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**DOI**

[10.1016/j.enpol.2020.111578](https://doi.org/10.1016/j.enpol.2020.111578)

**Publication date**

2020

**Document Version**

Final published version

**Published in**

Energy Policy

**Citation (APA)**

Wang, N., Heijnen, P., & Imhof, P. (2020). A multi-actor perspective on multi-objective regional energy system planning. *Energy Policy*, 143, Article 111578. <https://doi.org/10.1016/j.enpol.2020.111578>

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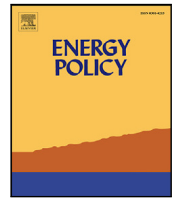
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# A multi-actor perspective on multi-objective regional energy system planning

Ni Wang<sup>\*</sup>, Petra W. Heijnen, Pieter J. Imhof

Faculty of Technology Policy and Management, Delft University of Technology, Jaffalaan 5, 2628BX Delft, The Netherlands

## HIGHLIGHTS

- We develop a multi-actor multi-objective regional energy system planning approach.
- Optimal investment decisions for multiple actors can be derived simultaneously.
- The degrees of optimality of results show the alignment of actors quantitatively.
- A case study is done for a standalone renewable-based regional system in Amsterdam.
- A sub-optimal but most satisfactory generation mix for all actors is obtained.

## ARTICLE INFO

### Keywords:

Multi-actor perspective  
Energy system planning  
Multi-objective optimization  
Land-use  
Visually impacted area  
Multi-criteria decision-making

## ABSTRACT

Renewable energy investment is a complex process where multiple actors are often involved with their own, sometimes conflicting, interests. Here we propose a multi-actor multi-objective regional energy system planning approach to help actors gain mutual understanding regarding each other's optimal investment wishes, in order to advance the planning process. This approach combines two models: Multi-Objective Optimization (MOO) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The approach uses illustrative objectives and actors which is then applied to the greater Amsterdam region to showcase its usage and strength. The four chosen objectives, i.e. total Capital Expenditure, total Operation & Maintenance costs, land-use and visually impacted area are minimized simultaneously to obtain a set of Pareto-optimal solutions. These solutions are then evaluated for governments, funders and local residents with different preferences using TOPSIS. The case study shows that our approach is unique and useful when multiple actors have to decide together upon the energy investment capacities. It is able to provide quantitative and optimal decision-aiding from the multi-actor perspective and generate also sub-optimal yet acceptable solutions for all the actors. Based on our approach, the impacts of policy options can be revealed from the actors' perspectives as well.

## 1. Introduction

### 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 (Alizadeh et al., 2016). However, the projection from McKinsey & Company (2019) 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

*Abbreviations:* TOPSIS, Technique for Order of Preference by Similarity to Ideal Solution; RES, Renewable Energy Sources; MOO, Multi-Objective Optimization; ICES, Integrated Community Energy Systems; MCDM, Multi-Criteria Decision-Making; LCA, Life Cycle Assessment; CBA, Cost Benefit Analysis; AHP, Analytical Hierarchy Process; PROMETHEE, Preference Ranking Organization METHOD for Enrichment of Evaluations; ELECTRE, ELimination Et Choix Traduisant la REALité; VIA, Visually Impacted Area; GA, Genetic Algorithm; CapEx, Capital Expenditure; O & M, Operation & Maintenance; V66, Vestas V66 wind turbines; V110, Vestas V110 wind turbines; PV-residential, residential PV; PV-utility, utility-scale PV; VRES, Variable Renewable Energy Sources; FOM, Fixed Operation & Maintenance; VOM, Variable Operation & Maintenance; TRS, Total Roof Surface; NSGA-II, Non-dominated Sorting Genetic Algorithm II; CC, Coefficient of Closeness; ENTSO-E, European Network of Transmission System Operators for Electricity; LCOE, Levelized Cost Of Electricity; AM, Arithmetic Mean

<sup>\*</sup> Corresponding author.

E-mail address: [n.wang@tudelft.nl](mailto:n.wang@tudelft.nl) (N. Wang).

<https://doi.org/10.1016/j.enpol.2020.111578>

Received 22 January 2020; Received in revised form 11 April 2020; Accepted 1 May 2020

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Nomenclature	
<b>Parameters</b>	
$\gamma$	storage conversion factor
$\omega_m^a$	weight for preference $m$ , actor $a$
$\phi_i$	land-use factor of technology $i$ (km <sup>2</sup> /kW)
LU <sup>max</sup>	maximum land that can be used (km <sup>2</sup> )
TRS	total roof surface (km <sup>2</sup> )
$v_i$	visual impact of one wind turbine of type $i$ (km <sup>2</sup> )
$a_i$	Fixed Operation & Maintenance costs of generation/storage technology $i$ per unit capacity per year (€/kW/yr)
$b_i$	Variable Operation & Maintenance costs of generation/storage technology $i$ per unit energy (€/kWh)
$C_i$	Capital Expenditure of generation/storage conversion technology $i$ (€/kW, €/kWh for storage)
$D_t$	energy demand at time $t$ (kWh)
$L_i$	lifetime of generation/storage technology $i$ (yr)
$p_i^{\text{rated}}$	rated power of wind turbines of type $i$ (kW)
$r$	discount rate
$\eta_{i,t}$	capacity factor of technology $i$ at time $t$
<b>Sets</b>	
A	all actors, A = {governments, funders, local residents}
G	all technologies, G = {Vestas V66 wind turbines, Vestas V110 wind turbines, utility-scale PV, residential PV, biomass, storage, storage conversion}
M	all preferences, M = {total Capital Expenditure, total Operation & Maintenance costs, land-use, Visually Impacted Area}
N	all Pareto-optimal solutions
VRES	wind and solar energy technologies, VRES = {Vestas V66 wind turbines, Vestas V110 wind turbines, utility-scale PV, residential PV}

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 (Prasad et al., 2014; Dagoumas and Koltaklis, 2019), such as optimization models and simulation models (see the recent reviews of Oree et al. (2017) and Tozzi and Jo (2017), respectively). Optimization models, being the most common approach in generation investment problems (Dagoumas and Koltaklis, 2019), are especially suitable for studies on long-term RES investment (Iqbal et al., 2014), 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 study focuses on the optimal future energy system designs and will therefore focus on optimization models instead of on simulation models.

In most optimization models, the objective is usually to minimize total cost (Prasad et al., 2014) to find the optimal RES generation

Variables	
$CC_n^a$	normalized Coefficient of Closeness for solution $n$ , actor $a$
$CC_n^{\text{average}}$	average normalized Coefficient of Closeness for solution $n$
$CoCl_n^a$	absolute Coefficient of Closeness for solution $n$ , actor $a$
$C^{\text{CapEx}}$	total Capital Expenditure (€)
$C^{\text{O\&M}}$	total Operation & Maintenance costs (€)
$I_m^{a+}$	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 $i$ (kW, kWh for storage)
$P_t^{\text{charging}}$	energy from charging the storage at time $t$ (kWh)
$P_t^{\text{deficit}}$	energy deficit after deploying wind and solar energy at time $t$ (kWh)
$P_t^{\text{discharging}}$	energy from discharging the storage at time $t$ (kWh)
$P_{i,t}$	energy production/storage of technology $i$ at time $t$ (kWh)
$Q_{nm}$	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 $a$
WT <sub><math>i</math></sub>	number of wind turbines of type $i$
LU	total land-use (km <sup>2</sup> )
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 (km <sup>2</sup> )

mix. The cost-optimal models have been extensively discussed in literature, e.g., see the recent review of Ringkjøb et al. (2018). However, according to IRENA (2018), 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 (IEA, 2019). This implies that, for the RES investment in practice, 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 (Strantzali and Aravossis, 2016). These factors need to be emphasized in research in order to help the stakeholders<sup>1</sup> 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 (Miller et al., 2013). Optimization models that can handle all these factors (provided they can be quantified) are Multi-Objective Optimization (MOO) models.

<sup>1</sup> Note that in this paper, the terms stakeholders, actors and decision-makers are used interchangeably.

## 1.2. Literature review

### 1.2.1. 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 [Alarcon-Rodriguez et al. \(2010\)](#) and [Fadaee and Radzi \(2012\)](#), 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 ([Wang and Rangaiah, 2017](#)), 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 afterwards (a posteriori). Using Pareto-optimal solutions is more methodical and less subjective ([Deb, 2015](#)) and allows to analyse the correlation between the objectives ([Alarcon-Rodriguez et al., 2010](#)). In fact, the comprehensive review of [Alarcon-Rodriguez et al. \(2010\)](#) concludes that most MOO studies in energy system planning generate a set of Pareto-optimal solutions instead of using scalarization.

The reviews of [Alarcon-Rodriguez et al. \(2010\)](#), [Fadaee and Radzi \(2012\)](#) and [Antunes and Henriques \(2016\)](#) give good overviews of earlier studies on MOO literature that provides Pareto-optimal solutions. To avoid repetition, the relevant literature in the recent 10 years is briefly reviewed here. [Tekiner et al. \(2010\)](#) proposes a multi-period multi-objective generation expansion approach to simultaneously minimize total cost and emissions. A model to design a RES-based energy system is presented by [Zou et al. \(2010\)](#), where it accounts for total cost and system reliability. [Perera et al. \(2013b\)](#) and [Clarke et al. \(2015\)](#) design standalone hybrid energy systems to minimize cost and emissions. The model of [Falke et al. \(2016\)](#) minimizes 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 is done by [Prebeg et al. \(2016\)](#), where the objectives are minimizing cost and maximizing the RES contribution. [Mahbub et al. \(2017\)](#) investigates the future energy scenarios in an Italian region to minimize cost and emissions. A MOO model for expansion with high-RES shares is developed by [Luz et al. \(2018\)](#), which is applied to a Brazilian case to give advice on the RES targets posed by the government. Furthermore, minimizing cost and emissions are also found in the studies of [Arnette and Zobel \(2012\)](#), [Fazlollahi et al. \(2012\)](#), [Gabrielli et al. \(2018\)](#) and [Di Somma et al. \(2018\)](#) for energy system planning with various focuses such as stochastic planning or seasonal storage. In addition, in studies focusing on system integration options ([Prasad Koirala et al., 2016](#)) such as community microgrids, virtual power plants, energy hubs and Integrated Community Energy Systems (ICES) ([Koirala, 2017](#)), Pareto-optimal solutions are also searched for. For example, [Guo et al. \(2014\)](#) selects the type and capacity of distributed generation units as the decision variables. A case study for a microgrid system is carried out. In the work of [Koirala et al. \(2016\)](#), the solutions are generated randomly for ICES 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 analysed 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) ([Alarcon-Rodriguez et al., 2010](#)). Therefore, multi-actor decision-making in energy system planning will be introduced in the next section.

### 1.2.2. Multi-actor decision-making in energy system planning

Given the complex nature of the energy system planning problem, the decision-making is not possible without considering the various interests and preferences from multiple actors ([Tsoutsos et al., 2009](#)). The multi-actor perspective can be considered using various methods, such as the Value Case Method ([Dittrich and van Dijk, 2013](#)) which identifies and aligns the values of multiple stakeholders by means of workshops and interviews for large innovation projects. According to [Strantzali and Aravossis \(2016\)](#), the most frequently used decision-making models in RES investment are Life Cycle Assessment (LCA), Cost-Benefit Analysis (CBA) and MCDM. While LCA mainly focuses on the environmental impacts of RES and CBA 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 ([Oree et al., 2017](#)).

MCDM is an evaluation method that considers criteria from different aspects simultaneously, such as technical, economic and environmental aspects ([Tsoutsos et al., 2009](#)). In this method, a set of alternatives are evaluated against those criteria and the output is usually ranking of the alternatives. MCDM methods in energy system planning have been reviewed comprehensively by [Pohekar and Ramachandran \(2004\)](#), [Løken \(2007\)](#), [Antunes and Henriques \(2016\)](#) and [Kumar et al. \(2017\)](#). Besides, the studies of [Alizadeh et al. \(2020\)](#) and [Beiragh et al. \(2020\)](#) also provide reviews on MCDM with various focuses. Generally, three types of methods are discussed in literature, which are value measurement methods, goal programming and outranking methods ([Løken, 2007](#)). This paragraph will now briefly introduce these methods and outline some studies from the recent 10 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 Analytical Hierarchy Process (AHP) ([Kaya and Kahraman, 2010](#); [Erol and Kilic, 2012](#); [Stein, 2013](#); [Afsordegan et al., 2016](#); [Çelikbilek and Tüysüz, 2016](#); [Štreimikiene et al., 2016](#); [Haddad et al., 2017](#); [Balin and Baracli, 2017](#); [Malkawi et al., 2017](#); [Büyükoçkan and Karabulut, 2017](#); [Beiragh et al., 2020](#)). 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 Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) ([Kaya and Kahraman, 2011](#); [Štreimikiene et al., 2012](#); [Alsayed et al., 2013](#); [Brand and Missaoui, 2014](#); [Sengül et al., 2015](#); [Afsordegan et al., 2016](#); [Balin and Baracli, 2017](#); [Baležentis and Štreimikiene, 2017](#)). 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 (PROMETHEE) ([Alsayed et al., 2013](#)) and ELimination Et Choix Traduisant la REALité (ELECTRE) ([Catalina et al., 2011](#); [Haurant et al., 2011](#)). Among those MCDM methods, TOPSIS offers a simple way of combining the preferences of multiple actors to allow for group decision-making ([Shih et al., 2007](#)), which is most relevant to this research. It has been used in other fields such as IT personnel selection ([Samanlioglu et al., 2018](#)), smart medical device selection ([Abdel-Basset et al., 2019](#)) and stock exchange ([Hatami-Marbini and Kangi, 2017](#)). The applications of TOPSIS in energy system planning are now reviewed, by elaborating on the aforementioned studies in the previous paragraph. [Kaya and Kahraman \(2011\)](#) proposes a modified fuzzy TOPSIS methodology and applies it to an energy decision-making problem. Wind energy is found to be the best RES alternative. Similarly, [Štreimikiene et al. \(2012\)](#) develops a framework to prioritize energy generation technologies. [Alsayed et al. \(2013\)](#) finds the optimal size of a wind turbine-PV energy system by comparing scenarios of different installed capacities. A Turkish case study is done by [Brand and Missaoui \(2014\)](#). They use inputs from stakeholders and evaluate five power mix scenarios. Also for Turkey, the study of [Sengül et al. \(2015\)](#) develops a framework to support the

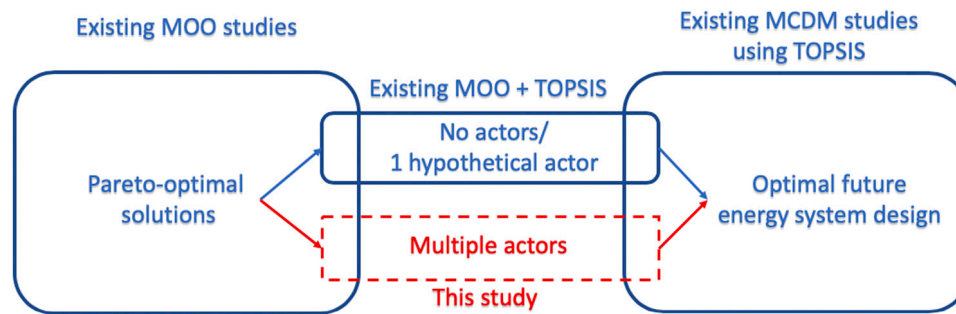


Fig. 1. Positioning of the paper in the literature on energy system planning.

ranking of RES and they find that hydro power is the best option. However, the study of [Balın and Baraçlı \(2017\)](#) shows that wind energy is the best alternative for Turkey by using a combination of fuzzy AHP and TOPSIS. Another modified fuzzy TOPSIS framework is proposed by [Afsordegan et al. \(2016\)](#) to rank seven energy alternatives under nine criteria. European Union energy development scenarios are evaluated by [Baležentis and Streimikiene \(2017\)](#). 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 the 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.

### 1.2.3. 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. \(2013\)](#) uses MOO and MCDM to rate and select the best green suppliers. The performance of the energy supply chain is assessed thoroughly with the help of combining various methods in [Shafiei Kaleibari et al. \(2016\)](#).

Model combinations are also studied in the field of energy system planning. For example, when criteria such as benefit, opportunity are crucial, strategic planning and MCDM can be jointly used to provide decision-support in prioritizing RES for policy-makers ([Alizadeh et al., 2020](#)). The need for using MOO and MCDM is recognized by [Antunes and Henriques \(2016\)](#). 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. \(2018\)](#) combines MOO and MCDM to identify the efficient strategies for system operators with a focus on demand response programmes.

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. \(2013a\)](#) uses fuzzy TOPSIS which is capable of handling the ambiguity associated with the relative weights of the objectives to analyse the Pareto-optimal solutions. Their approach would be useful for the decision-aiding for a particular decision-maker who has ambiguity on the relative importance of the objectives. [Jing et al. \(2018\)](#) uses MOO and MCDM to design a combined cooling, heat and power energy system with a focus on the 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. \(2013a\)](#) focuses 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 of [Jing et al. \(2018\)](#), TOPSIS is used to evaluate two objectives (cost and emissions), but actors are not included at all.

### 1.3. Research gap and contributions of the paper

We conclude that in the literature on energy system planning, the combination of MOO and MCDM has not drawn enough attention. Two studies which 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 ([Sunak and Madlener, 2016](#)) and the land-use of RES have 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 ([Palmer-wilson et al., 2019](#)) 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. [Fig. 1](#) pinpoints the positioning of our study with regard to the existing studies in the field of energy system planning.

The major contributions of the paper 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 the energy system planning. Furthermore, the approach is generic, indicating that other than the exemplary actors and the objectives which are considered in this paper, 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 modelled separately as two objectives.

#### 1.4. Overview of the proposed approach

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

##### 1.4.1. Scope of the models in this paper

The main contribution of the paper is to present a two-stage multi-actor multi-objective regional energy system planning approach that is able to give the 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 are then evaluated using TOPSIS to consider the actors and their preferences.

Considering the goal of the study, therefore, in this paper, 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 the 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.

##### 1.4.2. 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 with 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 (GA) (see Section 3.4 for details), will be used. In this study, the involved actors in energy system planning are simplified

**Table 1**  
The major preferences of the three actor groups.

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

to three main actor groups (see Section 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 GA, the Pareto-optimal solutions will be obtained regarding the four objectives. Within the common interests, they also have their major preferences (see Table 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 Fig. 2.

#### 1.5. Structure of the paper

The paper is organized as follows. Firstly, Section 2 describes the simulation model that simulates the energy flow. Then, the optimization model and the algorithm are discussed in Section 3. Next, the actors and their preferences are described and TOPSIS is formulated in Section 4. Section 5 introduces the case study and summarizes the input data. Later, results and discussions are presented and elaborated in Section 6. At last, conclusions are drawn and policy implications are given.

## 2. Simulation model

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

### 2.1. Considered technologies

As mentioned in Section 1.4.2, in this study, the modelling of the energy flow starts with the six considered technologies. They are Vestas V66 wind turbines (V66), Vestas V110 wind turbines (V110), residential PV (PV-residential), utility-scale PV (PV-utility), biomass (biomass) and hydrogen storage technology. Moreover, hydrogen storage technology consists of storage conversion (storage-conversion) and storage (storage). Accordingly, the decision variables are the numbers of the wind turbines ( $WT_i, \forall i \in \{V66, V110\}$ ) and the installed capacities of the other technologies ( $K_j, \forall j \in \{PV\text{-residential}, PV\text{-utility}, \text{biomass}, \text{storage}, \text{storage-conversion}\}$ ).

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 study. 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 modelling of hydrogen storage are considered out of scope.

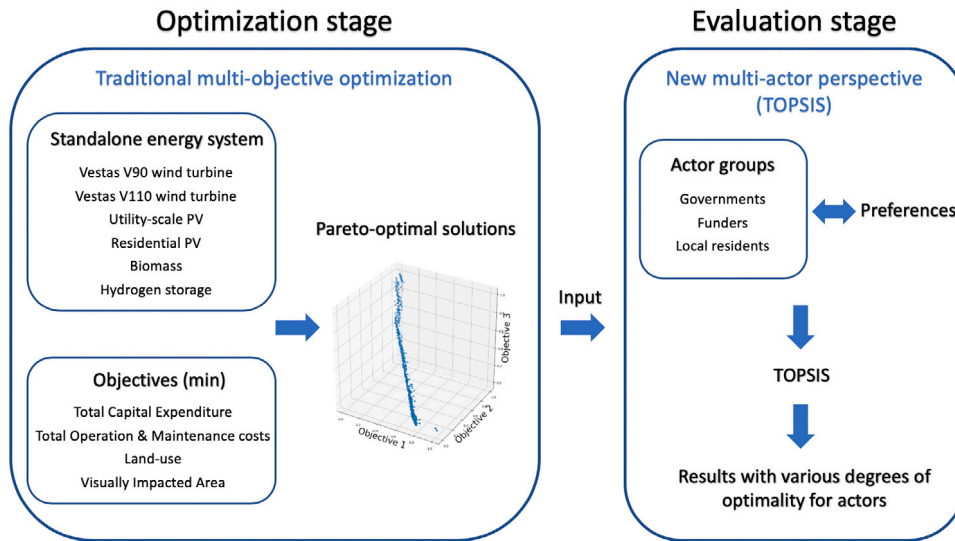


Fig. 2. Overview of the approach.

## 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 ( $i, \forall i \in \text{VRES}$ ). The installed capacity of the wind turbines ( $K_i$ ) is calculated as the sum of the rated power ( $P_i^{\text{rated}}$ ) and the number of the turbines ( $\text{WT}_i$ ).

$$K_i = P_i^{\text{rated}} \text{WT}_i \quad \forall i \in \{\text{V66}, \text{V110}\} \quad (1)$$

$$P_{i,t} = \eta_{i,t} K_i \quad \forall i \in \text{VRES}, \forall t \in \{1, 2, \dots, T\} \quad (2)$$

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

However, the generated energy ( $P_{i,t}$ ) may not be enough to fulfil 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:

$$P_t^{\text{deficit}} = D_t - \sum_{i \in \text{VRES}} P_{i,t} \quad \forall t \in \{1, 2, \dots, T\} \quad (3)$$

## 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  $\eta$ . The energy that is stored ( $P_{\text{storage},t}$ ) at all time steps is calculated by:

$$P_{\text{storage},t} = \begin{cases} P_{\text{storage},t-1} - \frac{1}{\eta} P_t^{\text{deficit}} & \forall t \in \{1, 2, \dots, T\} \text{ if } P_t^{\text{deficit}} \geq 0 \text{ and } P_{\text{storage},t-1} \geq \frac{1}{\eta} P_t^{\text{deficit}} \\ 0 & \text{if } P_t^{\text{deficit}} \geq 0 \text{ and } P_{\text{storage},t-1} < \frac{1}{\eta} P_t^{\text{deficit}} \\ P_{\text{storage},t-1} - \eta P_t^{\text{deficit}} & \forall t \in \{1, 2, \dots, T\} \text{ if } P_t^{\text{deficit}} < 0 \end{cases} \quad (4)$$

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

as non-negative variables:

$$P_t^{\text{discharging}} = \begin{cases} \eta(P_{\text{storage},t-1} - P_{\text{storage},t}) & \forall t \in \{1, 2, \dots, T\} \text{ if } P_t^{\text{deficit}} \geq 0 \\ 0 & \text{if } P_t^{\text{deficit}} < 0 \end{cases} \quad (5)$$

$$P_t^{\text{charging}} = \begin{cases} 0 & \text{if } P_t^{\text{deficit}} \geq 0 \\ \frac{1}{\eta}(P_{\text{storage},t} - P_{\text{storage},t-1}) & \forall t \in \{1, 2, \dots, T\} \text{ if } P_t^{\text{deficit}} < 0 \end{cases} \quad (6)$$

The model is initialized with the energy storage empty:

$$P_{\text{storage},0} = 0 \quad (7)$$

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

$$K_{\text{storage-conversion}} = \gamma K_{\text{storage}} \quad (8)$$

where  $\gamma$  is taken as 0.167 (Schlachtberger et al., 2017) in this study.

The constraints regarding the bounds of the storage will be given in Section 3.3.

## 2.4. Energy from biomass

The energy generated by biomass ( $P_{\text{biomass},t}$ ) at all time steps is used to fulfil 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 the biomass is calculated as follows.

$$P_{\text{biomass},t} = \begin{cases} P_t^{\text{deficit}} - \eta P_{\text{storage},t-1} & \forall t \in \{1, 2, \dots, T\} \text{ if } P_t^{\text{deficit}} \geq 0 \text{ and } P_{\text{storage},t} = 0 \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

The constraints regarding the bounds of the energy generated by biomass will be given in Section 3.3.

## 3. Multi-objective optimization model

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

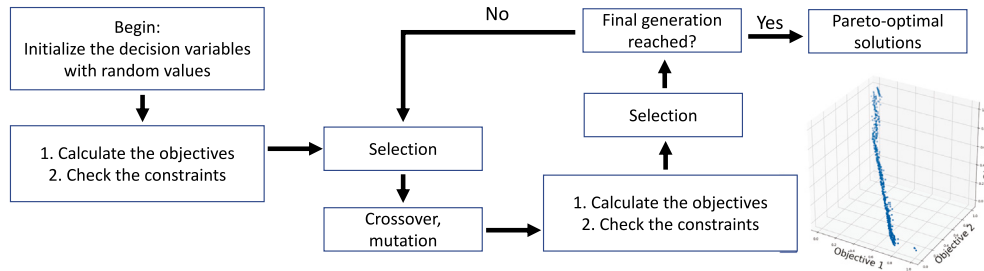


Fig. 3. Flowchart of the NSGA-II algorithm.

### 3.1. Choice of objectives

The four objectives that will be minimized are total CapEx, total O & M costs, land-use and VIA. CO<sub>2</sub> emissions are often used as an objective in MOO studies, however, in this study, they are treated as an implicit constraint that CO<sub>2</sub> emissions are considered to be reduced by 100% since only RES are used.

As stated in Section 1.4.1, in order to convey the main message which is an improved energy planning method by adding the multi-actor perspective to MOO, some modelling 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.

### 3.2. Objectives

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

$$C^{\text{CapEx}} = \sum_{i \in G} \frac{rC_i K_i}{1 - \frac{1}{(1+r)^{L_i}}} \quad (10)$$

where  $G = \{V66, V110, PV\text{-utility}, PV\text{-residential}, \text{biomass}, \text{storage}, \text{storage conversion}\}$ ,  $r$  is the discount rate, which is taken as 5% in this study (Wang et al., 2020),  $L_i$  is the lifetime of the technology ( $i$ ).

**Total O & M costs** The total O & M costs is 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 is calculated as:

$$C^{\text{O\&M}} = \sum_{i \in G} (a_i K_i + b_i \sum_{t \in \{1,2,\dots,T\}} P_{i,t}) \quad (11)$$

**Land-use** The total land-use of RES indicates the used land by RES technologies. It is quantified using the land-use factor ( $\phi_i$ ) 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 3.3).

$$LU = \sum_{i \in \{V66, V110, PV\text{-utility}\}} \phi_i K_i \quad (12)$$

**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 ( $v_i, \forall i \in \{V66, V110\}$ ), measured in area of impacted land

per wind turbine. Solar PV and biomass are not assumed to have any effects on visual impact.

$$VIA = \sum_{i \in \{V66, V110\}} v_i WT_i \quad (13)$$

### 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.

$$\sum_{i \in \text{VRES} \cup \{\text{Biomass}\}} P_{i,t} + P_t^{\text{discharging}} \geq D_t + P_t^{\text{charging}} \quad \forall t \in \{1, 2, \dots, T\} \quad (14)$$

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

$$0 \leq P_{\text{storage},t} \leq K_{\text{storage}} \quad \forall t \in \{1, 2, \dots, T\} \quad (15)$$

$$0 \leq P_t^{\text{deficit}} \leq K_{\text{storage-conversion}} \quad \forall t \in \{1, 2, \dots, T\} \quad (16)$$

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

$$0 \leq P_{\text{biomass},t} \leq K_{\text{biomass}} \quad \forall t \in \{1, 2, \dots, T\} \quad (17)$$

**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 ( $LU^{\text{max}}$ ) for wind turbines and utility-scale PV energy can be calculated following the approach of Wang et al. (2020).

$$\sum_{i \in \{V66, V110, PV\text{-utility}\}} \phi_i K_i \leq LU^{\text{max}} \quad (18)$$

**Residential PV constraint** The last constraint is about the available rooftop surface. Residential PV are solar panels which are placed on rooftops. The total area occupied by the residential PV has to be less than the Total Roof Surface (TRS). Same as suitable land for wind turbines and utility-scale PV, this TRS can also be estimated following the approach of Wang et al. (2020).

$$\phi_{PV\text{-residential}} K_{PV\text{-residential}} \leq TRS \quad (19)$$

### 3.4. Optimization algorithm

In this research, the Non-dominated Sorting Genetic Algorithm II (NSGA-II), which is one of the most widely used GA (Golchha and Qureshi, 2015), is used to find the set of Pareto-optimal solutions.

A GA 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. GA is specifically efficient for finding



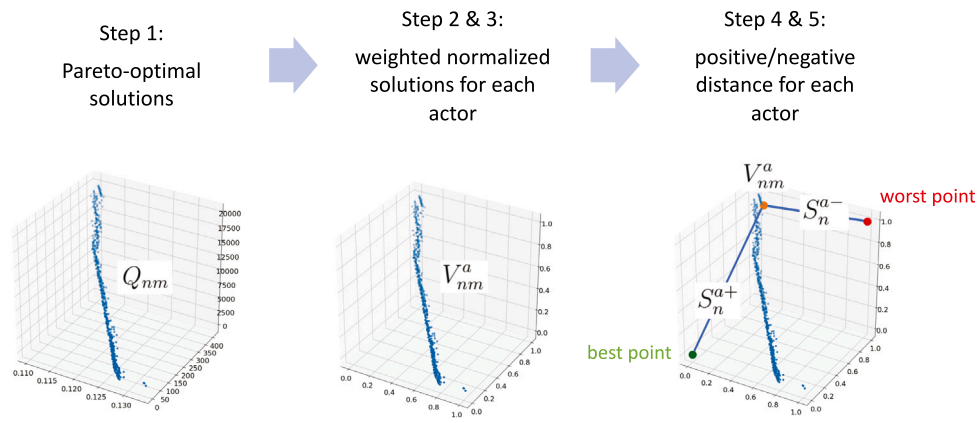


Fig. 4. Illustration of the step 1–5 of the TOPSIS method, where only three objectives are visualized.

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 Fig. 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 of Sawle et al. (2018) and are made larger to ensure convergence.

#### 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.

##### 4.1. Involved actors and their preferences

The involved actors and their preferences are inputs for the model. Since the focus and the contribution of this paper 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 Antunes and Henriques (2016), Prasad Koirala et al. (2016) and Al-falahi et al. (2017). 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 of solely 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 1.

It has to be noted that, as mentioned in Section 1.4.2, total CapEx, total O & M costs, land-use and VIA will be the objectives in the optimization model. These objectives are all considered as preferences

for all the actors. In Table 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. The 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.

##### 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. Shih et al. (2007) 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 step 1–5 are illustrated in Fig. 4.

**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  $M = \{\text{total CapEx, total O \& M costs, land-use, VIA}\}$ , 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  $m$ :

$$R_{nm} = \frac{Q_{nm} - Q_{\min,m}}{Q_{\max,m} - Q_{\min,m}} \quad \forall n \in N, \forall m \in M \quad (20)$$

**Step 3** is to define the weighted normalized decision matrix ( $V_{nm}^a$ ) for each actor  $a, \forall a \in A$ , where  $A = \{\text{governments, funders, local residents}\}$ . 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.

$$V_{nm}^a = w_m^a R_{nm} \quad \forall n \in N, \forall m \in M, \forall a \in A \quad (21)$$

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

$$I_m^{a+} = \min_{V_n \in N} V_{nm}^a \quad \forall m \in M, \forall a \in A \quad (22)$$

$$I_m^{a-} = \max_{V_n \in N} V_{nm}^a \quad \forall m \in M, \forall a \in A \quad (23)$$

**Step 5** is to derive the positive distance ( $S_n^{a+}$ ) and the negative distance ( $S_n^{a-}$ ) 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 ( $S_n^{a+}$ ) 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.

$$S_n^{a+} = \left( \sum_{m \in M} (I_m^{a+} - V_{nm}^a)^2 \right)^{\frac{1}{2}} \quad \forall n \in N, \forall a \in A \quad (24)$$

$$S_n^{a-} = \left( \sum_{m \in M} (I_m^{a-} - V_{nm}^a)^2 \right)^{\frac{1}{2}} \quad \forall n \in N, \forall a \in A \quad (25)$$

**Step 6** is to determine the so-called normalized Coefficient of Closeness (CC) ( $CC_n^a$ ) for each solution  $n$  for each actor  $a$ . To do this, first the absolute CC (CoCl $_n^a$ ) for each solution  $n$  for each actor  $a$  is calculated.

$$\text{CoCl}_n^a = \frac{S_n^{a-}}{S_n^{a+} + S_n^{a-}} \quad \forall n \in N, \forall a \in A \quad (26)$$

Then, CoCl $_n^a$  are normalized to CC $_n^a$ . CC $_n^a$  represents the degree of optimality of solution  $n$  for actor  $a$ , which will be referred to as CC score in the rest of the paper. 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.

$$CC_n^a = \frac{\text{CoCl}_n^a - \text{CoCl}_{\min}^a}{\text{CoCl}_{\max}^a - \text{CoCl}_{\min}^a} \quad \forall n \in N, \forall a \in A \quad (27)$$

**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 Shih et al. (2007) is used. The geometric mean of the CC scores for all actors is calculated to define an average CC score (CC $_n^{\text{average}}$ ). In the equations below,  $|A|$  represents the size of the set of actors  $A$ .

$$CC_n^{\text{average}} = \left( \prod_{a \in A} CC_{n,a} \right)^{\frac{1}{|A|}} \quad \forall n \in N \quad (28)$$

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 for a risk-neutral decision-maker.

$$\text{maximin} = \max_{V_n \in N} \left( \min_{V_a \in A} CC_n^a \right) \quad (29)$$

$$\text{minimax} = \min_{V_n \in N} \left( \max_{V_a \in A} CC_n^a \right) \quad (30)$$

## 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.



Fig. 5. The region Noord-Holland Zuid in the Netherlands (Noord-Holland Zuid, 2020).

### 5.1. Background

To combat climate change, in 2019, the Dutch government has concluded the National Climate Agreement to reduce the Netherlands' emissions by 49% by 2030, compared to 1990 levels, and by 95% by 2050 (Government of the Netherlands, 2019). 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 (Unie van Waterschappen, 2019), where each region is asked to come up with their plans on the RES investment capacity. Amsterdam is located in the region Noord-Holland Zuid (see Fig. 5). The region is currently working closely with the local and regional stakeholders and the governments (Noord-Holland Zuid, 2020) to propose their RES investment plan. The multi-actor nature of the complex regional energy planning process fits perfectly the scope of our study. Therefore, this region is chosen as the case to show the usage and the strength of our method and to give policy-relevant results.

Following the approach of Wang et al. (2020), in this region, the total suitable land for RES development (LU $^{\max}$ ) is 409 km $^2$  and TRS is 86 km $^2$ .

### 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 (ENTSO-E, 2019). In this research, the ENTSO-E data from 2015 is used.

### 5.3. Hourly wind and solar PV power output

The outputs of solar PV and wind turbines depend on their specific capacity factor (see Eq. (2)). In this research, the data is derived following the approach of Wang et al. (2020). 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 m (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 m (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 study as the inputs for wind and solar energy.

### 5.4. Techno-economic parameters

Table 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.

**Table 2**  
2050 estimations of the techno-economic parameters.

Technology	Parameter						
	CapEx (€/kW)	FOM costs (€/kW/yr)	VOM costs (€/kWh)	Lifetime (yr)	Land-use factor (km <sup>2</sup> /kW)	VIA per turbine (km <sup>2</sup> )	Source
Residential PV	1250	17	0	25	0.00003	/	KIC InnoEnergy (2015)
Utility-scale PV	850	27	0	25	0.00003	/	Palmer-wilson et al. (2019) and KIC InnoEnergy (2015)
Vestas V66 wind turbine	1205	45	0	25	0.00014	12.2	Wang et al. (2020)
Vestas V110 wind turbine	1205	45	0	25	0.00034	32.7	Wang et al. (2020)
Biomass	2640	90	0.0845	33	/	/	Wang et al. (2020)
Hydrogen storage conversion	2400	0.04	0	5	/	/	Wang et al. (2020) and IRENA (2017)
Hydrogen storage	0.06(€/kWh)	62% (in/out efficiency $\eta$ )	0	5	/	/	Wang et al. (2020) and IRENA (2017)

## 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.

### 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, the solution with the highest CC score should be the optimal solution for the particular actor. However, in this study, 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 1.2.2, 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 are enhanced. Secondly, the nature of MOO and GA 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 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 Perera et al. (2013a) and Jing et al. (2018). Nevertheless, the general trend in the optimal solutions is captured.

### 6.2. Optimal solutions for the actors

Fig. 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 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 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 the four objectives are considered as 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 of more wind turbines is the 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 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 is much lower and is 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 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 favour 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.

### 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 study, 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,

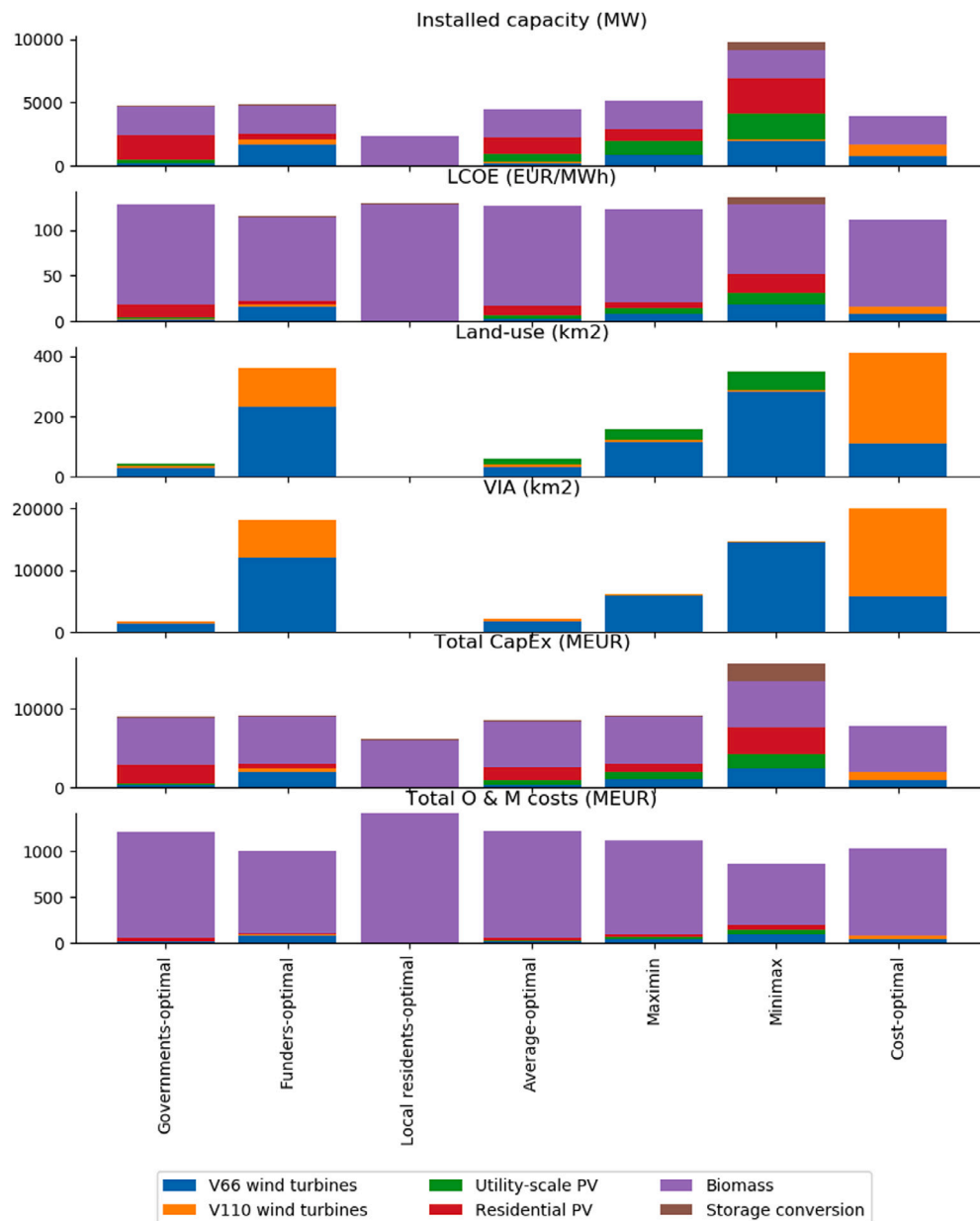


Fig. 6. The governments-optimal solution, the funders-optimal solution, the local residents-optimal solution, the average-optimal solution, the maximin solution, the minimax solution and the cost-optimal solution.

which is comparable to the funders-optimal solution. It is noticeable that the land-use has already reached its upper bound according to Eq. (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 study, 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 Eq. (28), it 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 Eq. (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 4 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 Eq. (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 in 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.

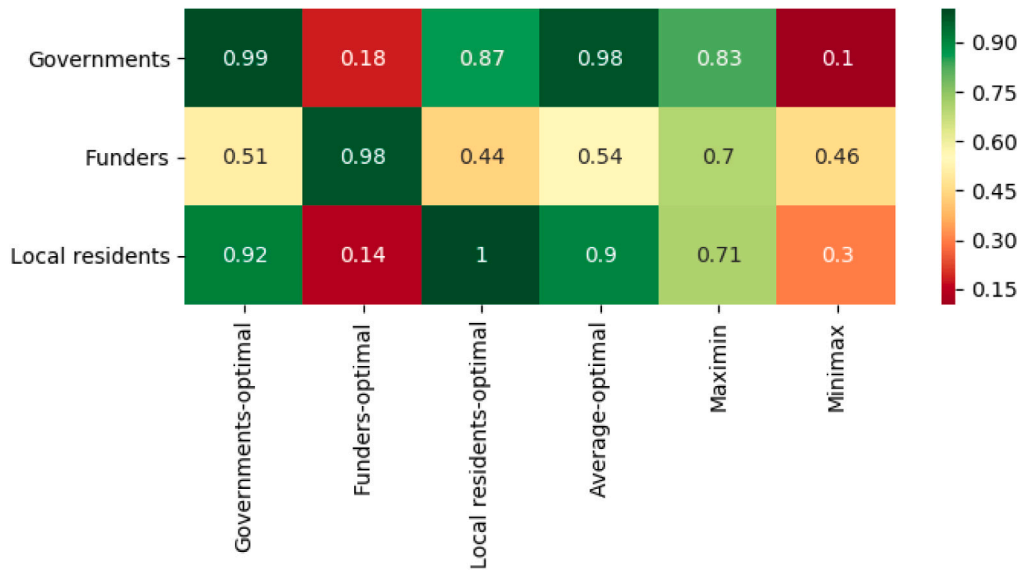


Fig. 7. The alignment of the solutions in terms of CC scores for the actors.

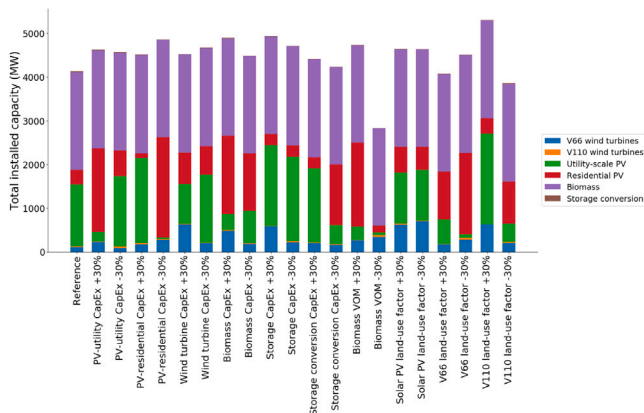


Fig. 8. Sensitivity studies for CapEx, VOM of biomass and land-use factors.

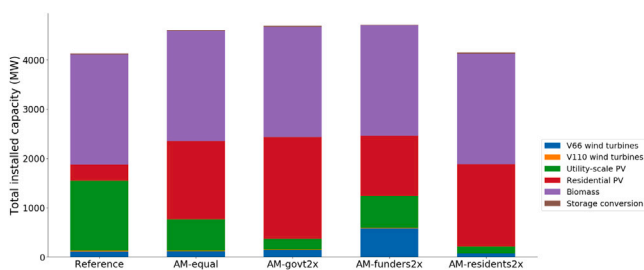


Fig. 9. Sensitivity studies for different weights allocated to the actors.

### 6.4. Alignment of the optimal solutions 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 analysed 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. Fig. 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 Eq. (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 as a bad solution for the government (with the CC score 0.18) and also for the local residents (with the CC score 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.

### 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 Fig. 8. It can be seen that all the input parameters have a significant but reasonable influence on the results. For example, the drop of 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 in 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 study, it is assumed that the weights of all the actors are equal (see Step 7 in Section 4.2). This assumption is made because the focus of this work is only to

**Table 3**  
Scenarios with different weights allocated to the actors.

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

showcase the usage of the proposed approach. However, the changes in weights of the actors may have effects on the results and therefore, their influences are investigated.

Four scenarios with different weights of the actor groups are introduced in Table 3. To be able to allocate different weights to the actors, the geometric mean cannot be used, because it multiplies all elements together (see Eq. (28)). Therefore, the Arithmetic Mean (AM) is used for these scenarios. The average-optimal solutions are shown in Fig. 9. The use of AM already changes the results, more residential PV is preferred, and utility-scale PV becomes less favourable. If governments are given more weights, 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 in VIA, local residents will try to minimize the use of wind turbines.

In this study, 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 impacts on the results. The data from ENTSO-E (2019) 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 Rijnswaterstraat (2020), which shows that our scaling method based on population only underestimates the demand by 8%. Nevertheless, Gasunie and TenneT (2020) 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 Fig. 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 (Wang et al., 2020). In terms of the generation mix, Wang et al. (2020) shows wind energy has the largest contribution. Our model results indicate that the optimal share of wind energy is 46%. This is because in Wang et al. (2020), 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.

## 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 interests 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 paper 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 simultaneously consider various actors in an energy system planning problem; 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 modelled 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 favoured 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 study) 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 to investigate the impacts of various policies on the 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 that 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.

### CRedit authorship contribution statement

**Ni Wang:** Conceptualization, Methodology, Software, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Petra W. Heijnen:** Methodology, Writing - review & editing, Supervision, Funding acquisition. **Pieter J. Imhof:** Conceptualization, Methodology, Software.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Acknowledgement

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

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