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Integrating Renewable Energy Supply Curves into Long-Term Energy System Modelling: A Case Study of Solar PV and Onshore and Offshore Wind in Poland

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Abstract

Long-term energy system models often represent renewable energy technologies using aggregated potentials and average capacity factors, which may insufficiently reflect the spatial and technological heterogeneity of weather-dependent resources. This study develops and implements resource- and performance-based renewable energy supply curves for solar photovoltaics, onshore wind and offshore wind in the TIMES-PL energy system model for Poland. These supply curves are coupled with time-dependent techno-economic assumptions in TIMES-PL, allowing the modelled attractiveness of individual renewable resource classes to change across model years. The proposed approach combines spatial resource assessment, GIS-based data processing and differentiated hourly capacity factor profiles. The supply curves were constructed using data from the JRC ENSPRESO database, the PVGIS interface and the Copernicus Climate Data Store, with QGIS applied to classify renewable resource potential according to regional conditions, wind farm location and photovoltaic panel orientation. Two model scenarios were compared: a base scenario without supply curves and a scenario with implemented supply curves. The results show that incorporating spatial and technological constraints changes the modelled optimal capacity mix, although the overall system-level differences remain moderate. Accordingly, the results should be interpreted primarily in terms of installed capacity expansion rather than as a full comparison of system costs, electricity generation, unit dispatch or balancing effects. The total installed capacity in the supply-curve scenario is 1.91–3.44 GW higher than in the base scenario, corresponding to less than 3% of total system capacity. This increase results from the model being required to use renewable resource classes with lower capacity factors once the most favourable potentials are fully utilised. This study demonstrates that renewable energy supply curves can improve the representation of spatially differentiated renewable deployment options in long-term national energy system modelling.

Keywords: energy system model; renewable energy sources; renewable energy supply curves; spatial analysis

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1. Introduction

Energy transition has fundamentally transformed the structure of energy systems across Europe, with Poland experiencing a rapid increase in renewable, weather-dependent energy sources. In 2025, renewable energy sources accounted for 47.98% of all installed capacity, covering 31.4% of electricity generation in the Polish power system [1,2]. This trend is expected to continue, as national and European energy policy increasingly relies on solar photovoltaic, onshore wind and offshore wind technologies to reduce emissions and diversify the electricity mix. Strategic documents shaping the energy transition in Poland, such as the Energy Policy of Poland until 2040, further emphasise this growth trajectory [3]. The growing role of variable renewable energy sources creates new challenges for long-term energy system modelling. These challenges are not limited to the temporal variability in generation, but also include the spatial heterogeneity of renewable resources, land-use constraints, technology-specific performance characteristics and regionally differentiated deployment potential. As a result, a key methodological challenge is how to represent renewable energy technologies in long-term energy system models without losing spatial and technological information that may affect model outcomes.

Many national-scale models, such as the MESSAGE model from the Polish Energy Market Agency [4], simplify renewable technologies by using aggregated capacity factors, uniform costs or single resource potentials. Such simplifications may be acceptable at low renewable penetration levels, but they become increasingly problematic when renewable technologies represent a major share of new capacity additions. The literature shows that spatial resolution and GIS-based analyses are increasingly important in energy system modelling, especially for assessing how meteorological conditions affect renewable generation, how infrastructure and land-use constraints shape deployment options, and how spatial data can be aggregated into modelling regions. Martínez-Gordon et al. argue that adding spatial resolution creates benefits, but also introduces trade-offs between spatial, temporal and technological detail [5].

The parametrisation of renewable energy supply curves is, therefore, a critical step in energy system modelling, as it determines how resource quality, deployment constraints, installable capacity and technology-specific generation profiles are translated into an optimisation framework. Renewable energy supply curves provide a practical way to bridge detailed spatial resource assessments and aggregated energy system models. In the broader literature, supply–cost curves synthesise the relationship between cumulative renewable potential and the corresponding cost or performance level, making them useful for short- and long-term energy-policy scenarios. Izquierdo et al. describe supply–cost curves as an essential tool for analysing geographically distributed renewable resources and show how GIS-based information can be translated into parameterised curves for use in modelling [6]. Similar concepts have been developed in the form of dynamic cost–resource curves, which combine static resource potentials with cost dynamics, technological learning and deployment restrictions. Resch shows that dynamic cost–resource curves can link resource limitations, technology diffusion, and changing costs, thereby supporting policy assessment and modelling of renewable energy deployment pathways [7].

More recent studies further emphasise that the quality of renewable resource representation can significantly affect model outcomes. Rausch and Zhang demonstrate that detailed representation of heterogeneous renewable resource grades improves the precision of policy simulations, particularly when supply curves contain near-flat or near-vertical sections that are difficult to capture with smooth aggregate functions [8].

The importance of resource heterogeneity is also reflected in applied renewable planning studies, where supply curves are used to decompose national targets into regional and technology-specific targets while accounting for technological progress and environmental value [9]. Recent NREL work similarly treats renewable potential assessment as a combination of resource quality, developable area, technology assumptions, siting constraints, and transmission-related considerations, producing representative supply curves for downstream modelling and analysis [10].

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The increasing penetration of weather-dependent renewable energy sources also raises system-integration challenges, since wind and solar generation vary in time and space. In order to respond to fluctuations in electricity generation from these sources, greater system flexibility is required on both the supply and demand sides [11]. A particularly important issue is the temporal mismatch between renewable energy availability and electricity demand.

Although this study does not explicitly address short-term balancing, these variability patterns are relevant for long-term planning because they affect the relative value of different renewable resource classes, locations and technology configurations. In the case of solar PVs, for example, different panel orientations may lead to lower annual output but more diversified generation profiles, which can influence the modelled attractiveness of east- or west-facing installations compared with conventional south-facing systems. Similarly, wind resource quality and available land differ across regions, affecting both feasible capacity and expected electricity generation.

The relevance of spatially differentiated renewable-resource representation extends beyond resource assessment itself. It is increasingly linked with the broader role of mathematical optimisation models as decision-support tools for translating policy targets into feasible investment pathways under multiple technical and spatial constraints. In this context, GIS-based information should be understood as an input layer for optimisation rather than as an end in itself. Hashemizadeh and Xie [12] illustrate this logic at the urban scale by formulating renewable-energy policy design as a multi-objective and robust optimisation problem in which spatially differentiated instruments are used to reconcile emissions, reliability, equity and infrastructure constraints. Although their study focuses on decentralised urban renewable-energy systems, the underlying modelling principle is also relevant for national-scale energy-system models, indicating that renewable deployment options should be represented with sufficient spatial, technical, and temporal detail so that optimisation models can identify capacity-expansion pathways consistent with wider policy and system constraints.

The model employed in this study, TIMES-PL, is an energy system model developed with the TIMES (The Integrated MARKAL-EFOM System) model generator for Poland. TIMES models determine the least-cost technology mix that satisfies exogenous energy-service demands and policy constraints under assumed techno-economic parameters, resource potentials and time-slice representations of variable generation and demands [13]. In TIMES, the energy system is represented as a Reference Energy System composed of processes, commodities, and flows, covering the chain from primary energy supply, imports, and transformation to final energy-use sectors. TIMES-PL is a national implementation of the TIMES developed for medium- and long-term analyses of the Polish energy system [14,15]. It belongs to the class of technology-rich, bottom-up, linear optimisation models. TIMES-PL used in this study covers the national fuel and energy system, including the power sector, district heating, fuel supply, industry, households, transport, services and agriculture. This structure allows technology choices, investments, fuel flows, emissions and selected policy constraints to be assessed consistently within one scenario framework. TIMES-PL should, therefore, be understood not as a power-system dispatch model, but as a long-term model for capacity expansion and energy-system development planning [16].

However, as in many long-term energy system models, renewable energy technologies require an appropriate level of aggregation to remain computationally manageable. This creates a need for methods that can incorporate spatial and technological diversity without excessively increasing model complexity.

In this context, the contribution of this study is to develop and implement renewable energy supply curves for solar PVs, onshore wind and offshore wind in the TIMES-PL

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energy system model. In this paper, supply curves are understood as resource- and performance-based representations of installable renewable capacity, differentiated by spatial and technological characteristics, such as wind resource classes, offshore locations, and PV orientations. Compared with a simplified representation based on aggregated potentials and average capacity factors, this approach allows the model to account for differences in available capacity, expected generation profiles and deployment constraints. The detailed procedure for linking these resource classes with time-dependent techno-economic parameters is described in the Methods section.

The novelty of this study lies in the integration of spatially explicit renewable resource assessment with a national long-term energy system optimisation model. While previous studies have developed renewable energy supply curves or analysed the importance of spatial resolution in energy modelling, this paper applies such an approach directly in the TIMES-PL model for the Polish power system. This study not only estimates the technical potential of renewable energy sources, but also translates differentiated resource classes, regional constraints and technology-specific hourly generation profiles into model-ready supply curves. This enables the comparison of a conventional aggregated representation of renewable technologies with a more detailed representation that accounts for spatial and technological heterogeneity. In addition, although the resource classes and capacity potentials are defined spatially, their economic interpretation in the TIMES-PL model is time-dependent, since technology-specific, techno-economic parameters, particularly investment costs, evolve across model years. As a result, each renewable resource class is associated not only with a specific generation profile and capacity limit, but also with changing unit generation costs over the modelling horizon. In this way, this paper contributes to the methodological development of long-term energy system modelling by showing how renewable resource heterogeneity can be incorporated without fundamentally changing the structure of the optimisation model.

The objective of this paper is, therefore, to assess how the implementation of renewable energy supply curves affects modelled capacity expansion results in the Polish power system. The assessment focuses on several key indicators: differences in installed capacity between the base scenario and the supply-curve scenario, the allocation of new renewable capacity across resource classes and technology variants, the use of available renewable potentials, and the resulting changes in selected conventional technologies and battery storage. By comparing a simplified representation of renewable technologies with a more detailed representation based on differentiated hourly capacity-factor profiles and capacity limits, this study evaluates how resource heterogeneity influences long-term capacity expansion pathways. In this way, this paper provides a methodological contribution to the integration of spatially explicit renewable resource information into long-term energy system modelling and offers insights into its relevance for modelling future renewable deployment in Poland.

The remainder of this paper is organised as follows. Section 2 describes the methodological approach, including the construction of renewable energy supply curves, the input data used in the analysis and their implementation in the TIMES-PL model. Section 3 presents the key modelling results, with particular focus on differences in installed capacity between the base scenario and the supply-curve scenario. Section 4 discusses the implications of these results, the methodological limitations and the relevance of the proposed approach for long-term energy system modelling. Finally, Section 5 summarises the main findings, highlights the contribution of this study and identifies directions for further research.

2. Methods

The methodology developed in this study links spatial renewable resource assessment with long-term energy system optimisation. The first step consists of identifying renewable resource classes for onshore wind, offshore wind and solar photovoltaics using spatial datasets, meteorological information and technology-specific assumptions. These classes are defined by available capacity potential, resource quality and hourly generation profiles. In the second step, existing renewable capacities are assigned to the corresponding classes and subtracted from the total technical potential in order to determine the remaining capacity available for future investment. Finally, the resulting resource classes are implemented in TIMES-PL as separate technology variants with class-specific capacity limits and availability profiles. This workflow allows GIS-derived information to enter the optimisation model as structured techno-economic input data rather than as a separate descriptive layer. In this study, the ENSPRESO database was used. ENSPRESO is an open-access European dataset containing potentials of renewable energy sources at various levels of resolution, provided by the Joint Research Centre of the European Commission [17].

2.1. The Mathematical Formulation of the TIMES-PL Model

The simplified mathematical representation of the TIMES optimisation problem is presented in Equation (1):

$$\mathrm{Obj} = \sum_{\mathrm{t \in T}} \frac{1}{(1+\mathrm{r})^{\mathrm{t}}} (\mathrm{INVCOST_t} + \mathrm{FIXCOST_t} + \mathrm{VARCOST_t} + \mathrm{DECOM_t}) \tag{1}$$

where Obj denotes the discounted total system cost, t is the model year, T is the set of model years, r is the discount rate, $INVCOST$ denotes investment costs, $FIXCOST$ is the fixed operation and maintenance costs, $VARCOST$ is the variable operation and maintenance costs, and $DECOM$ is the decommissioning costs. The modelling horizon in TIMES-PL extends to 2050, while the base year is 2020.

The main TIMES equations relevant for linking capacity, activity and commodity flows can be summarised as follows:

$$\mathrm{VAR\_ACT}_{p,t,s} \leq \mathrm{VAR\_CAP}_{p,t} \cdot \mathrm{CAP2ACT}_{p} \cdot \mathrm{AF}_{p,t,s} \tag{2}$$

$$VAR\_ACT_{p,t,s} = \sum_{c \in PCG} VAR\_FLO_{p,c^{out},t,s} \tag{3}$$

$$\mathrm{VAR\_FLO}_{p,c^{out},t,s} = \mathrm{VAR\_FLO}_{p,c^{in},t,s} \cdot \mathrm{EFF}_{p,t} \tag{4}$$

$$\sum_{p} \mathrm{VAR\_FLO}_{p,c,t,s} = \mathrm{DEM}_{c,t,s} \tag{5}$$

where p denotes the process or technology, c is the commodity, $c^{in}$and c^{out} are input and output commodities of the process, t is the model year or period, and s is the intra-annual time slice. PCG denotes the Primary Commodity Group of a process p, which here defines the output flow used to determine process activity. VAR_CAP represents available installed capacity, VAR_ACT is the process activity, and VAR_FLO is the commodity flow. $CAP2ACT$ is the capacity-to-activity conversion factor, AF is the time-slice availability factor, EFF is the process efficiency, and DEM is the commodity demand. These equations are solved simultaneously with the objective function, resource-potential limits, technology bounds and policy constraints, such as emission prices.

2.2. Implementation of Renewable Energy Supply Curves in TIMES-PL

The renewable energy supply curves developed in this study were implemented in TIMES-PL by disaggregating aggregated renewable technologies into resource- and per-

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formance-based technology variants. The implementation does not modify the objective function or the core TIMES equations. Instead, it affects the capacity-related variables and availability profiles.

In TIMES, the total available capacity of a technology, represented by VAR_CAP, consists of existing installed capacity inherited from the base year, and newly installed capacity, represented by VAR_NCAP, commissioned during the optimisation horizon. Existing renewable installations were first allocated to individual resource classes, such as wind clusters or PV orientation classes. This allocation defined the initial distribution of VAR_CAP across resource classes. The remaining technical potential in each class was then used to limit the maximum value of VAR_NCAP that could be installed in that class.

In addition to class-specific capacity limits, renewable resource classes were assigned individual time-slice availability factor profiles, $AF_{p,t,s}$, derived from the corresponding wind and photovoltaic generation data. For onshore wind, these profiles reflect differences in local wind conditions between clusters. For photovoltaic technologies, they reflect differences in panel orientation. Through the capacity–activity constraint in Equation (2), the AF parameter limits the maximum activity of each technology in each time slice. As a result, technologies assigned to different resource classes could have different annual full load hours and different temporal generation patterns. These differences are then reflected in process activity and electricity output through Equations (3)–(5).

This implementation allows TIMES-PL to account simultaneously for existing renewable capacity, remaining deployable potential, resource quality and temporal variability of renewable generation. Resource classes were also linked with technology-specific techno-economic parameters, including investment costs, which vary across model years. Therefore, although spatial capacity limits were defined exogenously, the economic attractiveness of each class changes over time. The implemented curves should, therefore, be understood as resource- and performance-based supply curves coupled with dynamic techno-economic assumptions, rather than as purely static supply–cost curves.

2.3. Onshore Wind

For evaluation of onshore wind potential, an updated dataset was used—ENSPRESO2 ONSHORE WIND 2nd edition [18]. The file wind_onshore_NUTS.tif, was downloaded and imported into QGIS Desktop 3.40.9 [19]. The file contains data on energy generation [GWh] and installable capacity [MW] in four different scenarios—reference, mid, low and high—which refer to setback distance of the installation with regard to residential areas. A description of each scenario has been provided in Table 1. For this purpose, the mid scenario was selected, which employs the most commonly used setback distance in European administrations (Table 1).

Table 1. Descriptions of setback distance scenarios in the ENSPRESO2 Onshore Wind dataset [20].

Scenario Name	Description
High	Uses a setback distance of 500 m, uniform across all countries, which is considered to be the approximate limit in terms of noise exposure for a population in the vicinity of wind farms.
Mid	Uses a setback distance of 1000 m, which is the most common setback distance used by in European administrations.
Low	Setback distance of 2000 m and is the largest setback distance actually implemented; this scenario is, therefore, the most restrictive setting.
Reference	Uses the current regulations that were in force at the beginning of 2025.

The dataset also includes different levels of spatial resolution—from NUTS0, country level, to NUTS3, counties or districts. The resolution chosen for this analysis was NUTS2, which represents voivodeships. In the dataset, Mazowieckie voivodeship is disaggregated into two regions, but for the purpose of this analysis was merged into a single region. To present data on a map with such resolution, a shapefile of Poland in NUTS2 resolution was exported from the source file and used from that point onward. The number of full load hours for each voivodeship was calculated using the following equation:

$$full\ load\ hours\ [\mathrm{h}] = \frac{wind\_onshore\_mid\_GWh\ [\mathrm{GWh}] \times 1000}{wind\_onshore\_nuts\_mid\_MW\ [\mathrm{MW}]}$$

The number of full load hours was used to divide the onshore wind turbines into four clusters at the voivodeship (NUTS2) level, determining regions with the most and least favourable wind conditions for an onshore wind installation. The results are shown in Figure 1, with cluster 1 being of the most favourable conditions, and cluster 4 being the least favourable.

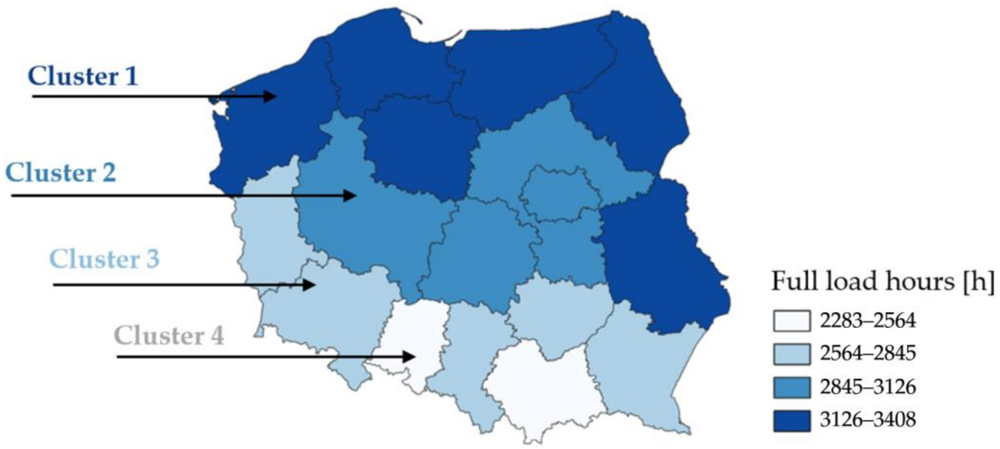

Figure 1. Onshore wind full load hours clusters for Poland at NUTS2 resolution.

To calculate potential installable capacity for each voivodeship, values were exported from the same dataset (the wind_onshore_nuts_mid_MW field in the layer). In order to determine the potential that can be deployed by the model to build new capacities, existing capacities had to be placed in corresponding clusters and subtracted from the installable capacity values. To achieve that, a dataset of existing renewable energy installations as of the end of the year 2025 by the Polish Energy Regulatory Body was used [21]. It provides a list of all existing renewable installations of a capacity above 0.05 MW, together with their location. Based on that, the list was filtered for onshore wind installations, and for each voivodeship, the cumulative capacity was calculated. Additionally, based on the data presented in Figure 1, an average number of full load hours for each cluster was calculated. The list of all of these values is provided in Table 2.

Table 2. Capacity potential, existing installation capacity and average full load hours for each analysed cluster.

Cluster	Voivodeship Name	ENSPRESO Capacity Potential [GW]	Existing Installations Capacity [GW]	Spare Potential (Voivodeships) [GW]	Spare Potential (Clusters) [GW]	Average Full Load Hours [h]
Cluster 4	opolskie	2.24	0.40	1.84	2.06	2399.16
	małopolskie	0.23	0.01	0.22		
Clus-	podkarpackie	1.51	0.25	1.26	8.94	2706.44

	świętokrzyskie	0.47	0.08	0.39		
	śląskie	0.83	0.25	0.57		
	dolnośląskie	4.54	0.33	4.21		
	lubuskie	2.77	0.26	2.51		
Cluster 2	mazowieckie	1.87	0.67	1.20	3.18	3051.19
	łódzkie	1.57	0.73	0.85		
	wielkopolskie	2.90	1.77	1.13		
Cluster 1	lubelskie	3.38	0.35	3.03	10.57	3279.26
	podlaskie	1.92	0.30	1.62		
	warmińsko-mazurskie	3.50	0.62	2.89		
	kujawsko-pomorskie	1.96	0.99	0.97		
	pomorskie	1.88	1.47	0.41		
	zachodniopomorskie	4.21	2.56	1.65		
	total sum	35.77	11.02	24.75	24.75	

With the data provided in Table 2, a supply curve for onshore wind was created as a graphical representation of the relationship between installable capacity in each cluster and the average number of full load hours (Figure 2). Additionally, existing capacities in each cluster are highlighted in pink.

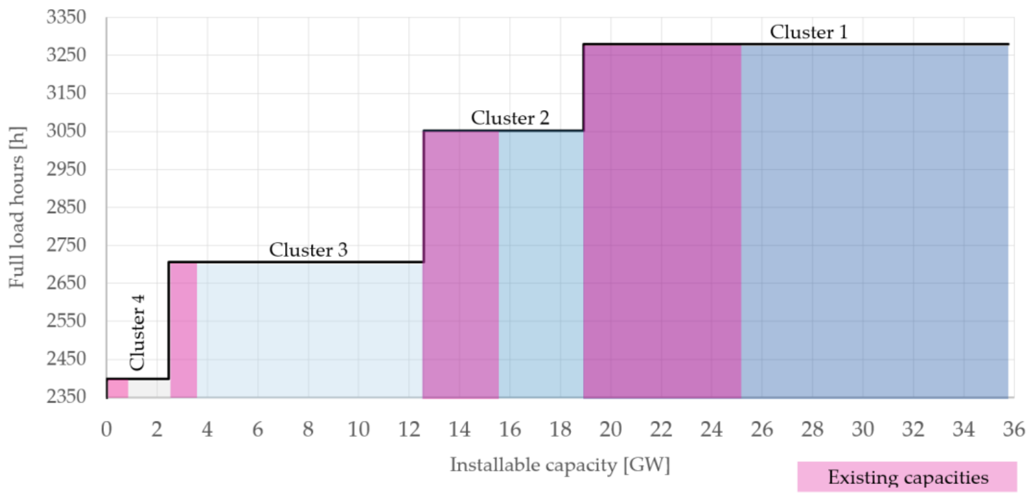

Figure 2. Supply curve for onshore wind.

To represent the varying operational conditions of installations in each cluster, appropriate hourly generation profiles were created. The initial generation profile was downloaded from the Copernicus Climate Data Store [22] as a historical wind onshore generation profile for the year 2025 from the ERA5 reanalysis, selecting the technology as 30 (existing technologies) and regional aggregation as PEON (Pan-European Onshore Zones). The output provides generation profiles as a capacity factor in each hour of the year for each onshore zone. The zone selected was PL01 (Poland).

The historical profile is characterised by a number of full load hours of its own; thus, it had to be scaled to match the average number of full load hours in each cluster, while maintaining realistic fluctuations in wind conditions throughout the year. In order to achieve that, the required number of full load hours in each cluster was divided by the actual number of full load hours in the profile, resulting in a multiplier for scaling the profile. The capacity factor for each hour was then multiplied. As a result, four hourly generation profiles were created to represent the operational conditions of the onshore wind turbines in each cluster (Figure 3).

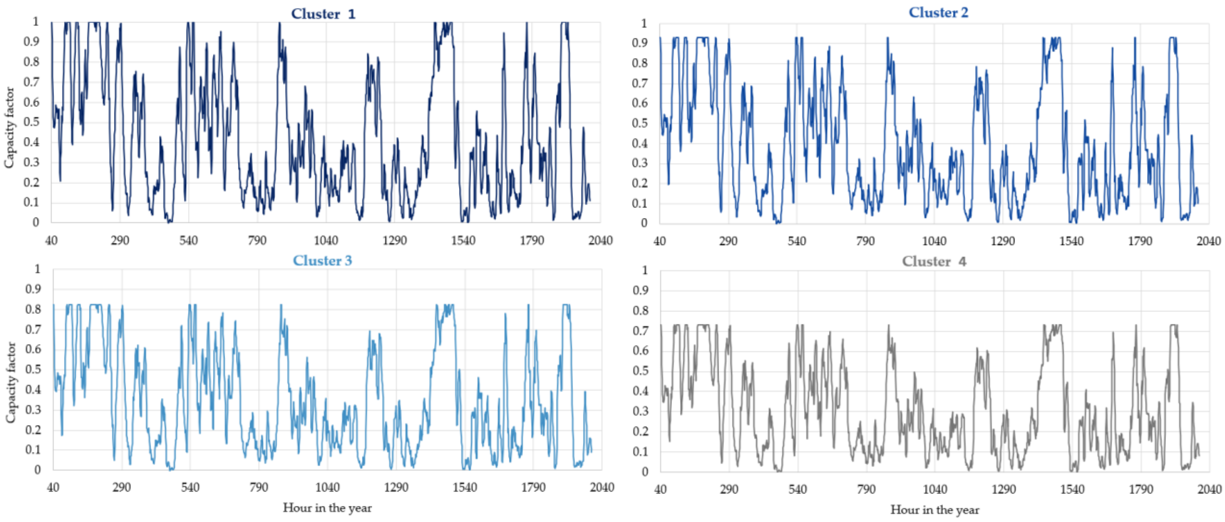

Figure 3. Hourly generation profiles in each cluster for a selected period.

2.4. Offshore Wind

In the case of offshore wind, the ENSPRESO 2—OFFSHORE WIND dataset was used [23]. The dataset provides offshore wind potential and energy generation in the European Union and neighbouring countries as raster files with 5 × 5 km resolution. Similarly to onshore wind, different scenarios are available—reference and low—describing such parameters as distance to shore, sea depth and shipping density [24]. The fixed mounting technique and reference scenario were selected for this analysis.

The selected raster files (enspreso2_offshore_wind_fixed_REF_GWh.tif and enspreso2_offshore_wind_fixed_REF_MW_CF30.tif*)*, as well as a vector file containing the countries' offshore zones (enspreso2_offshore_wind_eez_data.shx), were used to determine the offshore wind clusters. The raster files covering the mounting technique were altered by creating an Attribute Table and merging it appropriately. Then, using a process corresponding to the one described in Section 2.1, a field containing the number of full load hours for each pixel was calculated and classified into four clusters. In this way, sets (clusters) of 5 × 5 kilometres areas with the most and least favourable wind conditions for an offshore wind installation were determined (Figure 4). For each cluster, the average number of full load hours was calculated.

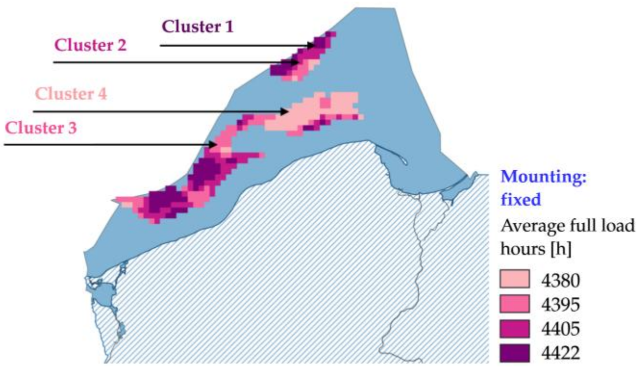

Figure 4. Offshore wind full-load-hour clusters for Poland in 5 × 5 km resolution, with fixed mounting.

In order to determine the total offshore wind capacity potential in each cluster, the values of installable capacity in each raster cell were summed based on their assignment to a given cluster. Together with the data shown in Figure 4, the supply curves for offshore wind were created (Figure 5).

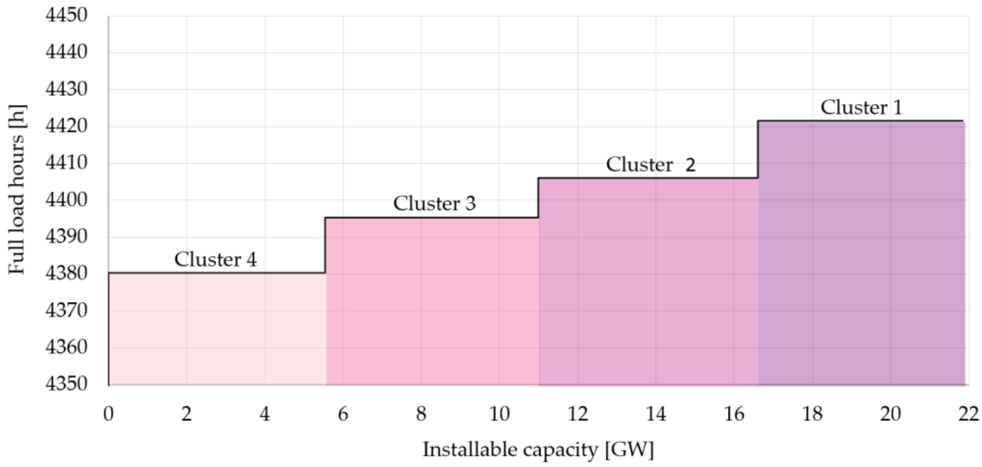

Figure 5. Supply curve for offshore wind, with fixed mounting.

As of 2025, there are no existing offshore wind installations in Poland. However, to further validate the data provided by the ENSPRESO database (Figure 4) and identify potential future areas of development, announced investments were layered over the area of reported offshore wind potential. A map of planned installations from the Offshore Wind Farm Development Program [25] was layered over the Polish Offshore Zone and the clusters developed within this work (Figure 6). The overlaid maps suggest that the favourable regions identified in this work largely coincide with planned investments.

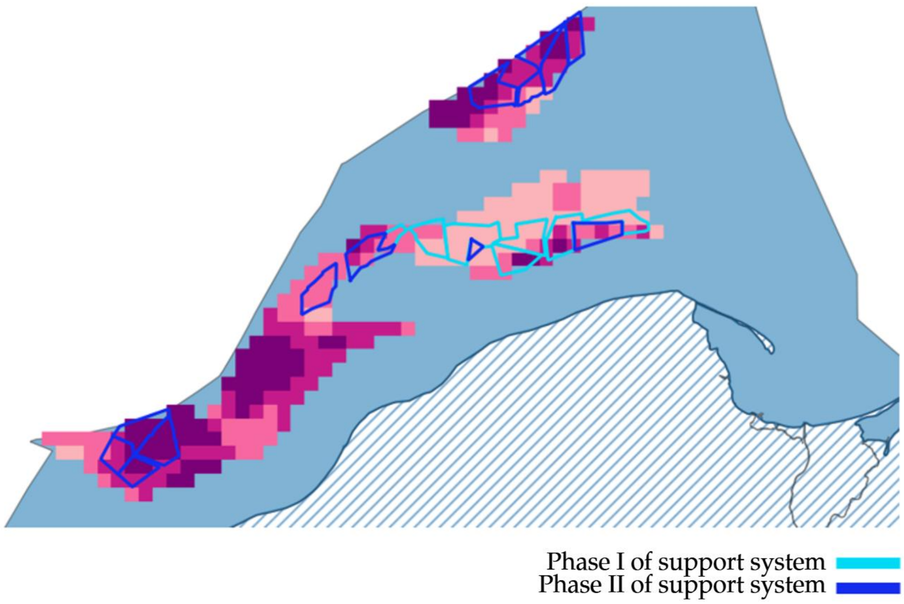

Figure 6. Planned offshore wind installations in Poland and area of ENSPRESO with fixed offshore wind turbine potential.

2.5. Solar Photovoltaics

Similarly to previous technologies, a spatial analysis of the number of full load hours has been performed for solar photovoltaics using the ENSPRESO—SOLAR—PV and CSP dataset [26]. The dataset contains several spreadsheets on solar photovoltaics potential in different scenarios, as well as supplementary data. The scenario used for the purpose of this analysis employs the following main assumptions:

- Irradiance: 170 MW/km^2;
- The share of the land that could be made available for open field photovoltaics: 3% of the available non-artificial area.

For the spatial analysis, the *NUTS2 170 W per m2 and 3%* dataset was used, which supplies data on the capacity factor, installable capacity and power production at the NUTS2 resolution. The capacity factor data was transferred to a map of Poland. The number of full load hours was calculated for each voivodeship by multiplying the capacity factor by 8760. Then, voivodeships were assigned into clusters as previously (Figure 7).

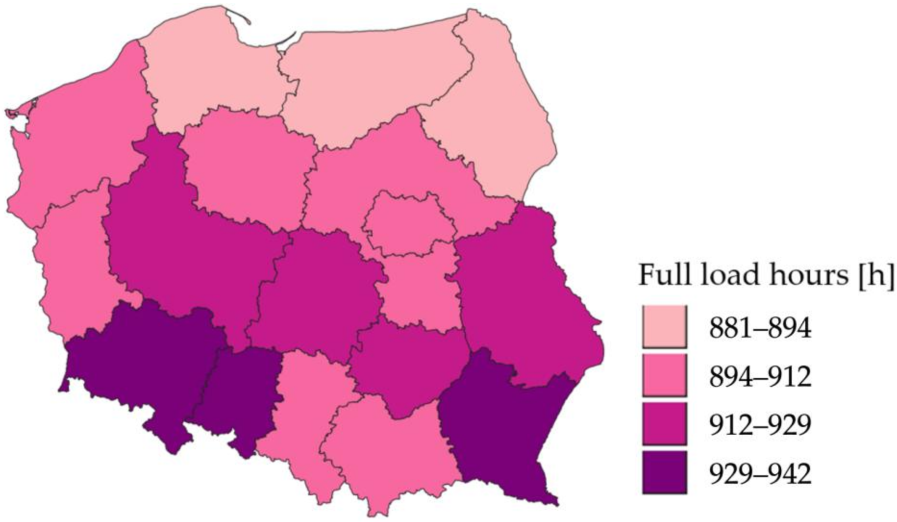

Figure 7. Solar photovoltaics full-load-hour clusters for Poland at NUTS2 resolution.

As can be seen in Figure 7, Poland is quite homogeneous in terms of irradiance, with a maximum percentage difference in the number of full load hours under 7% across voivodeships. Due to this, the impact of the location of a photovoltaic installation across the country on its operation was considered negligible, and a different parameter with a more significant impact was chosen.

Another parameter chosen for analysis was the azimuth of the installation. To assess the impact of the direction of photovoltaic panels with regard to cardinal directions on their operation, the PVGIS interface was used [27]. PVGIS allows for the downloading of yearly capacity factor profiles with various input data, including azimuth. In order to avoid the impact of local cloud cover on the output profile, the data were downloaded from several points. The points were determined as the centroids of each of the 16 voivodeships. The output (point coordinates) for each voivodeship is given in Table 3. The input data used in the PVGIS interface to download hourly data are given in Table 4.

As a result of this process, three different variants in hourly capacity factor profiles were achieved, representing different orientations of the photovoltaic installations. These profiles differ not only by their number of full load hours (Figure 8), but also by the moment in the day at which peak generation occurs (Figure 9).

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Table 3. Voivodeship centroid coordinates for Poland.

Voivodeship Name	Latitude [DD]	Longitude [DD]
Śląskie	50.328	18.992
Kujawsko-pomorskie	53.072	18.490
Wielkopolskie	52.327	17.250
Warmińsko-mazurskie	53.855	20.831
Zachodniopomorskie	53.579	15.558
Dolnośląskie	51.089	16.411
Opolskie	50.646	17.899
Łódzkie	51.604	19.416
Pomorskie	54.152	17.976
Lubuskie	52.193	15.342
Mazowieckie	52.363	21.094
Świętokrzyskie	50.763	20.769
Podkarpackie	49.952	22.170
Lubelskie	51.217	22.903
Małopolskie	49.858	20.271
Podlaskie	53.260	22.929

Table 4. Input data for data download from PVGIS interface.

Parameter	Value	Unit
Solar radiation database	PVGIS-SARAH3	-
Start year	2023	-
Mounting type	Fixed	-
Slope	35	[°]
Azimuth	0, 90, −90	[°]
PV technology	Crystalline silicon	-
Installed peak power	1	[kWp]
System loss	14	[%]

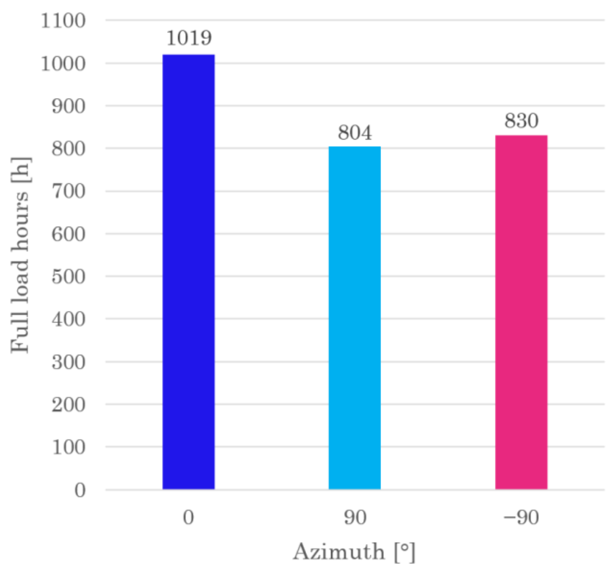

Figure 8. Generation profile variants for solar photovoltaics based on full load hours.

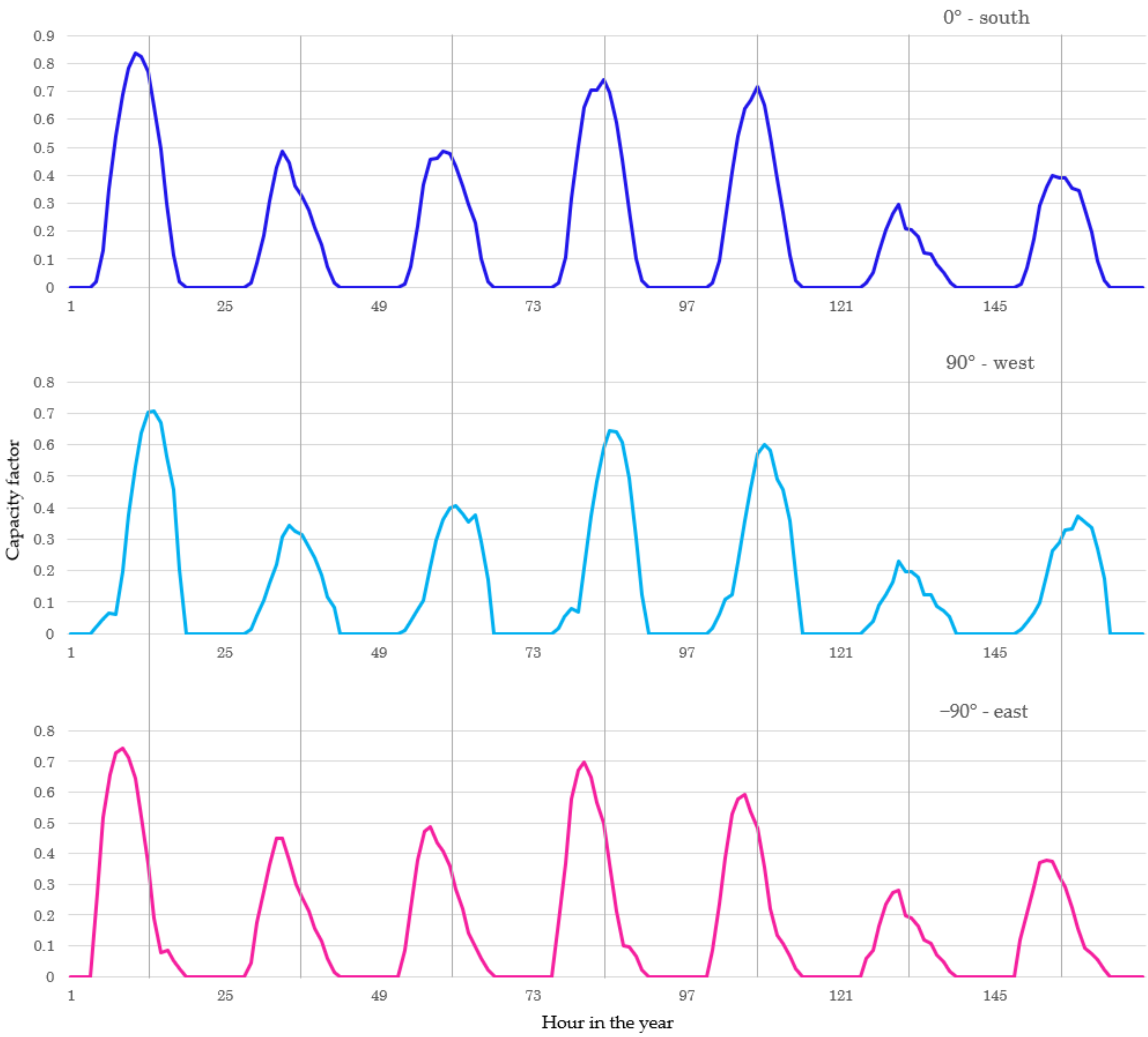

Figure 9. Hourly generation profile variants for solar photovoltaics—selected period.

The MS 170 W per m2 and 3% dataset was used to determine the installable capacity for each PV cardinal direction. The dataset supplies data on installable power and energy generation at the country resolution [26]. It contains several surfaces, which, for the purpose of this study, were divided into three categories: residential photovoltaics, rooftop large-scale photovoltaics and open large-scale photovoltaics for each cardinal direction (azimuth). Residential photovoltaics represent prosumer-scale rooftop micro-installations connected at the household level at a low-voltage, of capacity up to 50 kW. Rooftop large-scale photovoltaics represent building-mounted PV systems above this prosumer threshold, usually treated as commercial or utility-scale rooftop installations. Open large-scale photovoltaics represent ground-mounted PV farms. A list of the surfaces and how they were assigned for the purpose of calculations is given in Table 5. For the open large-scale photovoltaics, it is assumed that since there are no restrictions caused by the surface (buildings), all installations are south-oriented. With this assignment, the installable capacity for each category and azimuth was calculated.

Table 5. ENSPRESO solar photovoltaic surfaces and assignment to modelling category.

ENSPRESO Surface Name	Category	Azimuth
Residential areas rooftop south	Residential	South
Residential areas rooftop latitude tilt		
Residential areas facade south		
Residential areas rooftop east		East
Residential areas facade east		
Residential areas facade west		West
Residential areas rooftop west		
Industrial areas rooftop south	Rooftop large-scale	South
Industrial areas rooftop latitude tilt		
Industrial areas facade south		
Industrial areas rooftop east		East
Industrial areas facade east		
Industrial areas rooftop west		West
Industrial areas facade west		
Natural areas agriculture low irradiation	Open large-scale	South
Natural areas non-agriculture low irradiation		

To calculate the power potential that the model can invest in, the existing installations were subtracted. A list of existing renewable energy installations issued by URE (Polish Energy Regulatory Office) was used for the large-scale installation existing capacity [21]. For the existing capacity of residential photovoltaics, a report by the Energy Regulatory Office on electricity generated from RES and supplied into the grid in the year 2025 was used [28]. From these documents, the total installed capacity was calculated and divided between the azimuth variants based on the following assumptions:

- For residential photovoltaics: it was assumed that 80% of the existing capacity is south-oriented, 10% east-oriented, and 10% west-oriented;
- For large-scale photovoltaics: it was assumed that 60% of the existing capacity is open large-scale and south-oriented, and 40% is rooftop large-scale and south-oriented.

Because verified national statistics on the azimuth distribution of the existing PV installations were not available, the assumed split of existing PV capacity should be interpreted as a modelling assumption rather than an empirical estimate. It was used to test whether TIMES-PL reacts to differentiated PV profiles and remaining potentials.

The list of all calculated existing and potential capacities, together with their respective azimuth variant number of full load hours, is supplied in Table 6. With all of the acquired and calculated data, supply curves of residential, open large-scale and rooftop large-scale solar photovoltaics were created and are shown in Figures 10–12.

Table 6. Capacity potential, existing installation capacity, and average full load hours for each analysed variant of photovoltaic installations.

Azimuth	ENSPRESO Capacity Potential [GW]	Existing Installations Capacity [GW]	Spare Potential (Voivodeships) [GW]	Average Full Load Hours [h]
Residential photovoltaic installations				
South	19.98	11.09	8.89	1019.40
East	12.42	1.39	11.03	830.08
West	12.42	1.39	11.03	803.66
Sum	44.81	13.86	30.95	-

Rooftop large-scale photovoltaic installations				
South	32.19	4.63	27.56	1019.40
East	7.09	0.00	7.09	830.08
West	7.09	0.00	7.09	803.66
Sum	46.38	4.63	41.75	-
Open large-scale photovoltaic installations				
South	802.20	6.94	795.26	1019.40
Total sum	893.38	25.43	867.95	-

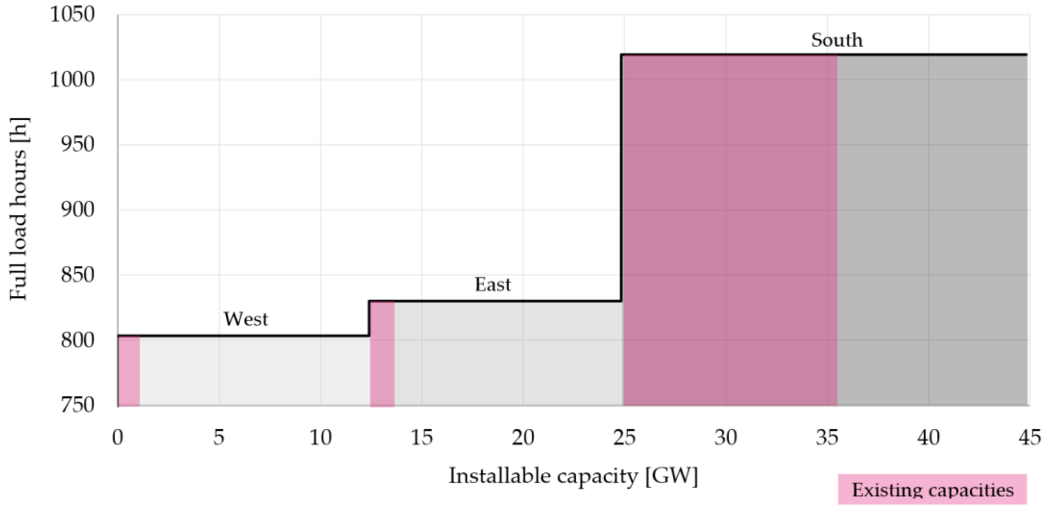

Figure 10. Supply curve for solar photovoltaics, residential.

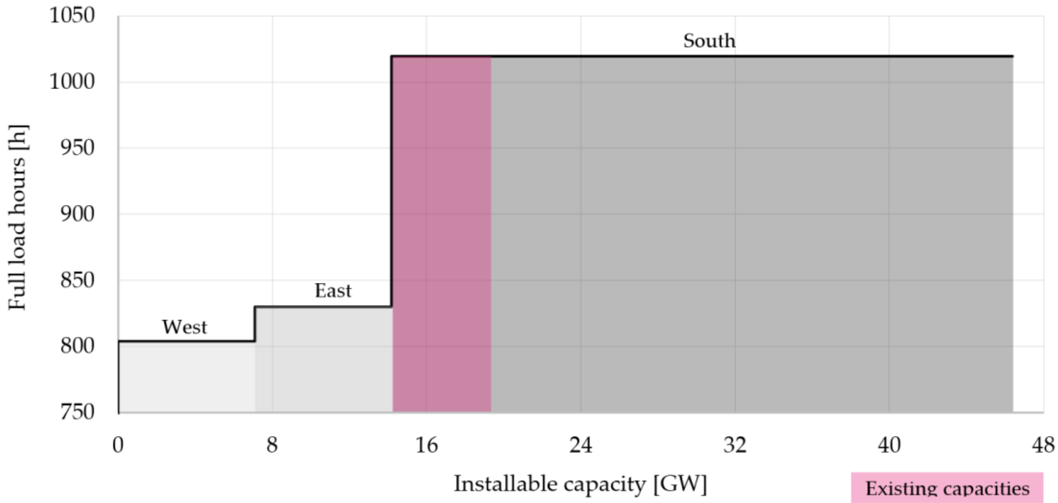

Figure 11. Supply curve for solar photovoltaics, rooftop large-scale.

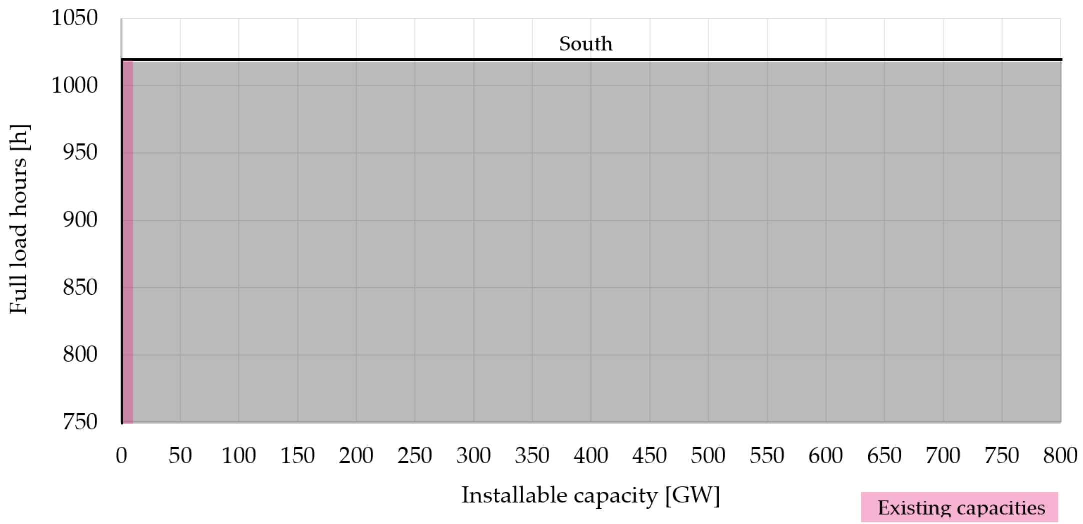

Figure 12. Supply curve for solar photovoltaics, open large-scale.

2.6. CO_2 Emission Allowance Price Assumptions

In the model, CO_2 allowance prices constitute one of the main drivers of the energy-system transformation, as they directly affect the relative competitiveness of fossil-fuel-based technologies and low-emission alternatives. The CO_2 allowance prices assumed in the analysis for sectors covered by the EU ETS are presented in Table 7. The price trajectories were based on historical values for 2020 and 2025 and on projections included in the updated National Energy and Climate Plan (NECP), developed using assumptions provided by the Polish Ministry of Climate and Environment and the European Commission guidelines.

Table 7. CO_2 allowance prices under the EU ETS schemes [EUR'2024/tCO_2eq].

Year	2020	2025	2030	2035	2040	2045	2050
EU ETS	25	72	120	144	300	300	300

The assumptions were further refined to reflect comments received during the public NECP consultation process for the 2030–2040 projections. For 2045 and 2050, emission allowance prices were assumed to remain at the 2040 level. The adopted trajectory reaches 300 EUR/t in 2040.

3. Results

Two scenarios were run in order to compare the results: (i) without implemented supply curves (base scenario), and (ii) with implemented supply curves. The output data of the model is very extensive. For the purpose of this study, only data on existing and newly built capacities in the power system were exported and analysed.

To evaluate the impact of implementing supply curves into the model, differences between the two scenarios in installed capacity for each technology in every modelling year were calculated (Figure 13). For the base year 2025, no difference is present. For the year 2030, the most significant difference of 1.76 GW is present for offshore wind. A very small difference is present for Natural Gas Open Cycle Turbines (OCGTs). From a system perspective, these values are small, with 88.14 GW and 90.05 GW of installed capacity in the Polish power system for the base and supply-curve scenarios, respectively (Table 8). For the year 2035, additional change is present for photovoltaics (large-scale) and Natural Gas Combined Cycle Turbines (CCGTs) with 104.42 GW (base scenario) and 107.47 GW (supply-curve scenario) of the total installed capacity in the system. This is similar for the year 2040. In the year 2045, the difference for offshore wind, photovoltaics (large-scale) and Natural Gas (CCGTs) remains the same. The installed capacity of onshore wind, as well as Natural Gas (OCGTs), is lower for the supply-curve scenario. Additionally, more battery storage capacity (0.81 GW) is present. For the year 2050, there is a further increase in differences for offshore wind and onshore wind, while the difference for Natural Gas (OCGTs) and battery storage decreases.

Overall, the difference in total installed capacity across all technologies between the base and supply-curve scenarios ranges from 1.91 to 3.44 GW, with these values being at most 2.92% of the total installed capacity and an average of 2.49%. The key modelling result is, therefore, not the absolute magnitude of the capacity difference, which remains moderate at the system level, but the direction and internal composition of the change. Introducing supply curves forces the model to exhaust the most favourable renewable resource classes first and then move to lower-yield classes with lower capacity factors or different generation profiles. This creates a need for additional installed capacity to satisfy the same electricity demand. The result confirms that aggregated renewable potentials can hide the declining quality of marginal renewable resources as deployment increases.

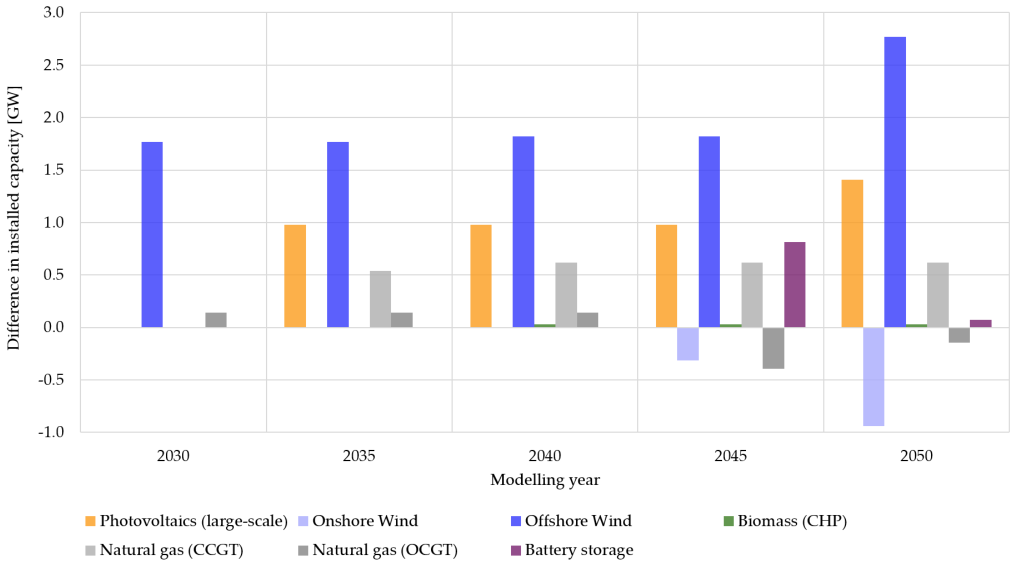

Figure 13. Differences in installed capacity between base and supply scenarios by technology for each modelling year. Positive value signifies higher value for supply-curve scenario.

Table 8. The total installed capacity across all technologies in the modelled power system for the base and supply-curve scenarios and the difference in the installed capacity between scenarios.

Scenario	Total Installed Capacity in the Power System [GW]					
	2025	**2030**	**2035**	**2040**	**2045**	**2050**
Base	72.36	88.14	104.42	119.38	134.46	138.12
Supply curves	72.36	90.05	107.47	122.59	137.64	141.56
Difference	0.00	1.91	3.05	3.21	3.17	3.44

For each renewable energy technology with a supply curve implemented, the newly installed capacity, together with the available potential unused by the model in each year, was analysed in order to observe how the created clusters are being utilised.

3.1. Onshore Wind

For the onshore wind turbines in the base scenario, the model utilises the entire available capacity potential up until the year 2050, where 4.5 GW of capacity is unused. The onshore wind installations built in the year 2025 reach the end of their life in 2050 and are decommissioned. The total installed capacity of onshore wind turbines in the year 2050 is over 27 GW (Figure 14).

In the scenario with implemented supply curves (Figure 15), the entire available capacity potential is utilised up until year 2045, where the only unused potential is present in the cluster with the least favourable wind conditions—cluster 4. For the year 2050, unused potential is present in every cluster. New capacity is being built in every cluster besides cluster 4, regardless of there being unused potential present in clusters with more favourable wind conditions. Similarly, all installations newly built in the year 2025 reach the end of their life and are decommissioned in 2050.

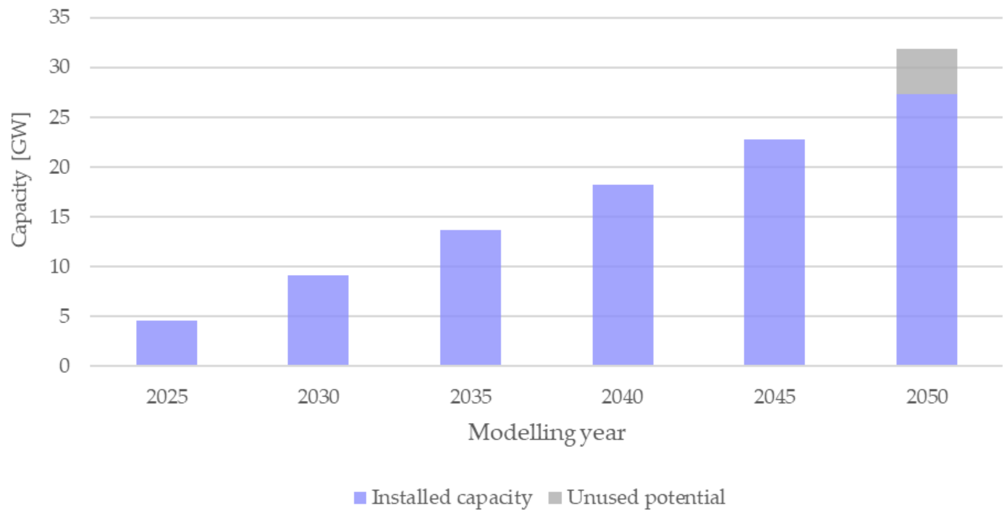

Figure 14. Onshore wind, base scenario—total installed new capacity and unused capacity potential in each modelling year.

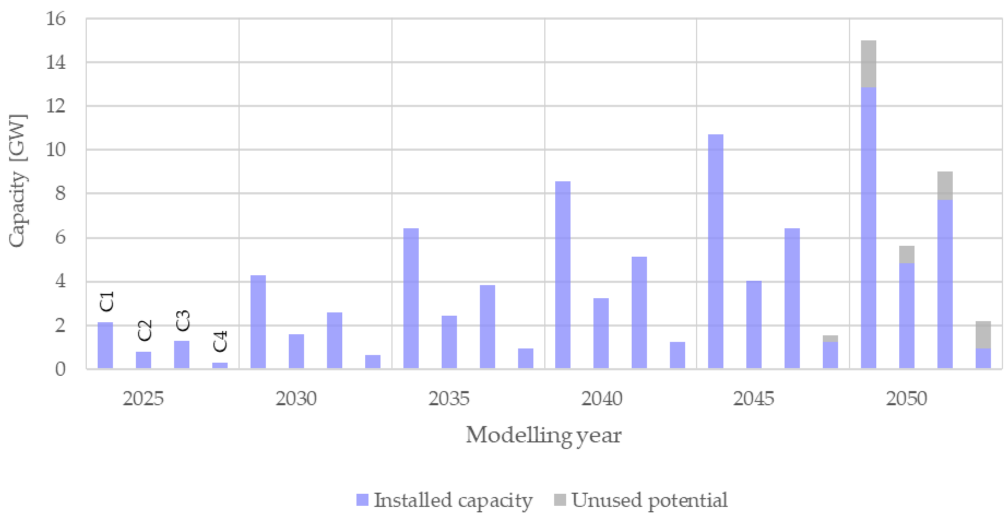

Figure 15. Onshore wind, supply-curve scenario—total installed new capacity and unused capacity potential in each modelling year for each cluster of wind onshore turbines. For every modelling year, columns correspond to clusters (left to right): cluster 1 (C1), cluster 2 (C2), cluster 3 (C3), and cluster 4 (C4).

3.2. Offshore Wind

In the case of offshore wind turbines in the base scenario (Figure 16), new capacities are built from the year 2030, which is the start year of offshore wind investments in the Polish power system, until the year 2040, beyond which no new capacities are built. The model does not utilise the entire available capacity potential, and new investments stagnate at just over 8 GW of capacity.

For scenarios with implemented supply curves (Figure 17), the model utilises available potential in clusters in the order of wind condition favourability, although not all potential in the preceding cluster is used before moving to the consecutive one. Contrary to the base scenario, there are new capacities built beyond the year 2040, with under 1 GW of new capacity in cluster 1 in the year 2050. The total installed capacity of wind offshore turbines in the year 2050 is higher than in the base scenario, at 10.78 GW.

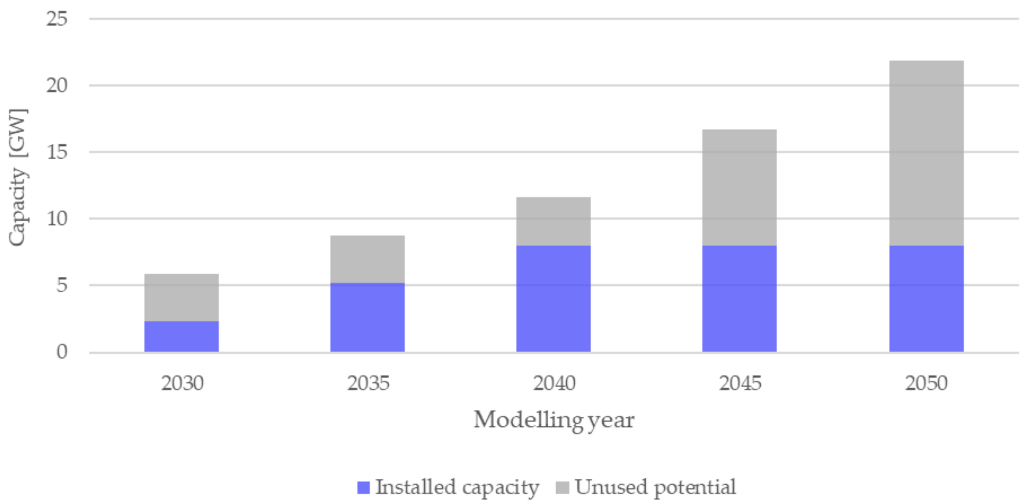

Figure 16. Offshore wind, base scenario—total installed new capacity and unused capacity potential in each modelling year.

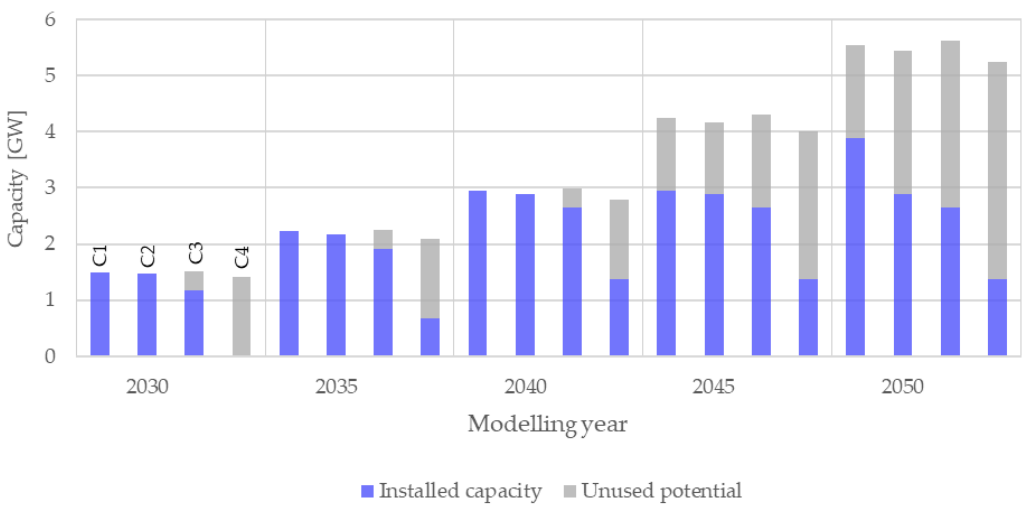

Figure 17. Offshore wind, supply-curve scenario—total installed new capacity and unused capacity potential in each modelling year for each cluster of offshore wind turbines. For every modelling year, columns correspond to clusters (left to right): cluster 1, cluster 2, cluster 3, and cluster 4.

3.3. Residential Solar Photovoltaics

For residential photovoltaic installations, in the base scenario, the entire available capacity potential is utilised until the year 2050, with 42 GW of total installed capacity (Figure 18). Corresponding to what was present in the onshore wind, all installations built in the year 2025 reach the end of their life in 2050 and are decommissioned.

For the supply-curve scenario, a similar situation is present (Figure 19). The total installed capacity value does not vary between scenarios.

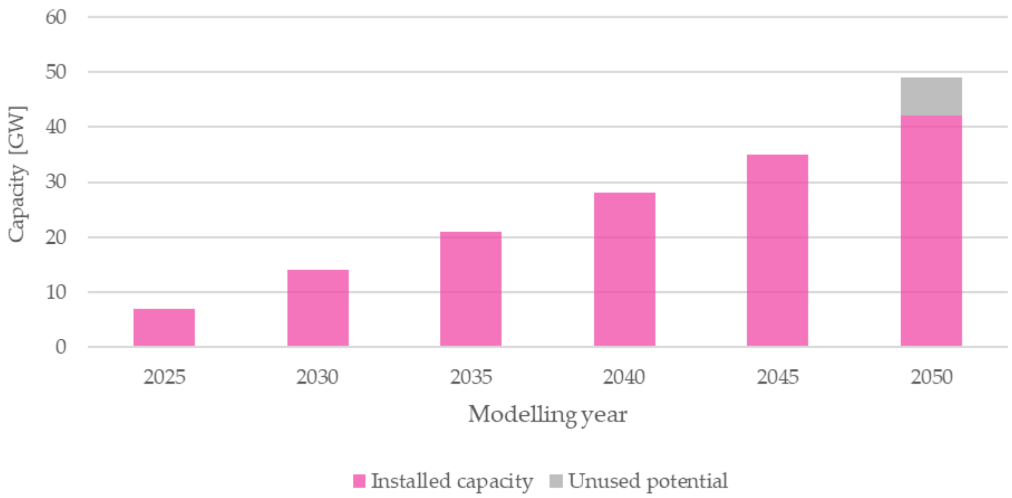

Figure 18. Solar photovoltaics (residential), base scenario—total installed new capacity and unused capacity potential in each modelling year.

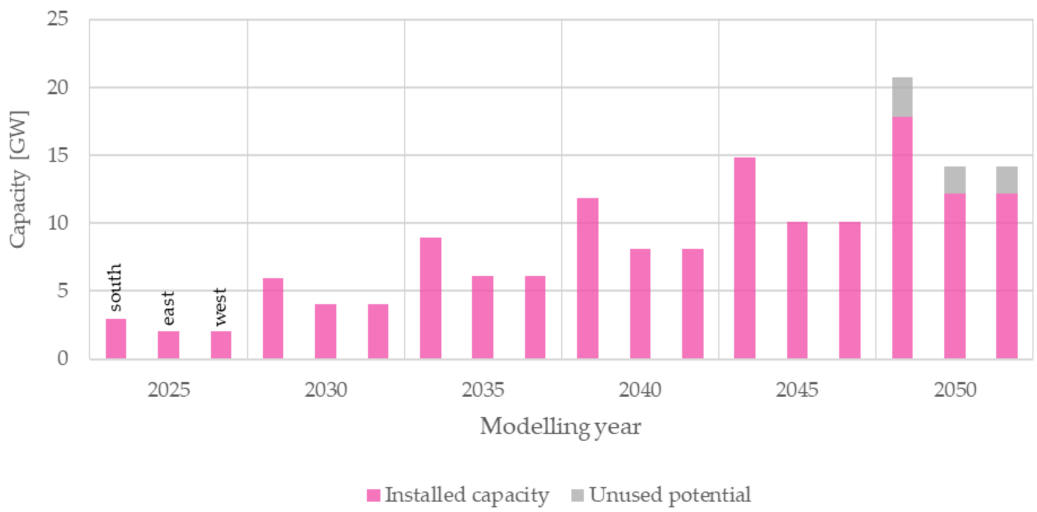

Figure 19. Solar photovoltaics (residential), supply-curve scenario—total installed new capacity and unused capacity potential in each modelling year for each azimuth of photovoltaic panels. For every modelling year, columns correspond to cardinal directions (left to right): south, east, and west.

3.4. Rooftop Large-Scale Photovoltaics

In the case of rooftop large-scale photovoltaic installations, in the base scenario, 7.64 GW of capacity is installed in the year 2025 (Figure 20), and the value is maintained without new capacities until the year 2050, when installations built in 2025 reach the end of their life and are decommissioned without being rebuilt. Therefore, no rooftop large-scale photovoltaics capacity is present in the system in 2050. A corresponding situation occurs for the scenario with implemented supply curves (Figure 21). The value of the installed capacity in 2025 is maintained and does not vary between scenarios.

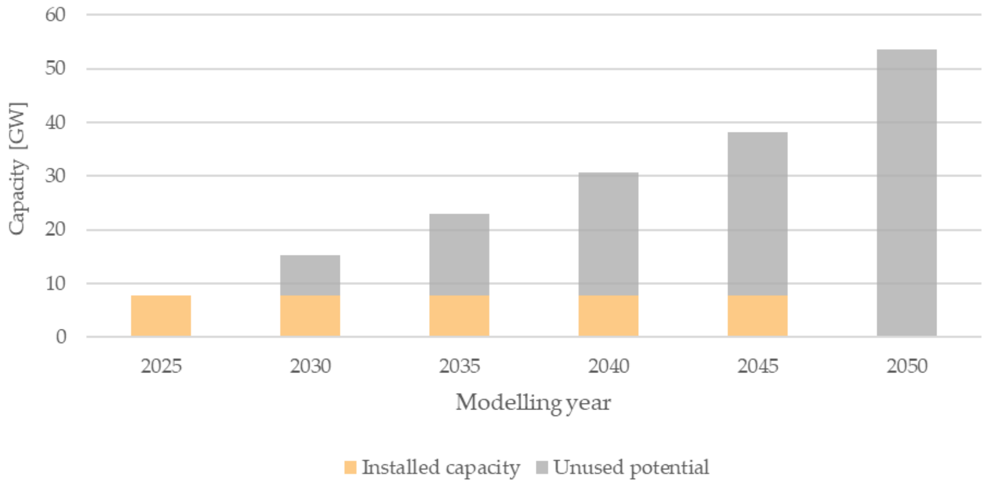

Figure 20. Solar photovoltaics (rooftop large-scale), base scenario—total installed new capacity and unused capacity potential in each modelling year.

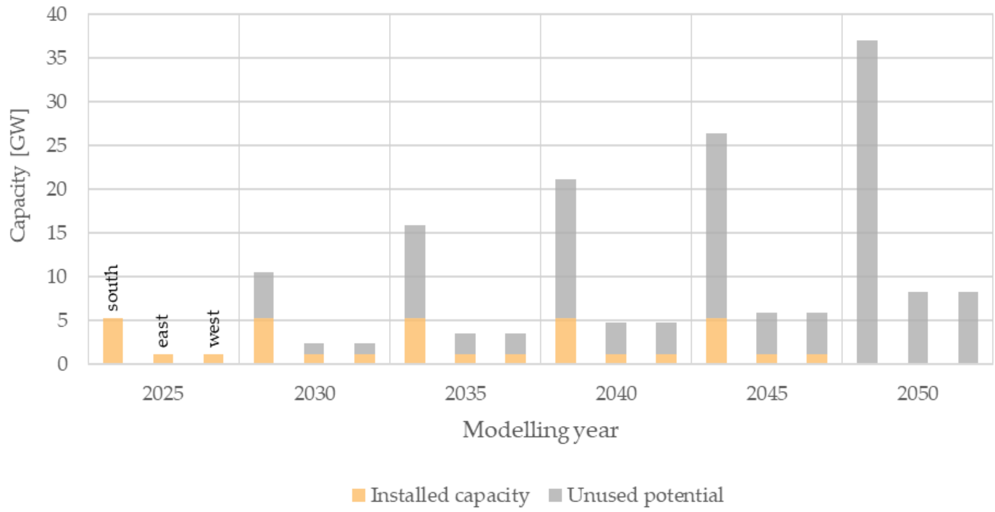

Figure 21. Solar photovoltaics (rooftop large-scale), supply-curve scenario—total installed new capacity and unused capacity potential in each modelling year for each azimuth of photovoltaic panels. For every modelling year, columns correspond to cardinal directions (left to right): south, east, and west.

3.5. Open Large-Scale Photovoltaics

In the base scenario for open large-scale photovoltaics, less than 4.6 GW of new capacity is built in the year 2025 and is maintained until the year 2045 (Figure 22). In 2050, all capacity built in 2025 reaches the end of its life and is decommissioned, with only 0.53 GW rebuilt.

For the supply-curve scenario, a total of 4.6 GW of capacity is built in 2025 evenly across all clusters (Figure 23). In 2035, more capacity is built only in the cluster with the most favourable conditions (the highest number of full load hours). This situation is maintained until 2045. In 2050, all capacity built in 2025 reaches the end of its life, and less than 2 GW is rebuilt in the first cluster only.

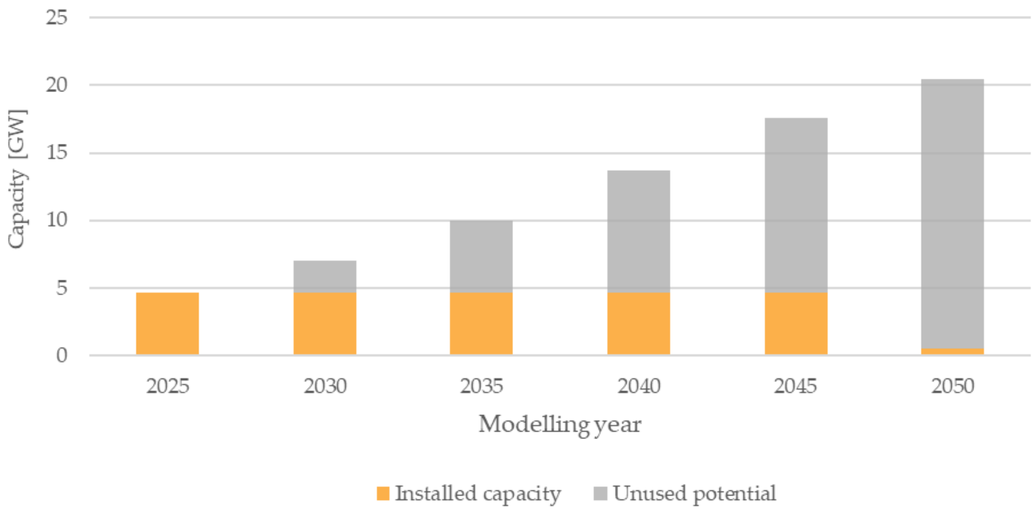

Figure 22. Solar photovoltaics (open large-scale), base scenario—total installed new capacity and unused capacity potential in each modelling year.

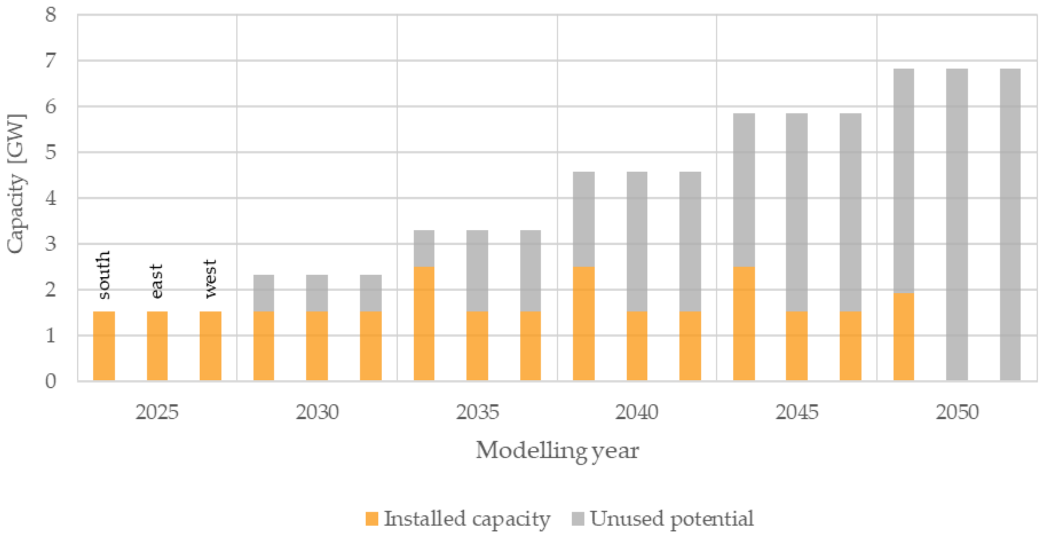

Figure 23. Solar photovoltaics (open large-scale), supply-curve scenario—total installed new capacity and unused capacity potential in each modelling year for each azimuth of photovoltaic panels. For every modelling year, columns correspond to cardinal directions (left to right): south, east, and west.

3.6. Assessment of Alternative Supply Curve Variants

To provide additional insight into the influence of the assumed renewable resource allocation, a limited sensitivity analysis was performed for photovoltaic variants and onshore wind resource classes. Offshore wind was not included because its resource quality is comparatively homogeneous within the available Polish offshore area. Two targeted variants were evaluated: (i) PV azimuth unconstrained, and (ii) onshore wind unconstrained. In the first variant, the capacity constraints associated with photovoltaic azimuth classes were removed, while the wind resource classes remained unchanged. In the second variant, the capacity constraints for onshore wind resource classes were removed, whereas the photovoltaic representation was left unchanged. The resulting changes in installed capacity and electricity generation were evaluated relative to the reference supply-curve scenario. The results of this analysis are presented in Figure 24, which compares the relative changes in the installed capacity (top) and electricity generation (bottom) for the analysed variants.

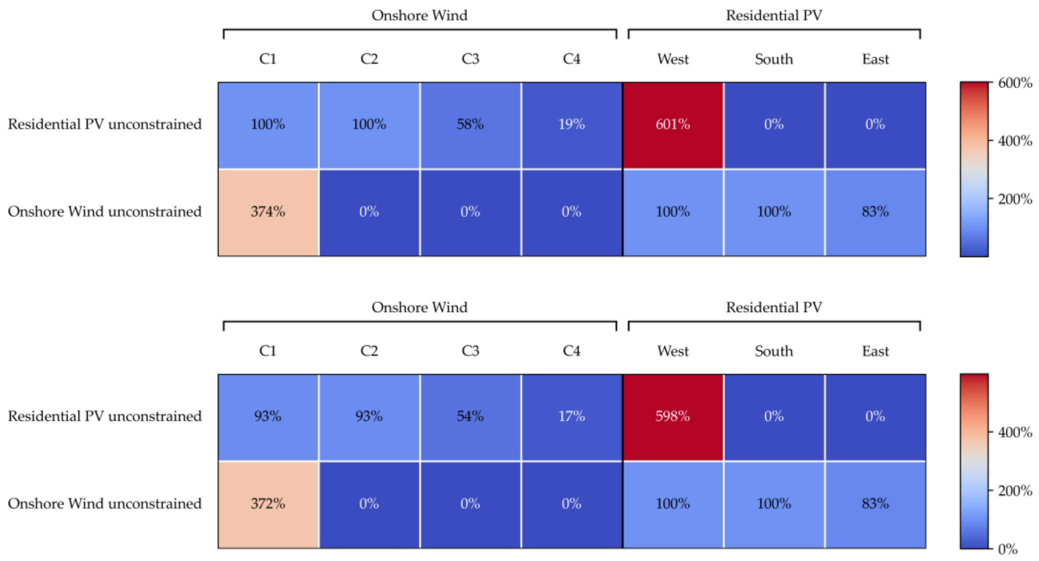

Figure 24. Relative changes in the installed capacity (**upper panel**) and electricity generation (**lower panel**) for the alternative supply curve variants compared with the reference scenario.

The photovoltaic sensitivity analysis shows that the assumed initial distribution of rooftop orientations does not determine the long-term deployment pathway. Once the azimuth-specific capacity constraints are removed, the optimisation model allocates almost the entire additional photovoltaic capacity to south-oriented systems. The installed capacity and electricity generation of south-facing PVs increase by approximately sixfold, while east- and west-oriented installations disappear almost completely from the optimal solution. This demonstrates that the optimisation process inherently favours the orientation providing the highest annual energy yield. Consequently, the inclusion of azimuth-specific supply curves is not merely a descriptive refinement but a necessary modelling feature that prevents the optimisation from converging towards an unrealistic concentration of installations in a single orientation. At the same time, the limited changes observed for the wind resource classes indicate that relaxing PV constraints has only a minor influence on the optimal allocation of wind capacity, confirming that the interactions among these technologies remain relatively weak. Even stronger effects are observed for onshore wind. When the capacity limits associated with individual wind resource classes are removed, the optimisation concentrates virtually all new wind investments in the highest-quality resource class. The installed capacity in cluster 1 increases to approximately 3.7 times the reference level, while investment in the remaining three resource classes is almost completely eliminated. A nearly identical pattern is observed for electricity generation, indicating that the optimisation systematically exploits only the locations with the highest full load hours whenever no spatial limitations are imposed. This behaviour is a direct consequence of cost-optimal optimisation, in which technologies with the highest productivity dominate unless constrained by resource availability.

3.7. System Cost Implications

Although the primary objective of this study is to evaluate how renewable energy supply curves affect long-term capacity expansion decisions, the implementation of supply curves also influences the total cost of electricity supply obtained by the optimisation model. Compared with the no-supply-curve scenario, the implementation of renewable supply curves increases the weighted average cost of the final electricity purchase by de-

mand sectors by approximately 3.5% over the period 2030–2050. This increase results from replacing a single aggregated renewable potential with multiple resource classes characterised by different capacity limits and generation profiles. Once the most favourable resource classes are fully utilised, additional renewable capacity must be deployed in classes with lower capacity factors, leading to a moderate increase in overall system costs.
To further investigate the effect of renewable resource constraints, two sensitivity variants, i.e., PV azimuth unconstrained and onshore wind unconstrained, were analysed relative to the supply-curve scenario. As expected, both variants reduce the total electricity supply cost relative to the supply-curve scenario since the optimisation model gains access to additional low-cost renewable generation resources. The magnitude of these reductions is shown in Figure 25.

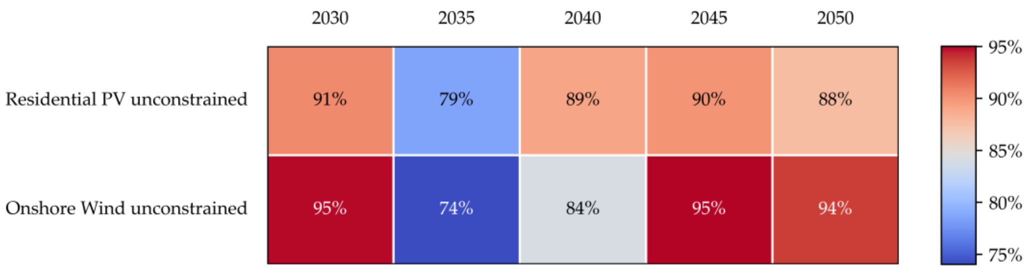

Figure 25. Relative changes in the weighted average cost of the purchase of final electricity by demand sectors. The losses and costs of transmission and distribution are included.

In the PV unconstrained variant, this effect is additionally influenced by the treatment of residential PV prosumers. In the model, 56% of the electricity generated by residential PV installations is assumed to be self-consumed. Consequently, this share of electricity is consumed behind the meter and is not subject to electricity network charges, which improves the economic attractiveness of residential PVs and contributes to the observed reduction in total electricity supply costs.

These results indicate that introducing renewable supply curves leads to a moderate increase in electricity supply costs while providing a more realistic representation of spatial and technological constraints affecting renewable deployment. Sensitivity analysis shows that cost differences between scenarios reflect not only technology–cost assumptions, but also the economic effect of explicitly representing spatial and resource-quality constraints in renewable deployment.

4. Discussion

Implementation of renewable energy supply curves in TIMES-PL leads to moderate system-level changes in installed capacity, but it substantially improves the realism of renewable resource representation. Across the analysed model years, the total installed capacity in the supply-curve scenario is higher than in the base scenario by 1.91–3.44 GW, corresponding to less than 3% of the total installed capacity. This increase results from the model being required to utilise renewable resource classes with lower capacity factors once the most favourable potentials are exhausted. Therefore, although the aggregate capacity differences are relatively small, they indicate that a more detailed representation of renewable resource heterogeneity affects long-term technology selection and capacity expansion.

The most visible differences are observed for wind technologies. The model generally prioritises clusters with higher full load hours, confirming that the implemented supply curves introduce meaningful resource differentiation. In 2050, onshore wind shows a higher degree of potential utilisation than offshore wind in the supply-curve scenario, with 83.8% of its available potential used, compared with 49.4% for offshore wind. However, cluster utilisation is not strictly sequential. In some cases, the capacity is installed in lower-quality classes before all potential in higher-quality classes is exhausted. This indicates that the optimisation does not depend only on annual capacity factors but also on interactions with the rest of the energy system, temporal generation profiles, capacity-expansion constraints and time-dependent investment decisions.

For photovoltaic technologies, the effect of supply-curve implementation is more limited. Residential PVs remain strongly favoured in both scenarios and represent the largest share of installed renewable capacity. In 2050, residential PVs reach 42 GW in the supply-curve scenario, accounting for 51.9% of total installed renewable capacity. Rooftop large-scale PVs show almost no additional development beyond the capacity already present in 2025, while open large-scale PVs are the only PV category that responds more visibly to the supply-curve representation. In this case, additional capacity is allocated mainly to south-oriented systems, reflecting the model's preference for the highest annual energy yield.

This tendency is further confirmed by the targeted analysis in which selected renewable capacity constraints were relaxed. The results of this analysis provide an important methodological insight. They demonstrate that renewable energy supply curves do not simply redistribute installed capacities among predefined resource classes. Instead, they prevent the optimisation model from producing physically unrealistic investment patterns by enforcing the gradual utilisation of progressively less favourable renewable resources. Without this representation, the model naturally concentrates investments in the most productive wind regions and exclusively south-oriented photovoltaic systems, thus overestimating the technical flexibility of renewable deployment. The proposed supply-curve formulation, therefore, plays a fundamental role in preserving the physical realism of long-term capacity expansion pathways, while maintaining the computational efficiency of the national-scale TIMES-PL model.

From the perspective of future power-system development, these findings also have practical implications. The model consistently favours technologies and configurations with the highest annual energy yield, even though such solutions may exacerbate operational challenges. In the case of photovoltaics, unrestricted deployment would reinforce the dominance of south-oriented systems, further concentrating electricity production around midday. Under conditions of rapidly growing PV penetration, this increases the likelihood of renewable curtailment, non-market redispatch of large-scale photovoltaic installations, and automatic inverter disconnections in low-voltage distribution networks caused by local overvoltage. Similarly, unrestricted wind deployment could unrealistically concentrate future investments in the most favourable regions, whereas actual development is constrained by land availability, environmental restrictions, social acceptance and grid infrastructure. Consequently, incorporating renewable energy supply curves improves not only the spatial representation of renewable resources but also the credibility of long-term investment pathways produced by the optimisation model.

Additionally, the implementation of supply curves of renewable energy technologies impacts non-renewable technologies deployment. The supply-curve scenario displayed higher battery storage capacity and changes in natural gas technologies. These differences indicate that modifications of renewable technology operation influence broader system balancing requirements. However, these changes did not alter the overall development trajectory of the modelled Polish power system. These differences are relatively small when considering them from a system perspective; however, they are another step in developing energy system models with the aim of being an accurate representation of reality.

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Several limitations should be noted. First, the analysis focuses primarily on installed capacity expansion. Additional effects may emerge when examining electricity generation, curtailment, dispatch patterns, storage operation and total system costs. Second, the current version of TIMES-PL does not include an explicit transmission-network representation. In reality, offshore wind development concentrated in northern Poland and spatially distributed onshore wind and PV deployment may create additional transmission needs, internal congestion, connection delays and curtailment. Therefore, the results should be interpreted as a resource- and technology-constrained long-term optimum, rather than as a fully grid-feasible expansion plan. Future work should extend the analysis towards operational indicators, network constraints and a broader assessment of system integration effects.

5. Conclusions

This research aimed to assess how introducing renewable energy supply curves affects long-term capacity expansion results in the TIMES-PL model. Supply curves were developed for solar photovoltaics, onshore wind, and offshore wind and implemented as resource classes with different capacity limits and operating characteristics. They combined available capacity potential, existing installed capacity, full-load-hour classes and hourly generation profiles. They were not treated in the model as purely static technical constraints. Although the spatial capacity limits remain fixed, each resource class was linked with time-dependent, techno-economic assumptions, particularly investment costs. As a result, the economic attractiveness of individual classes changed over time. The results show that using a single aggregated renewable potential may lead to an overly simplified representation of renewable deployment because it does not explicitly account for the fact that the most favourable locations are limited and become increasingly constrained as deployment grows. After the supply curves were introduced, the model still followed a broadly similar transition pathway, mainly because the system was driven by CO_2 emission allowance prices, but it required more installed capacity as part of the expansion shifted toward lower-yield resource classes. The results also indicate that the impact of supply curves was not limited to renewable technologies. Changes in renewable representation affected battery storage and gas technologies, which suggests that better modelling of renewable profiles influences broader system requirements. It can, therefore, be concluded that resource quality, spatial constraints, and technology-specific generation profiles should be considered when designing long-term renewable energy scenarios, as they affect not only the amount of capacity that can be installed, but also the realism and cost of its deployment. The main limitation of this study was that the spatial constraints and resource classes were kept fixed over time, while future changes in land-use regulations, protected areas, grid availability or local acceptance were not explicitly represented.

From a policy perspective, the results support the need for differentiated spatial planning of renewable energy deployment in Poland. A single national potential or average capacity factor may be sufficient for high-level screening, but it is insufficient for designing detailed deployment pathways. Planning instruments should account for regional resource quality, land-use constraints, local acceptance, connection availability and the sequencing of investments across resource classes. Such an approach provides policymakers and system planners with a clearer view of which parts of the national renewable potential are already used, where further deployment becomes constrained and when regulatory changes or alternative technology configurations may be needed. Future research should extend the analysis in several directions. First, alternative spatial–policy scenarios should be tested, particularly different setback-distance assumptions for onshore wind, as they directly affect the available capacity potential. Second, grid constraints, transmission limitations, and possible renewable curtailment should be represented in greater detail, es-

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pecially under higher shares of variable renewable generation. Third, the use of capacity-factor profiles based on multiple meteorological years would allow inter-annual variability in wind and solar resources to be better captured. Finally, future work should complement the installed-capacity comparison with a broader assessment of system costs, electricity generation, dispatch patterns and balancing requirements.

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