p_{i,n,t}^{\text{in}})$ is divided into two parts: one for the trading in the bilateral market and the other for trading in the pool. On the right-hand side of (5.1d) is the sum of all bilateral trades for node n.

Φ_n is a parameter between 0 - 1 that is determined by the node n itself, indicating the percentage of its net energy that n would like to trade bilaterally. The rest will be traded in the pool. This way of modeling the mixed markets strongly aligns with our conceptualization of the markets, i.e., one only has to decide ex-ante how much to trade in total in the bilateral market and in the pool market, without determining specifically who to trade with and how much to trade with each trading partner. Depending on the product differentiation, the model will help the nodes to find the optimal trading partners and the associated trading volumes. In case the trading partners and the associated trading volume are fixed ex-ante, then there are no further decisions to be made, and the amount could be deducted from the demands directly. Furthermore, this model is generic in that by changing the value of this parameter, the pool market (when $\Phi_n = 0$), the bilateral market (when $\Phi_n = 1$), or the mixed markets (when $0 < \Phi_n < 1$) can be modeled.

We would also like to continue the discussion on the assumption that the node n is identical to a market participant in this study. As previously introduced, it is a common simplification in ESOM in order to reduce the complexity of the model. In the same way with those models, if desired, one node can further be split into more generators and/or consumers. In that case, both sides of (5.1d) and (5.1e) will be changed such that instead of the net injection and the trades for one node, the sum of the generators and/or consumers will have to be used. Nevertheless, this assumption does not change the gist of the formulation and has no influence on the equivalent centralized optimization model that will be introduced in Section 5.3.2.

(5.1f) indicates that the energy production is constrained by the efficiency $E_{i,n,t}$ (capacity factor in case of variable renewable energy) and the capacity of the generation technologies. Here, $K_{i,n}$ is the existing capacity, and $k_{i,n}$ is the capacity to be expanded, essentially making the model a capacity expansion model. (5.1g) - (5.1j) are the storage constraints, indicating the change in state-of-charge, and the capacity limits for state-of-charge, charging, and discharging, which are modeled the same way as in [10]. The last constraint (5.1k) shows that the amount of emissions equals the number of carbon permits.

TSO's optimization problem The role of the TSO is two-fold. First, it ensures the feasibility of the energy flows and accordingly, invests in the transmission network capacity in a cost-optimal manner. Second, it harvests congestion rents by trading $z^{\text{bilateral}}_{n,m,t}$ and $z^{\text{pool}}_{n,t}$ in the mixed bilateral and pool markets.

The decision variables of TSO are represented by the set Γ^{TSO}, which includes the investment capacity k_l in line l, the bilateral trades $z^{\text{bilateral}}_{n,m,t}$ from n to m at time step t, the pool-based trades $z^{\text{pool}}_{n,t}$ for n at time step t and the energy flow $f_{l,t}$ in line l at times step t.

The objective function (5.2a) is to minimize the total annualized cost pertaining to its two roles. The first term in (5.2a) is the investment cost for the transmission network, where Δ_l is the length of the line l. In addition to the investment cost, the TSO receives the congestion rents from both electricity markets.

$$\min_{\Gamma^{\text{TSO}}} \sum_{l\in L} \frac{\Delta_l C_l k_l}{A_l} - \sum_{t\in T}\sum_{n\in N}\Big(\sum_{m\in\omega_n} \lambda^{\text{grid}}_{n,m,t} z^{\text{bilateral}}_{n,m,t} + \lambda^{\text{pool}}_{n,t} z^{\text{pool}}_{n,t}\Big) \tag{5.2a}$$

5

$$\text{subject to: } f_{l,t} = \sum_{n\in N} PTDF_{l,n}\Big(\sum_{m\in\omega_n} z^{\text{bilateral}}_{n,m,t} + z^{\text{pool}}_{n,t}\Big), \forall l\in L, \forall t\in T \tag{5.2b}$$

$$-(k_l + K_l) \le f_{l,t} \le k_l + K_l, \forall l\in L, \forall t\in T \tag{5.2c}$$

The energy flow is modeled using direct current power flow equations. In (5.2b), the flow $f_{l,t}$ is calculated based on the Power Transfer Distribution Factors ($PTDF$) matrix and the total net injection at every node $n\in N$. (5.2c) indicates the thermal limits of the energy flows, where K_l is the existing transmission capacity.

Energy market operator's optimization problem The energy market operator clears the mixed markets at each time step t by minimizing the energy imbalances, thus determining the corresponding prices.

The set of decision variables Γ^{energy} includes the bilateral trading price $\lambda^{\text{bilateral}}_{n,m,t}$ from n to m at time step t, the grid price $\lambda^{\text{grid}}_{n,m,t}$ from n to m at time step t, and the pool trading price $\lambda^{\text{pool}}_{n,t}$ for n at time step t.

It makes sure that the bilateral trades should be equal in quantity, the trading energy from the node $p^{\text{bilateral}}_{n,m,t}$ is equal to the bilateral arbitraging energy from the TSO $z^{\text{bilateral}}_{n,m,t}$ at each time step t, and the pool-based energy trades equal the energy arbitraged by the TSO $z^{\text{pool}}_{n,t}$ at each time step t.

$$\begin{aligned}\min_{\Gamma^{\text{energy}}} &\sum_{t\in T}\sum_{n\in N}\sum_{m\in\omega_n} \lambda^{\text{bilateral}}_{n,m,t}(p^{\text{bilateral}}_{n,m,t} + p^{\text{bilateral}}_{m,n,t}) + \sum_{t\in T}\sum_{n\in N}\sum_{m\in\omega_n} \lambda^{\text{grid}}_{n,m,t}(p^{\text{bilateral}}_{n,m,t} - z^{\text{bilateral}}_{n,m,t}) \\ &\sum_{t\in T}\sum_{n\in N} \lambda^{\text{pool}}_{n,t}(p^{\text{pool}}_{n,t} - z^{\text{pool}}_{n,t})\end{aligned} \tag{5.3}$$

Carbon market operator's optimization problem The government can determine the maximum amount of emissions that are allowed to be emitted, which will be regarded as a cap CAP^{CO_2} in the carbon market. All nodes need to buy carbon permits from the carbon market, which are equivalent to their emissions. The set of decision variables Γ^{CO_2}, which includes only the carbon price λ^{CO_2}, will be determined by the carbon market operator. The optimization problem of this operator is formulated as the following.

$$\min_{\Gamma^{CO_2}} \lambda^{CO_2}\Big(\sum_{n\in N} e_n^{CO_2} - \text{CAP}^{CO_2}\Big) \tag{5.4}$$

5.3.2. Equivalent centralized optimization problem: improved energy system optimization model

In the four optimization problems, the decision variables of one problem only exist in the objective function of others and not in the constraints. This observation indicates that only one solution will exist, which results in a Nash equilibrium. We follow the approach in market equilibrium studies [218], [219] where equivalent optimization problems are derived. We are then able to find the equivalent centralized optimization problem, i.e., the improved energy system model for the mixed bilateral and pool markets, which is formulated as follows.

5

$$\min_{\Gamma} \sum_{i\in(G+S)} \frac{C_i k_{i,n}}{A_i} + \sum_{i\in S} \frac{CS_i k_{i,n}^{\text{storage}}}{A_i} + \sum_{t\in T}\sum_{i\in G} B_i p_{i,n,t} + + \sum_{l\in L} \frac{\Delta_l C_l k_l}{A_l} \tag{5.5a}$$

$$+ \sum_{i\in G} E_{i,n}^{\text{capacity-ex}} k_{i,n} + \sum_{i\in G}\sum_{t\in T} E_{i,n}^{\text{production-ex}} p_{i,n,t} + \sum_{t\in T}\sum_{m\in\omega_n} E_{n,m}^{\text{bilateral-ex}} |p_{n,m,t}^{\text{bilateral}}| \tag{5.5b}$$

$$\text{subject to: } (5.1d) - (5.1k), \forall n \in N \tag{5.5c}$$

$$(5.2b) - (5.2c) \tag{5.5d}$$

$$p_{n,m,t}^{\text{bilateral}} = -p_{m,n,t}^{\text{bilateral}}, \forall n \in N, \forall m \in \omega_n, \forall t \in T\colon \lambda_{n,m,t}^{\text{bilateral}} \tag{5.5e}$$

$$p_{n,m,t}^{\text{bilateral}} = z_{n,m,t}^{\text{bilateral}}, \forall n \in N, \forall m \in \omega_n, \forall t \in T\colon \lambda_{n,m,t}^{\text{grid}} \tag{5.5f}$$

$$p_{n,t}^{\text{pool}} = z_{n,t}^{\text{pool}}, \forall n \in N, \forall t \in T\colon \lambda_{n,t}^{\text{pool}} \tag{5.5g}$$

$$\sum_{n\in N} e_n^{CO_2} = \text{CAP}^{CO_2}\colon \lambda^{CO_2} \tag{5.5h}$$

The decision variables belong to the set Γ, which includes all the decision variables of the nodes and the TSO. The objective function (5.5a) and (5.5b) is the summation of the objective functions of all the actors.

The constraints are also a gathering of all the constraints of the actors' problems. (5.5c) includes the constraints related to nodal energy balances, generation limits, and storage. (5.5d) refers to the power flow calculations and the thermal limits of the networks. (5.5e) - (5.5g) are the optimality conditions of the optimization problem of the energy market operator. (5.5e) is the reciprocity constraint, showing that the bilateral trades should be equal in quantity, where the dual variable $\lambda_{n,m,t}^{\text{bilateral}}$ is the bilateral trading price. (5.5f) and

(5.5g) are the energy balance constraints between the nodes and the TSO, where the dual variables are the grid price $\lambda^{\text{grid}}_{n,m,t}$ for the bilateral trade and the pool electricity price $\lambda^{\text{pool}}_{n,t}$ for the pool-based trade, respectively. (5.5h) gives the cap for all the carbon emissions, with the dual variable λ^{CO_2} being the carbon price.

5.4. Case study: Regional Energy Strategies in the Netherlands

In 2019, the Dutch government announced the climate agreement to reduce the Netherlands' greenhouse gas emissions by 49% by 2030 compared to 1990 levels [7]. In the electricity sector, a major focus is to increase the share of wind and solar energy, i.e., from 14.25 TWh in 2018 to 84 TWh in 2030. Accordingly, massive investments in wind and solar energy are needed. The investments are facilitated through a national program Regionale Energiestrategie (Regional Energy Strategies) [189]. In this program, the country is divided into 30 energy regions, where each region proposes its investments in onshore wind and solar energy. Meanwhile, the TSO proposes the transmission network expansion plan.

Due to land-use and social acceptance issues of wind energy, there are tensions between the national government and regional government, making it hard to transform national goals into regional proposals. The interim analysis [220] shows that the proposed production of solar energy and wind energy is comparable, despite the fact that wind energy is cheaper. In 2021, two years after the climate agreement has been announced, 1.0 version of the investment plan [221] has been published, which finally meets the target. The process is complex and involves considerations from different dimensions where cost, land- use, and social acceptance are some of the main drivers.

Given this background, the proposed approach is used in two different ways: the first part of the case study will show the optimal investment capacity to reach the RES target in 2030. In the second part, the focus is on the investment preferences of the regions, in particular related to the wind energy investment situation. The proposed approach is used as a simulator to study the effects of such decisions not to invest in wind energy.

The Netherlands is divided into 30 nodes that are connected by transmission lines. The considered time horizon is one year with hourly resolution. The input data includes, among others, the spatio-temporal variations of wind and solar capacity factors and their maximum potentials, which are obtained from [10]. Onshore wind turbines, solar PV, OCGT, hydrogen storage, and flow battery storage are considered technologies. Due to the differences in their efficiencies and cost parameters, hydrogen storage is best suited for long-term usage, whereas battery storage provides an option for short-term storage. Furthermore, in this national planning process, the regions are not asked to propose capacity in offshore wind, and thus offshore wind is not considered. Since quite a significant generation expansion is needed, the existing generation and storage capacities are not considered for the ease of presenting results. The existing transmission network is considered, and the capacity can be expanded. Direct current power flow calculations are performed based on the existing capacities. 2030 estimations for the techno-economic parameters are used and are taken from [47] except for the network cost parameter, which is taken from [10].

Although all three external costs in (5.5b) are of significance and interest in practice, in this case study, we will focus on the last item, which is related directly to bilateral trading, and show its effects on the results. This is because, from the modeling perspective, the first two items, representing social costs and taxes/subsidies, indicate a direct change in cost parameters. Their effects resemble a global sensitivity study which is a common approach to analyze results in optimization-based studies and thus are not further investigated in this work. The ratio of traded energy between the pool market and the bilateral market Φ_n is important in practice. Analyzing the effects of this parameter will add further complexity for understanding the model results. Therefore, we will show the results for a full pool market representation (when $\Phi_n = 0$) and a full bilateral market representation (when $\Phi_n = 1$) with various values of the bilateral trading terms.

5.5. Results and discussions

This section presents results from the analysis of the Regional Energy Strategies, followed by discussions and reflections on the approach.

5.5.1. Optimal investment decisions for a full pool market representation and a full bilateral market representation

This subsection presents the optimal total installed capacities for the system. We start with the pool market. Then, the bilateral markets are analyzed where $E^{\text{bilateral-ex}}_{n,m}$ represent increasing transaction costs (TC), starting from 10% of the average electricity price to 30%, 50%, 70%, and 90% to investigate the influences of TC on the planning decisions. The interpretation of TC in this case study is two-fold. On the one hand, the TC could be considered as actual costs. On the other hand, they can be deemed as a cost proxy for willingness to pay, i.e., bilateral trading barriers due to various rationales such as geopolitical considerations.

From left to right in Figure 5.2, the following observations are obtained. First, onshore wind capacity declines while solar and storage capacity increases. Second, hydrogen and battery storage play an equally important role, and both have a significant surge in capacity. Thirdly, the expansion of transmission network capacity is marginal for all the cases. To be more specific, onshore wind capacity needs to climb to around 35 GW. Even though offshore wind energy is not considered in this model, this indicates how much offshore wind capacity is needed. Given that the capacity factors for offshore wind turbines are generally higher than those of the onshore, the obtained result is more conservative than when the offshore wind is considered. Moreover, to reach the emission goals, the needed capacity for solar PV ranges from 41 GW to 55 GW. Due to the increase in solar capacity, the system levelized cost of energy (LCOE) increases for each case, which is 88 €/MWh, 90 €/MWh, 93 €/MWh, 96 €/MWh, 97 €/MWh and 99 €/MWh, respectively.

Figure 5.3 shows the optimal capacities over the country for the two markets, respectively. We start by looking at the planning decisions under full pool market representation (left figure). Cost-optimal results are obtained because no preferences are considered in the pool market. Wind capacity is mostly placed in coastal regions where the wind resources are good, i.e., northwestern borders. Compared to wind, the capacity factors of solar PV are more evenly spread over the country. The right figure shows the planning decisions under a full bilateral market representation with 10% TC. The results are significantly different from those in the left figure. Compared to the cost-optimal results,

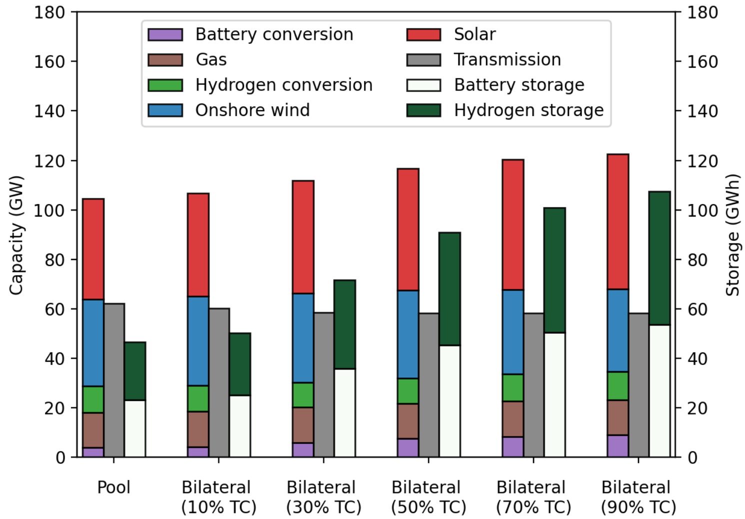

Figure 5.2: Optimal total installed capacities for the Netherlands under a full pool market representation and a full bilateral market representation with different transaction costs (% of the average electricity price).

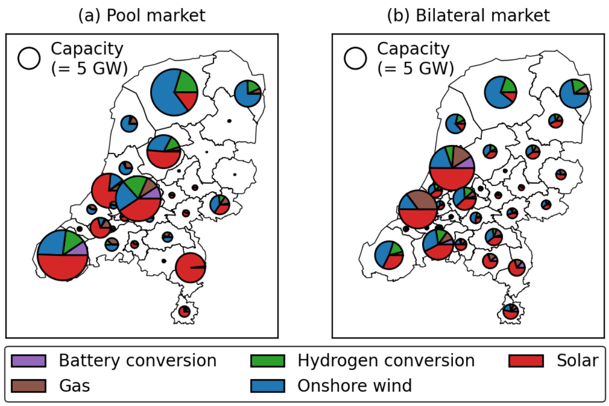

Figure 5.3: Optimal installed capacities over the Netherlands. Left to right: full pool market representation, full bilateral market representation with a 10% transaction cost.

trading barriers are introduced by the use of TC, and thus the resulting capacities are more local, where they are in line with the energy demands of the regions.

5.5.2. Abandoning wind energy for a region

Land-use and social acceptance issues of wind energy make it difficult for regions to invest in wind energy in a complex energy system environment. The potential choice of bypassing wind energy investment creates extra costs for the system and the individual nodes. In this subsection, we first look at the benchmark situation where there are no preferences towards certain RES, i.e., opposition to wind energy is not considered. Next, the investment preferences against wind energy are considered. These two situations will be referred to as benchmark and scenario 1, respectively. For illustration purposes, we consider only one region that acts against wind energy, and the influences of this choice will be presented.

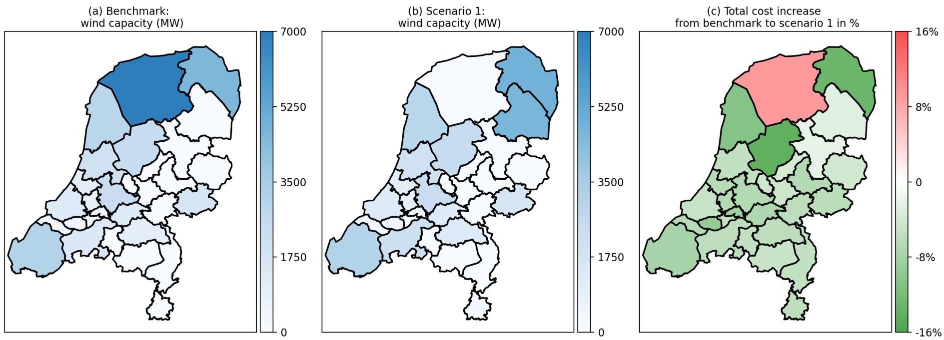

Figure 5.4: Geographical distributions of wind energy capacity in benchmark and scenario 1, and the net increase in total costs in %.

Figure 5.4 depicts the wind capacity distribution for the benchmark situation. It shows a concentration in capacity in the coastal regions (later referred to as capacity centers), i.e., the country's northwestern border. Due to the discrepancy between demand centers and capacity centers, most of the energy produced in capacity centers will be transmitted to the demand centers in the west and the middle.

Among the capacity centers, we look at the Friesland region. It is a farm region and is located in the north. There, energy demands are moderate (3% of the total energy demand), whereas the optimal wind capacity is the largest in the country (20% of the total wind capacity). For this reason, as a hypothetical case, we assume that this region proposes no investments in wind energy due to high social resistance. Other regions or other groups of regions may also be chosen, where the gist of this case study still applies. Taking this preference into account, Figure 5.4 also displays the new capacity distribution. Because of the decrease in wind capacity in Friesland, almost all other regions will have to build more generation capacities. In particular, the Drenthe region has to build 4680 MW more in wind energy.

In addition to capacity changes, we look at the cost changes, which are measured in percentages. In this case, the average costs for regions are calculated differently from the traditional cost of electricity. Traditionally, when calculating the cost of electricity, only the costs as shown in the objective function of the ESOM are considered. However, here, we also include the revenues/costs from selling and/or buying energy in the markets, where the prices are derived from the market balances (5.5e) - (5.5h). The underlying assumption is that a region is an aggregation of local producers and consumers where the costs are also assumed to be local. The financing of the generation assets from outside the region is out of the scope of the current study. While this study brings the market perspective into the ESOM, accordingly, the total costs include the revenues/costs in addition to the costs incurred from investing and operating the assets. Our way of analyzing the cost indicates that the average costs for a region can be negative, provided that lots of revenues are gained from energy trading. The interpretation should be that the region (i.e., the producers and consumers as a whole) is benefited, but it does not necessarily mean that the electricity prices for the consumers are low. Friesland, due to fewer costs in wind energy investment yet more costs for importing energy, ends up with a total cost of 16% higher. Although a few of its neighboring regions benefit by gaining more revenues from exporting energy, most regions incur more costs due to the large increases in investments. This demonstrates that the deliberate choice of one region influences the planning decisions of all other regions. More specifically, most regions suffer, though unwillingly, both in terms of increased total costs and forced wind energy investments locally.

This cost analysis is based on the pool-based electricity market. Under such a market, regions can bypass their wind energy investment and choose to import energy from other regions without binding penalties. As shown by the results, when wind turbines are placed at unfavorable locations in other regions, the cost of the system will increase, which will be borne by regions over the country. In this sense, as the hypothetical focal region in our case, Friesland is a free rider of the national RES investments, and other regions might do the same. As a result, the planning process stalls where no one commits to invest.

In practice, the planning process is far more complex than cost considerations. In this study, we approach this problem from the cost perspective and provide insights. The following subsection will illustrate how our approach can act as a negotiation tool in such a collaborative planning process.

5.5.3. Other regions' negotiation strategies

Collaborative RES planning is a negotiation process between the regions. When other regions are unwilling to comply with Friesland, which would be the case in our hypothetical example, their bilateral relationships deteriorate. This, in turn, affects Friesland as well. Here, our model is used to simulate the negotiations between the regions. This will be done by considering the external costs associated with the energy trades, which are used to represent the willingness to pay for the region. In this exemplary case, the willingness to pay for other regions concerning trades with Friesland becomes low due to Friesland's choice. In other words, a high cost is imposed on the trades from other regions as their negotiation strategy to Friesland's proposal.

Figure 5.5 shows the costs of Friesland in various scenarios. We start with the benchmark. Due to the large investment needs in wind energy, the fixed and variable costs (together referred to as investment costs) are high. However, since most generated energy

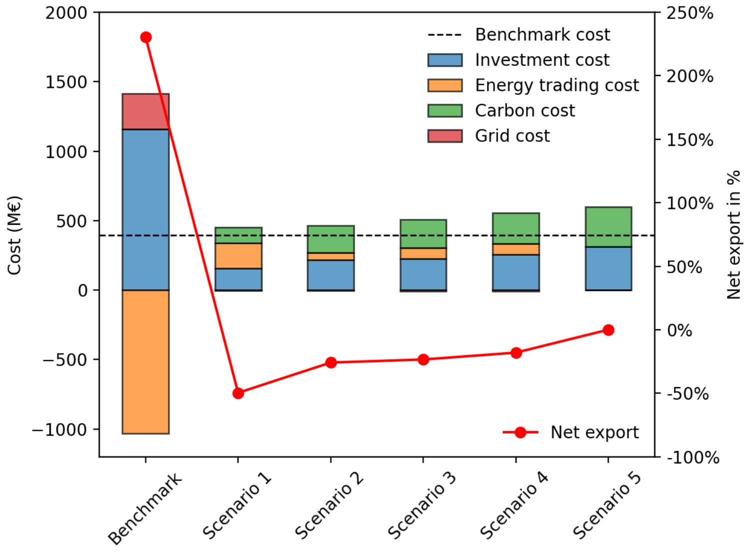

Figure 5.5: Costs of Friesland in various scenarios.

will be transmitted and sold to other regions, Friesland will gain significant revenues from selling energy. Overall, its total net cost in the benchmark case is 393 M€. The benchmark case provides the least cost solution for this region. If preferences against wind energy are taken into account, its cost will increase. In that case, its investment costs decline to 14% of those in the benchmark case. Accordingly, due to the lack of local generation capacities, it has to import energy, with the net export percentage dropping from 230% to - 50%.

Then, we look at the results of the following scenarios (2-4) when other regions start to negotiate with Friesland, with increasing levels of preference cost (10 €/MWh, 50 €/MWh, 100 €/MWh). These indicate degrees of willingness to pay with trades that involve Friesland. The results show that as the trading barriers between other regions and Friesland become larger, the energy trades shrink, and thus, Friesland will be forced to rely more on its energy production, which drives up its total costs. In the extreme case (scenario 5), the region will be isolated by others and has no other choice but to be energy self-sufficient. All these scenarios are not desirable for Friesland, and therefore, it has to reconsider its decision not to invest in wind energy.

Now we turn to the cost changes for other regions. A key question to answer here is, by imposing trade barriers with Friesland, what are the consequences for other regions? Figure 5.6 shows the cost changes relative to the benchmark cost for five cases. There are mainly two groups of regions to be discussed. One group is Friesland's neighboring regions with similar wind conditions and low energy demands. Among all, Drenthe builds more wind capacity and incurs more costs than the benchmark. Flevoland and Groningen have fewer costs since they benefit from more energy sales. The other group consists of the load centers, Noord-Holland Zuid (Amsterdam region) and Rotterdam-Den Haag, which rely heavily on imports. Due to the choice of Friesland, the energy prices go up,

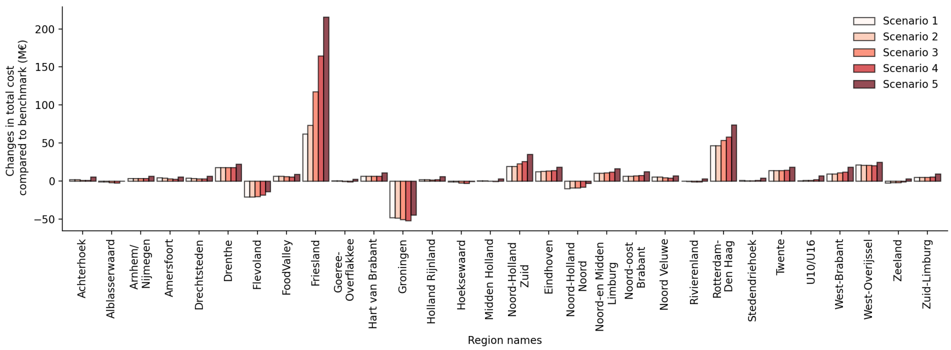

Figure 5.6: Costs of all the regions compared to the benchmark in scenario 1 to scenario 5.

leading to higher costs for the load centers as well. In particular, when Friesland does not invest in wind, and others take no action, Rotterdam-Den Haag has a higher cost increase than Friesland. Nevertheless, Friesland bears the most cost increase in all other cases, especially when the counteraction is strong in negotiations.

5.5.4. Discussions

We want to emphasize that the topic of this case study is not to argue for the best values to quantify the willingness to pay but rather to show how the product differentiation term can help express the region's preferences and simulate the inter-regional negotiation process. To this end, we have focused on Friesland as an illustrative region, but we would like to take the discussion away from Friesland into more general inter-regional negotiations. Moreover, we assume all regions have the same willingness to pay, and they all counter one particular region's choices. The exact values for willingness to pay depend on the bilateral relationships between other regions and the region under study, which can relate to economic aspects such as how much influence they perceive for their regions or socio-political factors such as the political tensions between them. Some regions may even benefit, as shown already. In addition, with various values for willingness to pay from the regions, they may again choose to change their perceptions depending on the results. Therefore, the actual results highly depend on the case-specific situation when the model is used in practice. Our case study highlights how this model can be used to investigate these kinds of policy-relevant challenges.

5.6. Conclusions

ESOM are known for their policy implications based on the resulting optimal long-term investment decisions, while they have a few key assumptions such as perfect foresight, perfect market, and a pool electricity market environment without external costs. This study presented an improved energy system model that considers bilateral trading with external costs.

We introduced this model step-by-step. Although the centralized formulation was used to solve the model, we started with an equilibrium formulation as a prerequisite.

First, four individual optimization problems were laid out for a producer, a TSO, a market operator, and a carbon market operator, respectively. This formulation helped to specify each market participant's objective function and the actions they can take. Afterward, the equivalent centralized problem was presented, which is an improved energy system model.

In this energy system model, we introduced three exogenous cost items that account for the social costs of technologies, carbon taxes/RES subsidies, and bilateral trading, respectively. The former two add costs to unit invested capacity or unit produced energy, and the last one is associated with bilateral trades. The bilateral external costs are interpreted in two ways. On the one hand, they represent an improved utility function beyond the economic cost to model willingness to pay. On the other hand, they can be used to model real economic costs, such as transaction costs.

The model was demonstrated using a proof-of-concept case study of the highly renewable Dutch power system in 2030. The first part of the case study focused on using bilateral external costs as transaction costs. It was found that incorporating bilateral trading changed the results when compared with the conventional cost-optimal ESOM in different ways. In terms of the generation mix of the system, the capacity of wind energy drops while that of solar PV increases. The geographical distribution also changes. The cost-optimal results indicate that more generation capacities are placed at locations with favorable weather conditions. However, the resulting capacities become more local when bilateral trading is considered. The second part studied the situation where a group of regions has to decide on their investments to meet a joint carbon target. We considered the technology preferences of the regions, in particular, an assumed unwillingness to invest in wind energy. The model was used as a negotiation simulator to inform the regions about the consequences of such a preference.

This study conceptualized bilateral trading as a peer-to-peer model. Research efforts can be put into other ways of conceptualizing bilateral trading or modeling different market players; hence, the resulting models and insights could be compared with ours.

6
Conclusions

This chapter concludes this thesis by providing insights resulting from the previous chapters. It starts with the answers to the main research questions and the sub-questions and continues with reflections and recommendations. This chapter ends with some final remarks on this research.

6.1. Conclusions and answers to research questions

The thesis has the objective *to improve optimization models by including institutions in energy system planning*. In line with that, the main research question of the thesis is:

How can institutions be incorporated into optimization models for energy system planning?

Technologies and institutions are closely related to each other in socio-technical systems. Despite the relevance, optimization-based energy system modelers and economists currently operate worlds apart. They have diverse narratives, and thus, the interrelationship between optimization models and institutions is only poorly understood. The economic worldview of the energy system modelers generally follows neoclassical economics. Decision-makers are assumed to have perfect rationality and act to maximize their utility. A cost-benefit analysis with regard to economic costs is often performed. On the contrary, institutional economists view decision-makers with bounded rationality, meaning they seek a satisfactory rather than an optimal solution.

The key to aligning the different worldviews is to find common ground. Under the assumption of perfect rationality and using cost-benefit analysis, optimization models are used to derive optimal results. This thesis concludes that optimization models are best utilized when studying non-evolving institutions, i.e., the institutions must be exogenous to the optimization model. Such institutions have been identified. They are policies, values of people, and governance structures, including electricity markets. These institutions are reflected in different components of the optimization problems and can be modeled accordingly. Governance structures embedded with an allocation of ownership and property rights feature a special institution. They serve as a context for the energy system planning problem, which can be centralized decision-making, collective decision-making, or electricity markets. Different typologies of optimization models should be used to model them, such as single-objective optimization models, multi-objective optimization models, or equilibrium-based optimization models. The other institutions should be modeled by the objective function, decision variables, constraints, and parameters.

Sub-question 1: What is the state-of-the-art on optimization-based institutional design of energy systems? Institutions were not defined consistently in energy research, which can be deducted from their general, but vague perception as rules. Therefore, it is essential to define the scope of institutions using a common language. To this end, we referred to Williamson's four-level institutional analysis framework, which exhaustively lists the institutions with different time scales.

After the scoping, we performed a literature review with two main conclusions. On the one hand, although some institutions have been modeled, they were not recognized as institutions, which mainly concerned governance structures. The governance structures can be modeled by generic types of optimization models, single-objective optimization models, multi-objective optimization models, and equilibrium-based optimization models. In the narrow sense, institutions mainly refer to policies in the context of energy system planning. However, we have shown that governance structures are also essential institutions. In that respect, we argue that all technical modeling represents an institutional element, regardless of whether the modeler has realized it or not. On the other hand, because there is a broad range of institutions, we conclude that research gaps remain on what institutions to model and how to model them. Optimization models can be further utilized to deal with these research gaps to provide energy system designs beyond the techno-economic focus. The most critical gaps were identified and answered by sub-questions 2 - 4, featuring the spatial aspects of RES integration, collective decision-making, and bilateral trading with external costs.

Sub-question 2: How can renewable energy potentials that take into account physical constraints and spatial policies be included in energy system optimization models? Renewable energy integration is increasingly a spatial issue. On the one hand, wind energy and solar energy are land-intensive. On the other hand, wind turbines raise public acceptance concerns due to their locations. The spatial aspects of RES need to be integrated into energy system optimization models. Otherwise, the planning results will deviate from what is feasible in reality.

The physical potential of RES can be estimated, in its simplest form, with the available area and the suitability factor. This can be done with either low-resolution spatial data or high-resolution spatial data. However, since public acceptance is correlated with the distance between the households and the RES locations, high-resolution spatial data that specifies the locations of the households is needed. To integrate physical constraints and the public acceptance of RES, we conclude that a spatially explicit approach is indispensable and have developed such an approach. This approach first determines the RES potential with high-resolution spatial data and then formulates land-use constraints as a part of an energy system optimization model. Besides the physical potentials, spatial policies based on the distance from the wind turbine locations to households can also be adjusted to determine the institutional potentials.

Sub-question 3: How can collective energy system planning be modeled using multi-objective optimization Collective energy system planning features multiple actors with different, sometimes conflicting, interests. Multi-objective optimization models are naturally suited to provide optimal system bounds for different criteria. However, they do not apply to a group decision-making process where several actors make decisions together. The answer to this sub-question is to combine multi-objective optimization models with one of the multi-criteria decision-making techniques, Technique for Order of Preference by Similarity to Ideal Solution. The main reason for choosing this technique or, in general, multi-criteria decision-making techniques is that multi-objective optimization does not specify the relationship between the interests and the actors. Therefore, when different stakeholders are involved, as in collective decision-making, multi-objective optimization alone can only offer limited values and needs to be complemented by other approaches.

Sub-question 4: How can decentralized planning processes considering bilateral trading be modeled? Although the actors' interests have been addressed in sub-question 3, the answer to that sub-question only provides a basis for discussions toward joint decision-making. The true decentralized decision-making where the actors maximize their interests can only be realized in competitive markets. Existing studies focus on marginal costs-based energy trading, while the externalities associated with the trades are rarely modeled.

This sub-question aimed to provide a generic formulation for modeling external costs in electricity markets with a focus on bilateral trade-based externalities. To differentiate the decentralized decision-making, we conclude that the objective problems of the market participants must be formulated separately, resulting in a set of optimization problems, i.e., an equilibrium problem. This equilibrium problem can be cast as an equivalent centralized problem based on non-cooperative game theory and can thus be solved. From the externality perspective, we conclude that externalities associated with bilateral trading offer great value in planning models. The model is strong at representing economic externalities, such as transaction costs, and other externalities beyond the economic costs, such as trading barriers and willingness to pay.

6.2. Reflections

Overall It is challenging to study institutions using an optimization approach. They seem to be mutually exclusive due to their different characteristics. Institutions are closely tied to actors who, in real life, are characterized by bounded rationality, limited foresight, and various interests other than cost. In contrast, most techno-economic optimization models aim to find a cost-optimal solution, indicating full rationality, perfect foresight, and a cost focus. However, this understanding was changed during the research. We found that optimization models are fully capable of modeling the institutions in the energy system. However, they must be used carefully to answer the right research questions.

Methods The answers to the main research question and the sub-questions are mainly methodological. Instrumentally, the proposed models are characterized by two features we would like to reflect on.

This thesis adopts a deterministic approach, meaning that uncertainty such as uncertain weather forecasts and demand profiles in the future is not considered. Nevertheless, we acknowledge that considering uncertainty can be essential. Hence, the centralized models (in Chapter 3 and Chapter 5) are formulated in such a way that uncertainty can be modeled to some extent. The perfect foresight issue can be remedied by either a myopic approach or a stochastic optimization. The former means a multi-year horizon that allows expansions in different years, an optimization-based simulation approach. The latter implies adding probabilities to the objective functions. The multi-objective model needs fundamental changes to incorporate uncertainty.

The models are simplified in terms of operational details. We include only the most crucial components of the modern energy system planning models, such as high-resolution spatial-temporally RES production profiles, energy storage, and network flow modeling, where ancillary services are not considered. Furthermore, we assume perfect competition in the electricity markets, where market power is left out of the scope.

Scope We would also like to make a remark on the system and geographical scope. This thesis focuses on generation and network expansion at the transmission level. Since the generation and network components were all modeled in a generic and modular way, the developed models are not limited to the transmission level and can deal with the distribution level or household level to some extent.

6.3. Recommendations

6.3.1. Future research

In this thesis, we started with a broad main research question and narrowed the scope down in the sub-questions, which, in turn, treated detailed knowledge gaps for specific types of optimization models. From this perspective, future research can be done in various ways that advance the developed models. Those potential improvements have already been given in relevant chapters and thus, are not repeated here.

Institutions in multi-energy systems Only the electric energy system has been studied in this thesis. Given the relevance of multi-energy systems, the institutions across energy carriers need to be further investigated. The interaction of the different energy systems complicates the problems due to the presence of different system operators and the rules for different energy systems. New governance structures may emerge, and the consistency of policies across different energy systems should be studied.

The role of information This concerns what information is available to what actors and at what costs. A central planner can plan a socially-optimal system. However, it may not be equipped with the correct information, such as future demand profiles and local spatial information, to achieve that. In this respect, more local decision-making, such as collective decision-making, might perform better, given the local data availability. Similarly, market imperfections would occur due to asymmetric information between the market participants. Further research should incorporate the value of information.

The help of distributed optimization A related recommendation is to investigate the practicality of using distributed optimization, which naturally addresses the information exchange issue. As distributed optimization is primarily used in operational models, using it in planning models might indicate a longer running time than in centralized models. Different decomposition techniques might be adopted, and ways to accelerate the convergence might be studied. Recent advances in distributed computing and machine learning may be referred to when selecting the relevant approaches.

More actors and their business models First, the energy transition is prompted bottom-up by the increasing share of distributed generation such as solar PV on the household level. These households participate in the wholesale market through retailers or aggregators or may join the local market, which may roll out in the future. These actors, such as households, retailers, aggregators, and local market operators, will play a role in the energy transition, and modeling them (and their interactions) would further enhance the understanding of the institutions.

Second, financing is a critical topic to address. In this thesis, we have sidestepped the role of financiers who provide capital in RES projects. Notably, the ownership structure might differ for market-based planning models, e.g., financiers own while generator companies run the assets. Therefore, further deliberations are needed on how to separate their optimization problems linked by contractual agreements regarding cost and benefit allocation.

The use of cooperative game theory On another methodological note, but also a rethinking of the governance structures, cooperative game theory is recommended for future works. Multi-objective optimization resulted in optimal system designs for different actors, and equilibrium-based optimization assumed non-cooperative games. However, actors may cooperate with each other by forming coalitions in local energy markets. Along this way of thinking, the potential use of cooperative game theory may lead to a market-based planning model considering actors with various interests. This direction would further contribute to understanding the use of optimization models for different actor relationships.

6.3.2. Recommendations for policy-makers

We make the following recommendations for policy-makers:

Consider more governance structures in policy-making In addition to making micro policies, we advise policy-makers to consider more macro policies, governance structures as studied in this thesis. Micro policies, in this context, refer to the policies dedicated to electricity markets. Instead of fine-tuning the functioning of the market, policy-makers could think more about how other governance structures might work. From a liberal standpoint, a market should be the only solution. Centralized decision-making, collective decision-making, and the combinations of different governance structures might work efficiently in some contexts as well, e.g., for a local energy system. Furthermore, under proper market designs, local markets can help to reach local emission goals. Policy-makers should assess the feasibility of such new markets and work on the regulations to facilitate their roll-outs.

Rethink the role of optimization models Currently, in policy-making, optimization models are mainly used to generate cost-optimal future energy system scenarios. However, this thesis has shown that optimization models can be used to include institutions beyond the economic cost perspective. Therefore, future energy system scenarios can be generated considering different governance structures, which helps to find robust elements and reveal more realistic bandwidths of the generation mix.

Design and consider spatial policies in planning We conclude that it is essential to design proper spatial policies and consider them in energy system planning. When they are not considered, the results from energy system planning models likely indicate high capacities in some places, i.e., where the meteorological conditions favor wind energy. Otherwise, the results may be infeasible due to public acceptance issues and physical availability.

Incentivize technologies considering the interests of stakeholders The market, which aims at economic efficiency, will likely converge to large shares of low-cost energy. However, other features for a future energy system can hardly be achieved by the market, which may be undesirable for many actors. To ensure a socially-acceptable energy system, policy-makers should engage stakeholders as much as possible and incentivize a comprehensive range of technologies not only from a cost perspective.

Address externalities to ensure RES adequecy We also found that the electricity market alone, which centers on marginal cost, can hardly incentivize RES investments because RES have zero marginal costs. As an alternative to giving RES subsidies or implementing a capacity market, we recommend the policy-makers account for the externalities of fossil-fueled generations by levying carbon taxes or introducing a full-fledged carbon market. More attention should be given to bilateral trades as they are crucial for investment decision-making. Policy-makers should investigate what interventions, such as modifying transaction costs, can be made regarding desired bilateral trades from a system level.

Facilitate a joint energy system planning Socially-optimal energy system planning can only be achieved if the generation and network assets are planned in a joint effort because no perfect markets exist. It is practically difficult to do this due to the lack of incentives and information barriers between the generation companies and network operators. We recommend that policy-makers make efforts, either market-based or non-market-based, to facilitate joint energy system planning.

6.4. Final remarks

Practitioners working on future energy system designs are always lagging behind. In many cases, what prevents the realization of a carbon-neutral future is not technological developments but how technologies are integrated into society. After all, humans create the future, not the technologies. Models are great for supporting human decision-making, but it is challenging to use the right models for the right questions. Optimization models are strong at sketching a normative future. Although humans cannot make perfect decisions, proper institutional designs help us get there. This thesis has modeled future unknowns in a simplified yet insightful way and hopefully has enriched the understanding of how the future energy system should be shaped.

Bibliography

[1] International Energy Agency, “Net Zero by 2050: A Roadmap for the Global Energy Sector”, International Energy Agency, Tech. Rep., 2021, p. 224.

[2] International Renewable Energy Agency, “World energy transitions outlook: 1.5 degrees pathway”, International Renewable Energy Agency, Tech. Rep., 2021, pp. 1–54.

[3] United Nations, *UN Energy goals*, 2015.

[4] International Energy Agency, “World Energy Outlook 2021”, International Energy Agency, Tech. Rep., 2021, pp. 1–386.

[5] Greenpeace, “Energy Revolution”, Tech. Rep., 2015, pp. 31–38.

[6] BP, “Energy Outlook 2022”, BP, Tech. Rep., 2022, p. 57.

[7] Government of the Netherlands, *National Climate Agreement*, 2019. (visited on 04/05/2020).

[8] Ministry of Economic Affairs and Climate, *Kabinet presenteert beleidsprogramma Klimaat*, 2022. [Online]. Available: `https://www.rijksoverheid.nl/ministeries/ministerie-van-economische-zaken-en-klimaat/nieuws/2022/06/02/kabinet-presenteert-beleidsprogramma-klimaat` (visited on 06/08/2022).

[9] N. Wang, R. Verzijlbergh, P. Heijnen, and P. Herder, “A review and analysis on the institutional paradigms in optimization models for energy system planning”, *Submitted*, 2022.

[10] N. Wang, R. A. Verzijlbergh, P. W. Heijnen, and P. M. Herder, “A spatially explicit planning approach for power systems with a high share of renewable energy sources”, *Applied Energy*, vol. 260, p. 114 233, Feb. 2020, ISSN: 03062619.

[11] N. Wang, P. W. Heijnen, and P. J. Imhof, “A multi-actor perspective on multi-objective regional energy system planning”, *Energy Policy*, vol. 143, 2020, ISSN: 03014215.

[12] N. Wang, R. Verzijlbergh, P. Heijnen, and P. Herder, “An energy system optimization model with bilateral trading and external costs: Application to the Dutch national program Regional Energy Strategies”, *Submitted*, 2022.

[13] S. Abu-Sharkh, R. Arnold, J. Kohler, *et al.*, “Can microgrids make a major contribution to UK energy supply?”, *Renewable and Sustainable Energy Reviews*, vol. 10, no. 2, pp. 78–127, Apr. 2006, ISSN: 1364-0321.

[14] B. Turnheim, F. Berkhout, F. Geels, *et al.*, “Evaluating sustainability transitions pathways: Bridging analytical approaches to address governance challenges”, *Global Environmental Change*, vol. 35, pp. 239–253, Nov. 2015, ISSN: 0959-3780.

[15] C. Freeman and F. Louca, *As Time Goes By: From the Industrial Revolutions to the Information Revolution.* Oxford University Press, 2002.

[16] E. Trutnevyte, "Does cost optimization approximate the real-world energy transition?", *Energy*, vol. 106, pp. 182–193, Jul. 2016, ISSN: 0360-5442.

[17] S. Pereira, P. Ferreira, and A. Vaz, "Optimization modeling to support renewables integration in power systems", *Renewable and Sustainable Energy Reviews*, vol. 55, pp. 316–325, 2016.

[18] S. Pfenninger, A. Hawkes, and J. Keirstead, "Energy systems modeling for twenty-first century energy challenges", *Renewable and Sustainable Energy Reviews*, vol. 33, pp. 74–86, May 2014, ISSN: 13640321.

[19] M. Fodstad, P. Crespo del Granado, L. Hellemo, *et al.*, "Next frontiers in energy system modelling: A review on challenges and the state of the art", *Renewable and Sustainable Energy Reviews*, vol. 160, p. 112 246, May 2022, ISSN: 18790690.

[20] L. Hofbauer, W. McDowall, and S. Pye, "Challenges and opportunities for energy system modelling to foster multi-level governance of energy transitions", *Renewable and Sustainable Energy Reviews*, vol. 161, p. 112 330, Jun. 2022, ISSN: 13640321.

[21] A. Krumm, D. Süsser, and P. Blechinger, "Modelling social aspects of the energy transition: What is the current representation of social factors in energy models?", *Energy*, vol. 239, p. 121 706, Jan. 2022, ISSN: 03605442.

[22] F. Emery and E. Trist, "Socio-technical Systems", in *Management Sciences Models and Techniques*, C.W. Churchman and M. Verhulst, Ed., Pergamon Press, 1960, pp. 83–97.

[23] E. Trist, *The Evolution of socio-technical systems*, 1981.

[24] G. Baxter and I. Sommerville, "Socio-technical systems: From design methods to systems engineering", *Interacting with Computers*, vol. 23, no. 1, pp. 4–17, 2011, ISSN: 0953-5438.

[25] G. M. Hodgson, *What are institutions?*, 2006.

[26] O. E. Williamson, "The economics of governance", *American Economic Review*, vol. 95, no. 2, pp. 1–18, 2005, ISSN: 00028282.

[27] M. D. McGinnis and E. Ostrom, "Social-ecological system framework: Initial changes and continuing challenges", *Ecology and Society*, 2014, ISSN: 17083087.

[28] J. Zoellner, P. Schweizer-Ries, and C. Wemheuer, "Public acceptance of renewable energies: Results from case studies in Germany", *Energy Policy*, vol. 36, no. 11, pp. 4136–4141, Nov. 2008, ISSN: 0301-4215.

[29] N. Hall, P. Ashworth, and P. Devine-Wright, "Societal acceptance of wind farms: Analysis of four common themes across Australian case studies", *Energy Policy*, vol. 58, pp. 200–208, Jul. 2013, ISSN: 0301-4215.

[30] J. A. M. Hufen and J. F. M. Koppenjan, "Local renewable energy cooperatives: revolution in disguise?", *Energy, Sustainability and Society*, vol. 5, no. 1, 2015.

[31] E. Viardot, “The role of cooperatives in overcoming the barriers to adoption of renewable energy”, *Energy Policy*, vol. 63, pp. 756–764, Dec. 2013, ISSN: 0301-4215.

[32] S. B. Mills, D. Bessette, and H. Smith, “Exploring landowners’ post-construction changes in perceptions of wind energy in Michigan”, *Land Use Policy*, vol. 82, pp. 754–762, Mar. 2019, ISSN: 0264-8377.

[33] A. Fattahi, J. Sijm, and A. Faaij, “A systemic approach to analyze integrated energy system modeling tools: A review of national models”, *Renewable and Sustainable Energy Reviews*, vol. 133, 2020, ISSN: 18790690.

[34] C. Oliveira and C. H. Antunes, “A multi-objective multi-sectoral economy-energy-environment model: Application to Portugal”, *Energy*, vol. 36, no. 5, pp. 2856–2866, 2011, ISSN: 03605442.

[35] Y. Cai, G. Huang, Z. Yang, Q. Lin, B. Bass, and Q. Tan, “Development of an optimization model for energy systems planning in the Region of Waterloo”, *International Journal of Energy Research*, vol. 32, no. 11, pp. 988–1005, 2008.

[36] M. Yazdanie, M. Densing, and A. Wokaun, “Cost optimal urban energy systems planning in the context of national energy policies: A case study for the city of Basel”, *Energy Policy*, vol. 110, pp. 176–190, 2017.

[37] A. Musselman, V. M. Thomas, D. Nazzal, D. J. Papageorgiou, A. Venkatesh, and D. S. Mallapragada, “The impact of development priorities on power system expansion planning in sub-Saharan Africa”, *Energy Systems*, 2021, ISSN: 18683975.

[38] J. Liu, Q. Lin, G. Huang, Q. Wu, and H. Li, “Energy systems planning and GHG-emission control under uncertainty in the province of Liaoning, China - A dynamic inexact energy systems optimization model”, *International Journal of Electrical Power and Energy Systems*, vol. 53, no. 1, pp. 142–158, 2013.

[39] J. Zhen, G. Huang, W. Li, C. Wu, and S. Wang, “Electric power system planning with renewable energy accommodation for supporting the sustainable development of Tangshan City, China”, *Journal of Cleaner Production*, vol. 139, pp. 1308–1325, 2016.

[40] D. Quiroga, E. Sauma, and D. Pozo, “Power system expansion planning under global and local emission mitigation policies”, *Applied Energy*, vol. 239, pp. 1250–1264, 2019, ISSN: 03062619.

[41] T. Li, Z. Li, and W. Li, “Scenarios analysis on the cross-region integrating of renewable power based on a long-period cost-optimization power planning model”, *Renewable Energy*, vol. 156, pp. 851–863, 2020, ISSN: 18790682.

[42] J. N. Yin, G. H. Huang, Y. L. Xie, and Y. K. An, “Carbon-subsidized inter-regional electric power system planning under cost-risk tradeoff and uncertainty: A case study of Inner Mongolia, China”, *Renewable and Sustainable Energy Reviews*, vol. 135, 2021, ISSN: 18790690.

[43] D. Möst, M. Genoese, A. Eßer, and O. Rentz, “European electricity and emission market modeling - The design of emission allocation plans and its effects on investment planning”, in *2008 5th International Conference on the European Electricity Market, EEM*, 2008, ISBN: 9781424417445.

[44] A. Lind and E. Rosenberg, “How do Various Risk Factors Influence the Green Certificate Market of Norway and Sweden?”, in *Energy Procedia*, vol. 58, 2014, pp. 9–15.

[45] L. Ju, Z. Tan, H. Li, Q. Tan, X. Zhang, and W. Zhang, “The optimization model for interregional power system planning considering carbon emissions trading and renewable energy quota mechanism”, *Discrete Dynamics in Nature and Society*, vol. 2016, 2016.

[46] O. Guerra, D. Tejada, and G. Reklaitis, “An optimization framework for the integrated planning of generation and transmission expansion in interconnected power systems”, *Applied Energy*, vol. 170, pp. 1–21, 2016.

[47] D. P. Schlachtberger, T. Brown, S. Schramm, and M. Greiner, “The benefits of cooperation in a highly renewable European electricity network”, *Energy*, vol. 134, pp. 469–481, 2017, ISSN: 03605442.

[48] B.-W. Yi, J.-H. Xu, and Y. Fan, “Coordination of policy goals between renewable portfolio standards and carbon caps: A quantitative assessment in China”, *Applied Energy*, vol. 237, pp. 25–35, 2019.

[49] M. Xiao, M. Wetzel, T. Pregger, S. Simon, and Y. Scholz, “Modeling the supply of renewable electricity to metropolitan regions in China”, *Energies*, vol. 13, no. 12, 2020, ISSN: 19961073.

[50] A. H. Seddighi and A. Ahmadi-Javid, “Integrated multiperiod power generation and transmission expansion planning with sustainability aspects in a stochastic environment”, *Energy*, vol. 86, pp. 9–18, 2015, ISSN: 03605442.

[51] S. S. Deshmukh and M. K. Deshmukh, “Micro-level integrated renewable energy system planning”, *International Energy Journal*, vol. 9, no. 1, pp. 9–20, 2008, ISSN: 1513718X.

[52] C. Unsihuay-Vila, J. W. Marangon-Lima, A. C. Zambroni De Souza, and I. J. Perez-Arriaga, “Multistage expansion planning of generation and interconnections with sustainable energy development criteria: A multiobjective model”, *International Journal of Electrical Power and Energy Systems*, vol. 33, no. 2, pp. 258–270, 2011, ISSN: 01420615.

[53] Y. Sawle, S. Gupta, and A. Bohre, “Socio-techno-economic design of hybrid renewable energy system using optimization techniques”, *Renewable Energy*, vol. 119, pp. 459–472, 2018.

[54] M. Rodgers, D. Coit, F. Felder, and A. Carlton, “Generation expansion planning considering health and societal damages – A simulation-based optimization approach”, *Energy*, vol. 164, pp. 951–963, 2018.

[55] A. Tash, M. Ahanchian, and U. Fahl, “Improved representation of investment decisions in the German energy supply sector: An optimization approach using the TIMES model”, *Energy Strategy Reviews*, vol. 26, 2019, ISSN: 2211467X.

6

[56] M. Lehtveer, M. Makowski, F. Hedenus, D. McCollum, and M. Strubegger, "Multi-criteria analysis of nuclear power in the global energy system: Assessing trade-offs between simultaneously attainable economic, environmental and social goals", *Energy Strategy Reviews*, vol. 8, pp. 45–55, 2015, ISSN: 2211467X.

[57] J. Fonseca, J.-M. Commenge, M. Camargo, L. Falk, and I. Gil, "Multi-criteria optimization for the design and operation of distributed energy systems considering sustainability dimensions", *Energy*, vol. 214, 2021.

[58] M. Jelić, M. Batić, and N. Tomašević, "Demand-side flexibility impact on prosumer energy system planning", *Energies*, vol. 14, no. 21, 2021, ISSN: 19961073.

[59] A. Perera, R. Attalage, K. Perera, and V. Dassanayake, "A hybrid tool to combine multi-objective optimization and multi-criterion decision making in designing standalone hybrid energy systems", *Applied Energy*, vol. 107, pp. 412–425, 2013.

[60] L. Nacken, F. Krebs, T. Fischer, and C. Hoffmanna, "Integrated renewable energy systems for Germany-A model-based exploration of the decision space", in *International Conference on the European Energy Market, EEM*, vol. 2019-Septe, 2019, ISBN: 9781728112572.

[61] R. Jing, K. Kuriyan, Q. Kong, *et al.*, "Exploring the impact space of different technologies using a portfolio constraint based approach for multi-objective optimization of integrated urban energy systems", *Renewable and Sustainable Energy Reviews*, vol. 113, 2019, ISSN: 18790690.

[62] Z. Huang, H. Yu, X. Chu, and Z. Peng, "A novel optimization model based on game tree for multi-energy conversion systems", *Energy*, vol. 150, pp. 109–121, 2018, ISSN: 03605442.

[63] R. McKenna, V. Bertsch, K. Mainzer, and W. Fichtner, "Combining local preferences with multi-criteria decision analysis and linear optimization to develop feasible energy concepts in small communities", *European Journal of Operational Research*, vol. 268, no. 3, pp. 1092–1110, 2018.

[64] S. G. Simoes, L. Dias, J. P. Gouveia, *et al.*, "InSmart – A methodology for combining modelling with stakeholder input towards EU cities decarbonisation", *Journal of Cleaner Production*, vol. 231, pp. 428–445, 2019, ISSN: 09596526.

[65] K. Hori, J. Kim, R. Kawase, M. Kimura, T. Matsui, and T. Machimura, "Local energy system design support using a renewable energy mix multi-objective optimization model and a co-creative optimization process", *Renewable Energy*, vol. 156, pp. 1278–1291, 2020, ISSN: 18790682.

[66] Z. Ming, F. Junjie, Z. Xiaoli, and X. Song, "Strategic interaction study between generation and transmission expansion planning with game-theory", *Optimization*, vol. 61, no. 10, pp. 1271–1281, 2012, ISSN: 02331934.

[67] M. Jenabi, S. M. T. Fatemi Ghomi, and Y. Smeers, "Bi-level game approaches for coordination of generation and transmission expansion planning within a market environment", *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 2639–2650, 2013, ISSN: 08858950.

[68] S. S. Taheri, J. Kazempour, and S. Seyedshenava, “Transmission expansion in an oligopoly considering generation investment equilibrium”, *Energy Economics*, vol. 64, pp. 55–62, 2017, ISSN: 01409883.

[69] V. Grimm, B. Rückel, C. Sölch, and G. Zöttl, “The impact of market design on transmission and generation investment in electricity markets”, *Energy Economics*, p. 104 934, 2020, ISSN: 01409883.

[70] Y. Tohidi, L. Olmos, M. Rivier, and M. R. Hesamzadeh, “Coordination of Generation and Transmission Development Through Generation Transmission Charges - A Game Theoretical Approach”, *IEEE Transactions on Power Systems*, vol. 32, no. 2, pp. 1103–1114, 2017, ISSN: 08858950.

[71] E. Spyrou, J. L. Ho, B. F. Hobbs, R. M. Johnson, and J. D. McCalley, “What are the Benefits of Co-Optimizing Transmission and Generation Investment? Eastern Interconnection Case Study”, *IEEE Transactions on Power Systems*, vol. 32, no. 6, pp. 4265–4277, 2017, ISSN: 08858950.

[72] H. Lei, S. X. Zhou, Y. X. Wang, *et al.*, “Coordinated development based grid-source-load collaborative planning method of uncertainty and multi-agent game”, in *E3S Web of Conferences*, vol. 233, 2021.

[73] S. Mishra, C. Bordin, A. Tomasgard, and I. Palu, “A multi-agent system approach for optimal microgrid expansion planning under uncertainty”, *International Journal of Electrical Power and Energy Systems*, vol. 109, pp. 696–709, 2019.

[74] M. S. Javadi and M. Saniei, “Sustainable generation and transmission expansion planning in competitive power markets”, *Indian Journal of Science and Technology*, vol. 5, no. 2, pp. 2113–2119, 2012, ISSN: 09746846.

[75] J. H. Roh, M. Shahidehpour, and L. Wu, “Market-based generation and transmission planning with uncertainties”, *IEEE Transactions on Power Systems*, vol. 24, no. 3, pp. 1587–1598, 2009, ISSN: 08858950.

[76] J. Wang, M. Shahidehpour, Z. Li, and A. Botterud, “Strategic generation capacity expansion planning with incomplete information”, *IEEE Transactions on Power Systems*, vol. 24, no. 2, pp. 1002–1010, 2009.

[77] W. Lyzwa, M. Wierzbowski, and B. Olek, “MILP formulation for energy mix optimization”, *IEEE Transactions on Industrial Informatics*, vol. 11, no. 5, pp. 1166–1178, 2015, ISSN: 15513203.

[78] F. López-Ramos, S. Nasini, and M. H. Sayed, “An integrated planning model in centralized power systems”, *European Journal of Operational Research*, vol. 287, no. 1, pp. 361–377, 2020, ISSN: 03772217.

[79] S. Hagspiel, C. Jägemann, D. Lindenberger, T. Brown, S. Cherevatskiy, and E. Tröster, “Cost-optimal power system extension under flow-based market coupling”, *Energy*, vol. 66, pp. 654–666, 2014.

[80] E. L. Cano, M. Groissböck, J. M. Moguerza, and M. Stadler, “A strategic optimization model for energy systems planning”, *Energy and Buildings*, vol. 81, pp. 416–423, 2014, ISSN: 03787788.

6

[81] J. DeCarolis, H. Daly, P. Dodds, *et al.*, “Formalizing best practice for energy system optimization modelling”, *Applied Energy*, vol. 194, pp. 184–198, 2017, ISSN: 03062619.

[82] K. Shaw, S. D. Hill, A. D. Boyd, L. Monk, J. Reid, and E. F. Einsiedel, “Conflicted or constructive? Exploring community responses to new energy developments in Canada”, *Energy Research and Social Science*, vol. 8, pp. 41–51, 2015, ISSN: 22146296.

[83] P. Enevoldsen and B. K. Sovacool, “Examining the social acceptance of wind energy: Practical guidelines for onshore wind project development in France”, *Renewable and Sustainable Energy Reviews*, vol. 53, pp. 178–184, 2016, ISSN: 18790690.

[84] R. Van Haaren and V. Fthenakis, “GIS-based wind farm site selection using spatial multi-criteria analysis (SMCA): Evaluating the case for New York State”, *Renewable and Sustainable Energy Reviews*, vol. 15, no. 7, pp. 3332–3340, 2011, ISSN: 13640321.

[85] S. E. Shmelev and J. C. Van Den Bergh, “Optimal diversity of renewable energy alternatives under multiple criteria: An application to the UK”, *Renewable and Sustainable Energy Reviews*, vol. 60, pp. 679–691, 2016, ISSN: 18790690.

[86] S. Rauner, M. Eichhorn, and D. Thrän, “The spatial dimension of the power system: Investigating hot spots of Smart Renewable Power Provision”, *Applied Energy*, vol. 184, pp. 1038–1050, 2016, ISSN: 03062619.

[87] K. Shiraishi, R. G. Shirley, and D. M. Kammen, “Geospatial multi-criteria analysis for identifying high priority clean energy investment opportunities: A case study on land-use conflict in Bangladesh”, *Applied Energy*, vol. 235, pp. 1457–1467, 2019, ISSN: 03062619.

[88] H. K. Ringkjøb, P. M. Haugan, and I. M. Solbrekke, “A review of modelling tools for energy and electricity systems with large shares of variable renewables”, *Renewable and Sustainable Energy Reviews*, vol. 96, pp. 440–459, 2018, ISSN: 18790690.

[89] A. Arnette and C. W. Zobel, “An optimization model for regional renewable energy development”, *Renewable and Sustainable Energy Reviews*, vol. 16, no. 7, pp. 4606–4615, 2012, ISSN: 13640321.

[90] S. Hong, C. J. Bradshaw, and B. W. Brook, “Global zero-carbon energy pathways using viable mixes of nuclear and renewables”, *Applied Energy*, vol. 143, pp. 451–459, 2015, ISSN: 03062619.

[91] S. Pfenninger and J. Keirstead, “Renewables, nuclear, or fossil fuels? Scenarios for Great Britain’s power system considering costs, emissions and energy security”, *Applied Energy*, vol. 152, pp. 83–93, 2015, ISSN: 03062619.

[92] B. Elliston, J. Riesz, and I. MacGill, “What cost for more renewables? The incremental cost of renewable generation - An Australian National Electricity Market case study”, *Renewable Energy*, vol. 95, pp. 127–139, 2016, ISSN: 18790682.

[93] J. Hörsch, F. Hofmann, D. Schlachtberger, and T. Brown, “PyPSA-Eur: An open optimisation model of the European transmission system”, *Energy Strategy Reviews*, vol. 22, no. July 2017, pp. 207–215, 2018, ISSN: 2211467X.

6

[94] J. Arán Carrión, A. Espín Estrella, F. Aznar Dols, M. Zamorano Toro, M. Rodríguez, and A. Ramos Ridao, *Environmental decision-support systems for evaluating the carrying capacity of land areas: Optimal site selection for grid-connected photovoltaic power plants*, 2008.

[95] N. Y. Aydin, E. Kentel, and S. Duzgun, *GIS-based environmental assessment of wind energy systems for spatial planning: A case study from Western Turkey*, 2010.

[96] R. McKenna, S. Hollnaicher, and W. Fichtner, "Cost-potential curves for onshore wind energy: A high-resolution analysis for Germany", *Applied Energy*, vol. 115, pp. 103–115, 2014, ISSN: 03062619.

[97] T. Egli, J. Bolliger, and F. Kienast, "Evaluating ecosystem service trade-offs with wind electricity production in Switzerland", *Renewable and Sustainable Energy Reviews*, vol. 67, pp. 863–875, 2017, ISSN: 18790690.

[98] E. Rinne, H. Holttinen, J. Kiviluoma, and S. Rissanen, "Effects of turbine technology and land use on wind power resource potential", *Nature Energy*, vol. 3, no. 6, pp. 494–500, 2018, ISSN: 20587546.

[99] R. Deshmukh, G. C. Wu, D. S. Callaway, and A. Phadke, "Geospatial and techno-economic analysis of wind and solar resources in India", *Renewable Energy*, vol. 134, pp. 947–960, 2019, ISSN: 18790682.

[100] G. He and D. M. Kammen, "Where, when and how much wind is available? A provincial-scale wind resource assessment for China", *Energy Policy*, vol. 74, pp. 116–122, 2014, ISSN: 03014215.

[101] E. Dupont, R. Koppelaar, and H. Jeanmart, "Global available wind energy with physical and energy return on investment constraints", *Applied Energy*, vol. 209, pp. 322–338, 2018, ISSN: 03062619.

[102] L. Ramirez Camargo and G. Stoeglehner, "Spatiotemporal modelling for integrated spatial and energy planning", *Energy, Sustainability and Society*, vol. 8, no. 1, pp. 1–29, 2018, ISSN: 21920567.

[103] *Regionale Energie Strategie*. [Online]. Available: `https://www.regionale-energiestrategie.nl/home/default.aspx` (visited on 06/14/2019).

[104] *OpenStreetMap*. [Online]. Available: `https://www.openstreetmap.org` (visited on 06/14/2019).

[105] *CORINE Land Cover — Copernicus Land Monitoring Service*. [Online]. Available: `https://land.copernicus.eu/pan-european/corine-land-cover` (visited on 06/14/2019).

[106] P. Denholm, M. Hand, M. Jackson, and S. Ong, "Land Use Requirements of Modern Wind Power Plants in the United States", 2009.

[107] G. He and D. M. Kammen, "Where, when and how much solar is available? A provincial-scale solar resource assessment for China", *Renewable Energy*, vol. 85, pp. 74–82, 2016, ISSN: 18790682.

[108] S. Pfenninger and I. Staffell, "Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data", *Energy*, 2016, ISSN: 03605442.

[109] *Royal Netherlands Meteorological Institute(KNMI).* [Online]. Available: `https://www.knmi.nl/home` (visited on 06/14/2019).

[110] *European Network of Transmission System Operators for Electricity(ENTSO-E).* [Online]. Available: `https://www.entsoe.eu/data` (visited on 06/14/2019).

[111] M. Fürsch, S. Hagspiel, C. Jägemann, S. Nagl, D. Lindenberger, and E. Tröster, "The role of grid extensions in a cost-efficient transformation of the European electricity system until 2050", *Applied Energy*, 2013, ISSN: 03062619.

[112] A. Schröder, F. Kunz, J. Meiss, R. Mendelevitch, and C. von Hirschhausen, "Current and prospective costs of electricity generation until 2050", Berlin, DIW Data Documentation 68, 2013.

[113] C. Bussar, M. Moos, R. Alvarez, *et al.*, "Optimal allocation and capacity of energy storage systems in a future European power system with 100% renewable energy generation", in *Energy Procedia*, 2014.

[114] H. C. Gils, Y. Scholz, T. Pregger, D. Luca de Tena, and D. Heide, "Integrated modelling of variable renewable energy-based power supply in Europe", *Energy*, 2017, ISSN: 03605442.

[115] *Basisinformatie Energie-infrastructuur.* [Online]. Available: `https://www.regionale-energiestrategie.nl/Nieuws/1305967.aspx` (visited on 06/14/2019).

[116] T. Economics, *Netherlands - Electric power transmission and distribution losses.* [Online]. Available: `https://tradingeconomics.com/netherlands/electric-power-transmission-and-distribution-losses-percent-of-output-wb-data.html` (visited on 09/03/2019).

[117] TenneT, "Market Review 2015", Tech. Rep. 2, 2015, pp. 183–189.

[118] B. Elliston, I. MacGill, and M. Diesendorf, "Least cost 100% renewable electricity scenarios in the Australian National Electricity Market", *Energy Policy*, vol. 59, pp. 270–282, 2013, ISSN: 03014215.

[119] G. Krajačić, N. Duić, and M. d. G. Carvalho, "How to achieve a 100% RES electricity supply for Portugal?", *Applied Energy*, 2011, ISSN: 03062619.

[120] D. M. Gioutsos, K. Blok, L. van Velzen, and S. Moorman, "Cost-optimal electricity systems with increasing renewable energy penetration for islands across the globe", *Applied Energy*, 2018, ISSN: 03062619.

[121] R. Alizadeh, P. D. Lund, A. Beynaghi, M. Abolghasemi, and R. Maknoon, "An integrated scenario-based robust planning approach for foresight and strategic management with application to energy industry", *Technological Forecasting and Social Change*, vol. 104, pp. 162–171, 2016, ISSN: 00401625.

[122] McKinsey & Company, "Global Energy Perspective 2019 : Reference Case", Tech. Rep. January, 2019, p. 31.

[123] R. D. Prasad, R. C. Bansal, and A. Raturi, "Multi-faceted energy planning: A review", *Renewable and Sustainable Energy Reviews*, vol. 38, pp. 686–699, 2014, ISSN: 13640321.

6

[124] A. S. Dagoumas and N. E. Koltsaklis, "Review of models for integrating renewable energy in the generation expansion planning", *Applied Energy*, vol. 242, pp. 1573–1587, 2019, ISSN: 03062619.

[125] V. Oree, S. Z. Sayed Hassen, and P. J. Fleming, *Generation expansion planning optimisation with renewable energy integration: A review*, 2017.

[126] P. Tozzi and J. H. Jo, *A comparative analysis of renewable energy simulation tools: Performance simulation model vs. system optimization*, 2017.

[127] M. Iqbal, M. Azam, M. Naeem, A. S. Khwaja, and A. Anpalagan, "Optimization classification, algorithms and tools for renewable energy: A review", *Renewable and Sustainable Energy Reviews*, vol. 39, pp. 640–654, 2014, ISSN: 13640321.

[128] IRENA, "Renewable power generation costs in 2018", IRENA, Tech. Rep., 2018.

[129] IEA, "Renewables 2019", IEA, Paris, Tech. Rep., 2019.

[130] E. Strantzali and K. Aravossis, "Decision making in renewable energy investments: A review", *Renewable and Sustainable Energy Reviews*, vol. 55, pp. 885–898, 2016, ISSN: 18790690.

[131] C. A. Miller, A. Iles, and C. F. Jones, "The Social Dimensions of Energy Transitions", *Science as Culture*, vol. 22, no. 2, pp. 135–148, 2013, ISSN: 09505431.

[132] A. Alarcon-Rodriguez, G. Ault, and S. Galloway, "Multi-objective planning of distributed energy resources: A review of the state-of-the-art", *Renewable and Sustainable Energy Reviews*, vol. 14, no. 5, pp. 1353–1366, 2010, ISSN: 13640321.

[133] M. Fadaee and M. A. Radzi, *Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: A review*, Jun. 2012.

[134] Z. Wang and G. P. Rangaiah, "Application and Analysis of Methods for Selecting an Optimal Solution from the Pareto-Optimal Front obtained by Multiobjective Optimization", *Industrial and Engineering Chemistry Research*, vol. 56, no. 2, pp. 560–574, 2017, ISSN: 15205045.

[135] K. Deb, "Multi-objective evolutionary algorithms", in *Springer Handbook of Computational Intelligence*, 2015, ISBN: 9783662435052.

[136] C. H. Antunes and C. O. Henriques, "Multi-Objective Optimization and Multi-Criteria Analysis Models and Methods for Problems in the Energy Sector", in *Multiple Criteria Decision Analysis: State of the Art Surveys*, S. Greco, M. Ehrgott, and J. R. Figueira, Eds., Springer New York, 2016, pp. 1067–1165, ISBN: 978-1-4939-3094-4.

[137] H. Tekiner, D. W. Coit, and F. A. Felder, "Multi-period multi-objective electricity generation expansion planning problem with Monte-Carlo simulation", *Electric Power Systems Research*, vol. 80, no. 12, pp. 1394–1405, 2010, ISSN: 03787796.

[138] K. Zou, A. P. Agalgaonkar, K. M. Muttaqi, and S. Perera, "Multi-objective optimisation for distribution system planning with renewable energy resources", in *2010 IEEE International Energy Conference and Exhibition, EnergyCon 2010*, 2010, ISBN: 9781424493807.

[139] A. T. Perera, R. A. Attalage, K. K. Perera, and V. P. Dassanayake, “Designing standalone hybrid energy systems minimizing initial investment, life cycle cost and pollutant emission”, *Energy*, vol. 54, pp. 220–230, 2013, ISSN: 03605442.

[140] D. P. Clarke, Y. M. Al-Abdeli, and G. Kothapalli, “Multi-objective optimisation of renewable hybrid energy systems with desalination”, *Energy*, vol. 88, pp. 457–468, 2015, ISSN: 03605442.

[141] T. Falke, S. Krengel, A. K. Meinerzhagen, and A. Schnettler, “Multi-objective optimization and simulation model for the design of distributed energy systems”, *Applied Energy*, vol. 184, pp. 1508–1516, 2016, ISSN: 03062619.

[142] P. Prebeg, G. Gasparovic, G. Krajacic, and N. Duic, “Long-term energy planning of Croatian power system using multi-objective optimization with focus on renewable energy and integration of electric vehicles”, *Applied Energy*, vol. 184, pp. 1493–1507, 2016, ISSN: 03062619.

[143] S. Mahbub, D. Viesi, S. Cattani, and L. Crema, “An innovative multi-objective optimization approach for long-term energy planning”, *Applied Energy*, vol. 208, no. May, pp. 1487–1504, 2017, ISSN: 0306-2619.

[144] T. Luz, P. Moura, and A. de Almeida, “Multi-objective power generation expansion planning with high penetration of renewables”, *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 2637–2643, 2018, ISSN: 18790690.

[145] S. Fazlollahi, P. Mandel, G. Becker, and F. Maréchal, “Methods for multi-objective investment and operating optimization of complex energy systems”, *Energy*, vol. 45, no. 1, pp. 12–22, 2012, ISSN: 0360-5442.

[146] P. Gabrielli, M. Gazzani, E. Martelli, and M. Mazzotti, “Optimal design of multi-energy systems with seasonal storage”, *Applied Energy*, vol. 219, pp. 408–424, 2018, ISSN: 03062619.

[147] M. Di Somma, G. Graditi, E. Heydarian-forushani, M. Sha, and P. Siano, “Stochastic optimal scheduling of distributed energy resources with renewables considering economic and environmental aspects”, *Renewable Energy*, vol. 116, pp. 272–287, 2018.

[148] B. Prasad Koirala, E. Koliou, J. Friege, R. A. Hakvoort, and P. M. Herder, “Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems”, *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 722–744, 2016, ISSN: 1364-0321.

[149] B. Koirala, “Integrated community energy systems”, English, Ph.D. dissertation, Delft University of Technology, Oct. 2017, ISBN: 978-94-6186-827-5.

[150] L. Guo, W. Liu, B. Jiao, B. Hong, and C. Wang, “Multi-objective stochastic optimal planning method for stand-alone microgrid system”, *IET Generation, Transmission and Distribution*, vol. 8, no. 7, pp. 1263–1273, 2014, ISSN: 17518687.

[151] B. Koirala, J. Chaves Ávila, T. Gómez, R. Hakvoort, and P. Herder, “Local Alternative for Energy Supply: Performance Assessment of Integrated Community Energy Systems”, *Energies*, vol. 9, no. 12, p. 981, Nov. 2016, ISSN: 1996-1073.

[152] T. Tsoutsos, M. Drandaki, N. Frantzeskaki, E. Iosifidis, and I. Kiosses, “Sustainable energy planning by using multi-criteria analysis application in the island of Crete”, *Energy Policy*, vol. 37, no. 5, pp. 1587–1600, 2009, ISSN: 03014215.

[153] K. Dittrich and W. van Dijk, *The Value Case Methodology. A Methodology Aligning Financial and Non-Financial Values in Large Multi-Stakeholder Innovation Projects*, 2013.

[154] S. D. Pohekar and M. Ramachandran, “Application of multi-criteria decision making to sustainable energy planning - A review”, *Renewable and Sustainable Energy Reviews*, vol. 8, pp. 365–381, 2004, ISSN: 13640321.

[155] E. Løken, “Use of multicriteria decision analysis methods for energy planning problems”, *Renewable and Sustainable Energy Reviews*, vol. 11, no. 7, pp. 1584–1595, 2007, ISSN: 13640321.

[156] A. Kumar, B. Sah, A. R. Singh, *et al.*, “A review of multi criteria decision making (MCDM) towards sustainable renewable energy development”, *Renewable and Sustainable Energy Reviews*, vol. 69, no. November 2016, pp. 596–609, 2017, ISSN: 18790690.

[157] R. Alizadeh, L. Soltanisehat, P. D. Lund, and H. Zamanisabzi, “Improving renewable energy policy planning and decision-making through a hybrid MCDM method”, *Energy Policy*, vol. 137, no. December 2019, p. 111 174, 2020, ISSN: 03014215.

[158] R. G. Beiragh, R. Alizadeh, S. S. Kaleibari, *et al.*, “An integrated Multi-Criteria Decision Making Model for Sustainability Performance Assessment for Insurance Companies”, *Sustainability*, vol. 12, no. 3, p. 789, 2020.

[159] T. Kaya and C. Kahraman, “Multicriteria renewable energy planning using an integrated fuzzy VIKOR & AHP methodology: The case of Istanbul”, *Energy*, vol. 35, no. 6, pp. 2517–2527, 2010, ISSN: 03605442.

[160] Ö. Erol and B. Kilkiş, “An energy source policy assessment using analytical hierarchy process”, *Energy Conversion and Management*, vol. 63, pp. 245–252, 2012, ISSN: 01968904.

[161] E. W. Stein, “A comprehensive multi-criteria model to rank electric energy production technologies”, *Renewable and Sustainable Energy Reviews*, vol. 22, pp. 640–654, 2013, ISSN: 13640321.

[162] A. Afsordegan, M. Sánchez, N. Agell, S. Zahedi, and L. V. Cremades, “Decision making under uncertainty using a qualitative TOPSIS method for selecting sustainable energy alternatives”, *International Journal of Environmental Science and Technology*, vol. 13, no. 6, pp. 1419–1432, 2016, ISSN: 17352630.

[163] Y. Çelikbilek and F. Tüysüz, “An integrated grey based multi-criteria decision making approach for the evaluation of renewable energy sources”, *Energy*, vol. 115, pp. 1246–1258, 2016, ISSN: 03605442.

[164] D. Štreimikiene, J. Šliogeriene, and Z. Turskis, “Multi-criteria analysis of electricity generation technologies in Lithuania”, *Renewable Energy*, vol. 85, pp. 148–156, 2016, ISSN: 18790682.

6

[165] B. Haddad, A. Liazid, and P. Ferreira, “A multi-criteria approach to rank renewables for the Algerian electricity system”, *Renewable Energy*, vol. 107, pp. 462–472, 2017, ISSN: 18790682.

[166] A. Balin and H. Baraçli, “A fuzzy multi-criteria decision making methodology based upon the interval Type-2 fuzzy sets for evaluating renewable energy alternatives in Turkey”, *Technological and Economic Development of Economy*, vol. 23, no. 5, 2017, ISSN: 20294921.

[167] S. Malkawi, M. Al-Nimr, and D. Azizi, “A multi-criteria optimization analysis for Jordan’s energy mix”, *Energy*, vol. 127, no. 13, pp. 680–696, 2017, ISSN: 03605442.

[168] G. Büyüközkan and Y. Karabulut, “Energy project performance evaluation with sustainability perspective”, *Energy*, vol. 119, pp. 549–560, 2017, ISSN: 03605442.

[169] T. Kaya and C. Kahraman, “Multicriteria decision making in energy planning using a modified fuzzy TOPSIS methodology”, *Expert Systems with Applications*, vol. 38, no. 6, pp. 6577–6585, 2011, ISSN: 09574174.

[170] D. Streimikiene, T. Balezentis, I. Krisciukaitien, and A. Balezentis, “Prioritizing sustainable electricity production technologies: MCDM approach”, *Renewable and Sustainable Energy Reviews*, vol. 16, no. 5, pp. 3302–3311, 2012, ISSN: 13640321.

[171] M. Alsayed, M. Cacciato, G. Scarcella, and G. Scelba, “Multicriteria optimal sizing of photovoltaic-wind turbine grid connected systems”, *IEEE Transactions on Energy Conversion*, vol. 28, no. 2, pp. 370–379, 2013, ISSN: 08858969.

[172] B. Brand and R. Missaoui, “Multi-criteria analysis of electricity generation mix scenarios in Tunisia”, *Renewable and Sustainable Energy Reviews*, vol. 39, pp. 251–261, 2014, ISSN: 13640321.

[173] Ü. Şengül, M. Eren, S. Eslamian Shiraz, V. Gezder, and A. B. Sengül, “Fuzzy TOPSIS method for ranking renewable energy supply systems in Turkey”, *Renewable Energy*, vol. 75, pp. 617–625, 2015, ISSN: 18790682.

[174] T. Baležentis and D. Streimikiene, “Multi-criteria ranking of energy generation scenarios with Monte Carlo simulation”, *Applied Energy*, vol. 185, pp. 862–871, 2017, ISSN: 03062619.

[175] T. Catalina, J. Virgone, and E. Blanco, “Multi-source energy systems analysis using a multi-criteria decision aid methodology”, *Renewable Energy*, vol. 36, no. 8, pp. 2245–2252, 2011, ISSN: 09601481.

[176] P. Haurant, P. Oberti, and M. Muselli, “Multicriteria selection aiding related to photovoltaic plants on farming fields on Corsica island: A real case study using the ELECTRE outranking framework”, *Energy Policy*, vol. 39, no. 2, pp. 676–688, 2011, ISSN: 03014215.

[177] H.-s. Shih, H.-j. Shyur, and E. S. Lee, “An extension of TOPSIS for group decision making”, *Mathematical and computer modelling*, vol. 45, pp. 801–813, 2007.

[178] F. Samanlioglu, Y. E. Taskaya, U. C. Gulen, and O. Cokcan, “A Fuzzy AHP–TOPSIS-Based Group Decision-Making Approach to IT Personnel Selection”, *International Journal of Fuzzy Systems*, vol. 20, no. 5, pp. 1576–1591, 2018, ISSN: 2199-3211.

[179] M. Abdel-Basset, G. Manogaran, A. Gamal, and F. Smarandache, “A Group Decision Making Framework Based on Neutrosophic TOPSIS Approach for Smart Medical Device Selection”, *Journal of Medical Systems*, vol. 43, no. 2, p. 38, 2019, ISSN: 1573-689X.

[180] A. Hatami-Marbini and F. Kangi, “An extension of fuzzy TOPSIS for a group decision making with an application to tehran stock exchange”, *Applied Soft Computing Journal*, vol. 52, pp. 1084–1097, 2017, ISSN: 15684946.

[181] D. Kannan, R. Khodaverdi, L. Olfat, A. Jafarian, and A. Diabat, “Integrated fuzzy multi criteria decision making method and multiobjective programming approach for supplier selection and order allocation in a green supply chain”, *Journal of Cleaner Production*, vol. 47, pp. 355–367, 2013, ISSN: 09596526.

[182] S. Shafiei Kaleibari, R. Gharizadeh Beiragh, R. Alizadeh, and M. Solimanpur, “A framework for performance evaluation of energy supply chain by a compatible network data envelopment analysis model”, *Scientia Iranica*, vol. 23, no. 4, pp. 1904–1917, 2016, ISSN: 10263098.

[183] N. Hajibandeh, M. Shafie-khah, G. J. Osório, J. Aghaei, and J. P. Catalão, “A heuristic multi-objective multi-criteria demand response planning in a system with high penetration of wind power generators”, *Applied Energy*, vol. 212, no. December 2017, pp. 721–732, 2018, ISSN: 03062619.

[184] R. Jing, X. Zhu, Z. Zhu, *et al.*, “A multi-objective optimization and multi-criteria evaluation integrated framework for distributed energy system optimal planning”, *Energy Conversion and Management*, vol. 166, no. April, pp. 445–462, 2018, ISSN: 01968904.

[185] Y. Sunak and R. Madlener, “The impact of wind farm visibility on property values: A spatial difference-in-differences analysis”, *Energy Economics*, vol. 55, pp. 79–91, 2016, ISSN: 01409883.

[186] K. Palmer-wilson, J. Donald, B. Robertson, *et al.*, “Impact of land requirements on electricity system decarbonisation pathways”, *Energy Policy*, vol. 129, no. February, pp. 193–205, 2019, ISSN: 0301-4215.

[187] A. Golchha and S. G. Qureshi, “Non-Dominated Sorting Genetic Algorithm-II – A Succinct Survey”, *International journal of computer science and information technologies*, vol. 6, no. 1, pp. 252–255, 2015.

[188] M. D. Al-falahi, S. D. Jayasinghe, and H. Enshaei, “A review on recent size optimization methodologies for standalone solar and wind hybrid renewable energy system”, *Energy Conversion and Management*, vol. 143, pp. 252–274, 2017, ISSN: 01968904.

[189] Unie van Waterschappen, *Regionale Energie Strategie*, 2019. [Online]. Available: `https://www.regionale-energiestrategie.nl/default.aspx` (visited on 06/14/2019).

[190] Noord-Holland Zuid, *Energy Region NHZ*, 2020. [Online]. Available: `https://energieregionhz.nl` (visited on 01/14/2020).

6

[191] ENTSO-E, *ENTSO-E Transparancy Platform*, 2019. [Online]. Available: `https://transparency.entsoe.eu` (visited on 06/18/2019).

[192] KIC InnoEnergy, "Future renewable energy costs: solar photovoltaics", KIC InnoEnergy, Tech. Rep., 2015.

[193] IRENA, "Electricty storage and renewables: costs and markets to 2030", IRENA, Tech. Rep., 2017.

[194] Rijswaterstraat, *Klimaatmonitor*, 2020. [Online]. Available: `https://klimaatmonitor.databank.nl` (visited on 04/05/2020).

[195] Gasunie and TenneT, "Infrastructure Outlook 2050 Fase II", Tech. Rep., 2020, p. 68.

[196] M. Groissböck, "Are open source energy system optimization tools mature enough for serious use?", *Renewable and Sustainable Energy Reviews*, vol. 102, 2019, ISSN: 18790690.

[197] X. Deng and T. Lv, "Power system planning with increasing variable renewable energy: A review of optimization models", *Journal of Cleaner Production*, vol. 246, 2020, ISSN: 09596526.

[198] I. J. Ferez-Arriaga and C. Meseguer, "Wholesale marginal prices in competitive generation markets", *IEEE Transactions on Power Systems*, vol. 12, no. 2, pp. 710–717, 1997, ISSN: 08858950.

[199] B. F. Hobbs, "Linear complementarity models of nash-Cournot competition in bilateral and POOLCO power markets", *IEEE Transactions on Power Systems*, vol. 16, no. 2, 2001, ISSN: 08858950.

[200] Y. He, L. Wang, and J. Wang, "Cap-and-trade vs. carbon taxes: A quantitative comparison from a generation expansion planning perspective", *Computers and Industrial Engineering*, vol. 63, no. 3, pp. 708–716, 2012, ISSN: 03608352.

[201] W. El-Khattam, K. Bhattacharya, Y. Hegazy, and M. Salama, "Optimal Investment Planning for Distributed Generation in a Competitive Electricity Market", *IEEE Transactions on Power Systems*, vol. 19, no. 3, pp. 1674–1684, 2004, ISSN: 0885-8950.

[202] R. G. Karandikar, S. A. Khaparde, and S. V. Kulkarni, "Strategic evaluation of bilateral contract for electricity retailer in restructured power market", *International Journal of Electrical Power and Energy Systems*, vol. 32, no. 5, pp. 457–463, 2010, ISSN: 01420615.

[203] Y. Tang, J. Ling, C. Wu, N. Chen, X. Liu, and B. Gao, "Game-theoretic optimization of bilateral contract transaction for generation companies and large consumers with incomplete information", *Entropy*, vol. 19, no. 6, 2017, ISSN: 10994300.

[204] M. Pourakbari-Kasmaei, M. Asensio, M. Lehtonen, and J. Contreras, "Trilateral Planning Model for Integrated Community Energy Systems and PV-Based Prosumers-A Bilevel Stochastic Programming Approach", *IEEE Transactions on Power Systems*, vol. 35, no. 1, 2020, ISSN: 15580679.

[205] A. A. Nazari and R. Keypour, "A two-stage stochastic model for energy storage planning in a microgrid incorporating bilateral contracts and demand response program", *Journal of Energy Storage*, vol. 21, 2019, ISSN: 2352152X.

[206] A. M. Foley, B. P. Ó Gallachóir, J. Hur, R. Baldick, and E. J. McKeogh, "A strategic review of electricity systems models", *Energy*, vol. 35, no. 12, 2010, ISSN: 03605442.

[207] J. Bower and D. W. Bunn, "Model-based comparisons of pool and bilateral markets for electricity", *Energy Journal*, vol. 21, no. 3, 2000, ISSN: 01956574.

[208] F. Lopes, T. Rodrigues, and J. Sousa, "Negotiating bilateral contracts in a multi-agent electricity market: A case study", in *Proceedings - International Workshop on Database and Expert Systems Applications, DEXA*, 2012.

[209] K. Imran, J. Zhang, A. Pal, A. Khattak, K. Ullah, and S. M. Baig, "Bilateral negotiations for electricity market by adaptive agent-tracking strategy", *Electric Power Systems Research*, vol. 186, 2020, ISSN: 03787796.

[210] E. Bompard and Y. Ma, "Modeling bilateral electricity markets: A complex network approach", *IEEE Transactions on Power Systems*, vol. 23, no. 4, 2008, ISSN: 08858950.

[211] N. Wang, R. Verzijlbergh, P. Heijnen, and P. Herder, "Modeling the decentralized energy investment and operation in the prosumer era: a systematic review", *2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, pp. 1079–1083, Oct. 2020.

[212] Y. Yang, S. Zhang, and Y. Xiao, "Optimal design of distributed energy resource systems coupled withenergy distribution networks", *Energy*, vol. 85, pp. 433–448, 2015, ISSN: 03605442.

[213] U. J. Hahnel, M. Herberz, A. Pena-Bello, D. Parra, and T. Brosch, "Becoming prosumer: Revealing trading preferences and decision-making strategies in peer-to-peer energy communities", *Energy Policy*, vol. 137, 2020, ISSN: 03014215.

[214] E. Sorin, L. Bobo, and P. Pinson, "Consensus-Based Approach to Peer-to-Peer Electricity Markets with Product Differentiation", *IEEE Transactions on Power Systems*, vol. 34, no. 2, pp. 994–1004, 2019, ISSN: 08858950.

[215] T. Morstyn and M. D. McCulloch, "Multiclass Energy Management for Peer-to-Peer Energy Trading Driven by Prosumer Preferences", *IEEE Transactions on Power Systems*, vol. 34, no. 5, pp. 4005–4014, 2019, ISSN: 15580679.

[216] T. Baroche, F. Moret, and P. Pinson, "Prosumer markets: A unified formulation", *2019 IEEE Milan PowerTech, PowerTech 2019*, pp. 1–6, 2019.

[217] T. Baroche, P. Pinson, R. L. G. Latimier, and H. Ben Ahmed, "Exogenous Cost Allocation in Peer-to-Peer Electricity Markets", *IEEE Transactions on Power Systems*, vol. 34, no. 4, pp. 2553–2564, 2019, ISSN: 15580679.

[218] Steven A. Gabriel, Antonio J. Conejo, J. David Fuller, *et al.*, *Complementarity Modeling in Energy Markets*. Springer-Verlag New York, 2013, vol. 180, pp. XXVI, 630, ISBN: 978-1-4419-6123-5.

[219] F. Moret, A. Tosatto, T. Baroche, and P. Pinson, "Loss allocation in joint transmission and distribution peer-to-peer markets", *IEEE Transactions on Power Systems*, vol. 36, no. 3, pp. 1833–1842, 2020, ISSN: 23318422.

6

[220] Netherlands Environmental Assessment Agency, *Regionale Energie Strategieën; Een tussentijdse analyse*, 2020.

[221] Unie van Waterschappen, *RES 1.0 per regio*, 2021. [Online]. Available: `https://www.regionale-energiestrategie.nl/bibliotheek/res++media/1643638.aspx?t=RES-10-per-regio` (visited on 11/13/2022).

6

About the author

Ni Wang was born on the 5th of February in Luoyang City, Henan Province, China. He became interested in the energy transition during his bachelor's study in Energy and Environment Systems Engineering at Zhejiang University. After an exchange study at the Technical University of Munich, he decided to pursue a master's degree in Europe. In 2013, he started a master's program in Sustainable Energy Technology in the Netherlands. After graduation, he worked as an application engineer in 2016 and returned to academia to begin his doctoral research at the Delft University of Technology in 2017.

The doctoral research topic is the intersection of renewable energy integration and economics, which meets his ambitions since his bachelor's study. In addition to the publications, he presented his work on various occasions, including at conferences, workshops, stakeholder meetings, and in a guest lecture. He also enjoyed teaching activities. He acted as the daily supervisor for five master's graduation projects and the teaching assistant for courses on agent-based modeling and energy system optimization.

List of Publications

Peer-reviewed journal papers

1. N. Wang, R. A. Verzijlbergh, P. W. Heijnen, and P. M. Herder, “A spatially explicit planning approach for power systems with a high share of renewable energy sources”, *Applied Energy*, vol.260, 2020.
2. N. Wang, P. W. Heijnen, and P. J. Imhof, “A multi-actor perspective on multi-objective regional energy system planning”, *Energy Policy*, vol.143, 2020.
3. N. Wang, Z. Liu, P. Heijnen, and M. Warnier, “A peer-to-peer market mechanism incorporating multi-energy coupling and cooperative behaviors”, *Applied Energy*, vol.311, 2022.
4. N. Wang, R. A. Verzijlbergh, P. W. Heijnen, and P. M. Herder, “A review and analysis on the institutional paradigms in optimization models for energy system planning”, Submitted, 2022.
5. N. Wang, R. A. Verzijlbergh, P. W. Heijnen, and P. M. Herder, “An energy system optimization model with bilateral trading and externalities: Application to the Dutch national program Regional Energy Strategies”. Submitted, 2022.

Peer-reviewed conference contributions

1. N. Wang, R. A. Verzijlbergh, P. W. Heijnen, R. W. Kunneke, and P. M. Herder, “Optimization modeling of regional energy systems considering coordination mechanisms”, abstract presented at *SUES 2018: Sustainable Urban Energy Systems Conference*, 2018.
2. N. Wang, R. A. Verzijlbergh, P. W. Heijnen, R. W. Kunneke, and P. M. Herder, “Formulating coordination mechanisms in the investment optimization models of self-sufficient regional energy systems”. abstract presented at *Energy-Open 2018*, 2018.
3. N. Wang, R. A. Verzijlbergh, P. W. Heijnen, and P. M. Herder, “Modeling the decentralized energy investment and operation in the prosumer era: a systematic review”, *2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, 1079–1083, 2020.