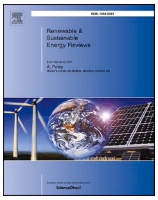
Renewable and Sustainable Energy Reviews 191 (2024) 114099

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser



# The effect of time resolution on energy system simulation in case of intermittent energies

Viktor M. Kiss [a], Zsolt Hetesi [b,*], Tibor Kiss [c]

[a] Metropolitan State University of Denver, CO, USA
[b] University of Public Service, Faculty of Water Science & University of Pécs, Faculty of Natural Sciences, Blue Economy Research Centre, Hungary
[c] University of Pécs, Faculty of Business and Economics, Blue Economy Research Centre, Hungary

ARTICLE INFO

*Keywords:*
Energy system models
Capacity planning
Time resolution
Intermittent renewable energy sources
Energy policy

ABSTRACT

The management and integration of intermittent renewable energy sources, such as wind and solar power, require precise capacity planning due to their variable nature. This study investigated the efficacy of using hourly time resolution in energy system models, a common practice in capacity planning. Concerns have been raised about the ability of hourly data to accurately represent rapid fluctuations in energy production and demand since it inherently constantly under- or overestimates actual real-time conditions. This research compared the outputs of energy models using 60-min resolution data with those utilizing a 1-min resolution benchmark across various dimensions: stability of outputs, temporal performance, geographical performance, impact of starting time shifts in data sampling, and trend effects. Results indicate that models using 60-min resolution data maintain a high level of accuracy, with output deviations of less than 2 % from the benchmark. This finding provides strong support that the current significant number of research studies, based on 60-min resolution data, do not carry potentially biased results due to their time resolution and are suitable for capacity planning decisions, thereby aiding in policy formulation.

## 1. Introduction

The integration and effective management of renewable energy sources, such as solar and wind power, within energy systems have become pivotal in the transition towards sustainable energy landscapes. These sources exhibit inherent intermittency and variability, with energy production fluctuating based on weather conditions and time of day. Accurately capturing these fluctuations is paramount for optimal capacity planning and ensuring the reliability of energy systems. Currently, a large proportion of studies and models predominantly rely on hourly resolution data for capacity planning purposes. However, there is a concern that such resolution may not be sufficient to precisely represent the rapid and frequent variations in renewable energy production and electricity demand. This lack of granularity may lead to oversimplified representations of energy systems, causing potential inaccuracies in predictions and, subsequently, suboptimal decision-making and planning.

In energy system modeling, different time resolutions serve specific purposes. Time resolution refers to periodic sampling, a systematic interval-based sampling method, where data points are recorded at consistent intervals, spanning from seconds to years. The choice of time resolution depends on the particular application and analytical needs of the energy system model. At the microsecond to the second scale, the focus is on regulating load dynamics. Moving to the minute-to-hour range, models generally address power changes and capacity planning while considering economic and security factors. Daily and weekly resolutions are utilized for weekly generation planning and schedule management, integrating weather-related elements. Over weeks to months, the focus shifts towards demand prediction and schedule planning. At the yearly level, models handle demand change planning, capacity construction, scenario analysis, and cost-benefit assessment, catering to long-term strategic considerations.

In this study, our primary focus is on capacity planning with a specific emphasis on different time resolutions. Energy system models for capacity planning are essential computational tools used to assess and plan energy resource allocation and infrastructure development. They aim to meet future demand while ensuring aspects such as reliability, efficiency, and sustainability. These models take into account a wide range of factors, including available energy resources (both renewable and non-renewable), load forecasting, technology options, transmission

---

* Corresponding author.
*E-mail address:* hetesizs@gamma.ttk.pte.hu (Z. Hetesi).

https://doi.org/10.1016/j.rser.2023.114099
Received 8 June 2023; Received in revised form 12 November 2023; Accepted 13 November 2023
Available online 22 November 2023
1364-0321/© 2023 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

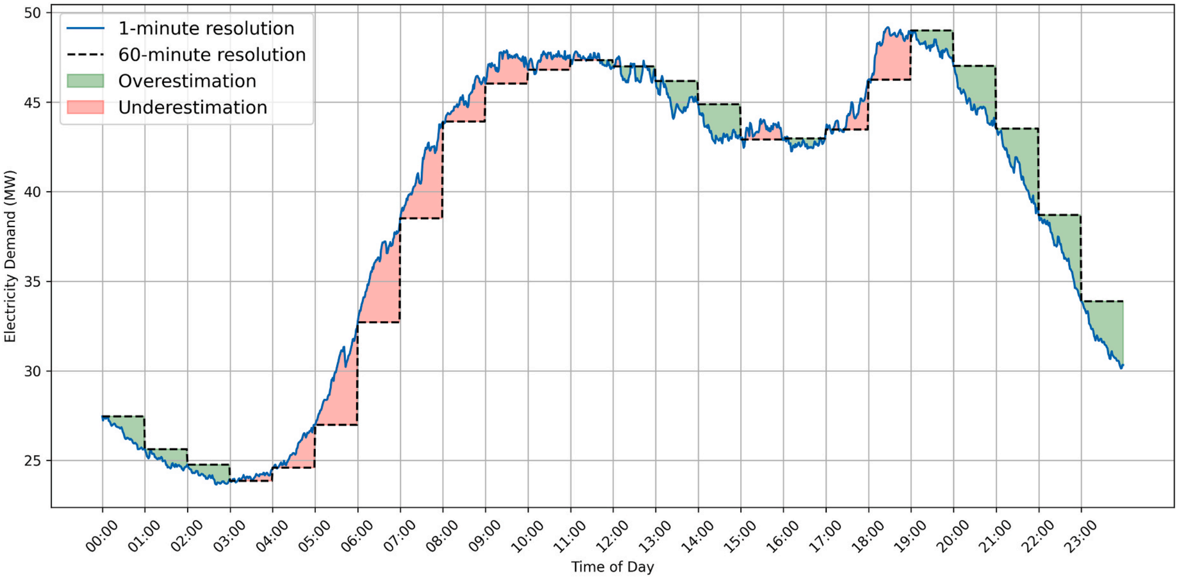


**Fig. 1.** Systematic under- and overestimation due to periodic sampling.

and distribution networks, policy and regulatory frameworks, environmental impacts, and economic analyses. Additionally, they can incorporate scenario analysis and optimization techniques to explore various future conditions and determine the most cost-effective and environmentally friendly solutions.

Their operation is as follows: They model a given time period, typically one year. At each discrete time step for which they have data, these models assess the energy system's demand and allocate available sources to fulfill that demand based on predefined rules, while considering factors such as availability, cost, and more. At the end, these models summarize aggregated key information for the modeled time period, including energy production from different sources, total costs, environmental factors, and other relevant data.

One notable aspect of these models is their reliance on hourly data. The choice of this time resolution aims to strike a balance between model precision and data availability, allowing for the capture of critical variations in energy supply and demand. However, it's worth noting that the accuracy and potential issues associated with using hourly data rarely discussed.

Utilizing hourly or coarser data - as opposed to finer resolutions - in energy systems modeling can lead to oversimplification, since it may not adequately capture rapid fluctuations, potentially resulting in less accurate modeling outcomes. Fig. 1 illustrates this concept. The continuous blue line in the figure represents the minute-by-minute electricity demand for a city. The black dashed line represents the model input when a periodic sampling of 1-h is applied, resulting in one data point every 60 min. The model extrapolates this value until the next data point becomes available, assuming a constant value until that point. This characteristic leads to consistent underestimation or overestimation of the actual values, the amount of which can be seen colored red and green in the figure.

This issue is exacerbated by the growing use of intermittent energy sources, such as solar and wind power data, because electricity produced by those capacities can result in rapid changes, often occurring well within periodically observed points. Since this is a known issue, most energy models aim to use the most granular data available that fits their purpose, which (as the literature review will point out) is typically a 60-min resolution.

However, the question remains: Does the use of hourly data in energy models provide sufficient accuracy to achieve their objectives, considering potential issues related to low granularity resolutions? The primary goal of this present study is to investigate the reliability of outputs generated by 60-min resolution energy models and assess whether they significantly diverge from those obtained at a finer, 1-min resolution.

## 2. Literature review

The literature review comprises two main sections. The first section highlights the prevalence of energy models with 60-min time resolutions, while the second section provides an overview of research efforts addressing time resolution challenges in energy models.

### *2.1. Exploring energy models with hourly time resolution*

This section highlights the widespread use of 60-min models in simulating energy systems across different countries and regions, emphasizing their role in influencing and evaluating policymaking processes.

Wierzbowski et al. [1] drew attention to Poland's heavy reliance on coal-based electricity generation, constituting over 80 % of the energy mix, emphasizing the need for a balanced energy policy. Meanwhile, Van Sluisveld et al. [2] scrutinized low-carbon strategies in Denmark, France, Germany, the Netherlands, and the UK, revealing diverse approaches to EU greenhouse gas reduction goals, with a strong emphasis on cross-border collaboration and stakeholder involvement. Shifting focus to Ireland, Mulholland et al. [3] addressed the challenge of decarbonizing the private car sector with a multi-model approach. They provide a comprehensive framework, including a cost-optimal technology pathway, a policy roadmap, and enabling measures, all aimed at achieving an 80 % carbon reduction by 2050.

Hache and Palle [4] explored the integration of variable renewable energy sources into power networks, identifying research trends and stressing the need for a systemic vision that considers complex para meters beyond power systems. Sasanpour et al. [5] delved into the role of hydrogen in a 100 % renewable European power system, revealing potential cost savings and varied impacts across countries. Meanwhile, Zhou et al. [6] focused on Norway's decarbonization efforts in transportation and offshore industries, emphasizing the critical role of zero-emission vehicles in achieving net-zero emissions by 2050. Focusing more on the heating/cooling systems, Paardekooper et al. [7] conducted a comprehensive assessment of excess heat volumes in the EU, identifying regions suitable for district heating implementation and stressing the need for greater recognition of the heat sector in EU energy policy.

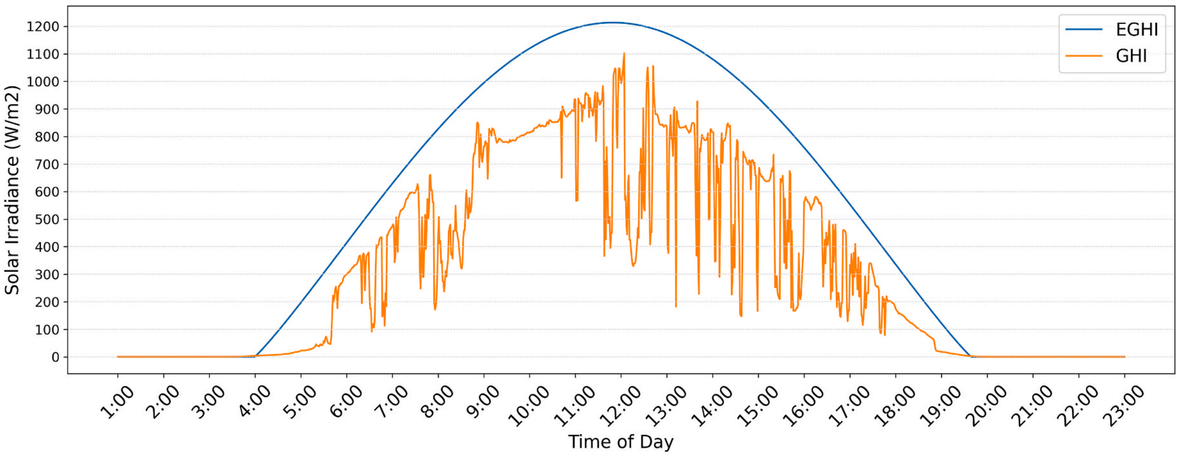


**Fig. 2.** EGHI vs. GHI for a 24-h period in Pécs.

Researchers in various European countries are actively exploring the feasibility of transitioning to 100 % renewable energy systems, guided by hourly time resolution models. Denmark's analysis, led by Lund et al., suggests that achieving a 100 % renewable energy supply is possible. However, it faces a choice between biomass and wind power as primary resources, each with distinct implications for efficiency and land use [8]. In Ireland, Connolly et al. have outlined initial steps toward a 100 % renewable energy system, exploring scenarios involving biomass, hydrogen, and electricity [9]. Portugal, as outlined by Krajačić et al., is working to reduce its energy dependence on imports by integrating various energy storage solutions for wind, solar, and ocean wave energy sources to ensure a reliable energy supply [10], meanwhile, Doepfert and Castro [11] examined how a high share of intermittent renewable sources would operate within the country's system.

Australia's study, conducted by Elliston et al., suggests that renewable options are cost-effective and low-risk for emissions reduction, given favorable conditions [12]. In Japan, Morel et al. proposed a strategy for achieving carbon neutrality through 100 % renewable energy generation in a cold region, with an emphasis on eliminating CO2 emissions and maintaining a stable power grid frequency [13]. The Hungarian energy system was modeled for several purposes using hourly models: Safian [14] conducted an initial study to check the compatibility of wind and solar energy resources in the country, Kiss et al. [15] explored several scenarios with different renewable energy penetration while Campos et al. explored different renewable capacities to study their potential outcome [16].

France's study, led by Krakowski et al., investigated the impact of high renewable energy penetration on power system reliability, emphasizing the need for additional capacity and flexibility options [17]. Israel, as explored by Weiss et al., is looking into market design options for a 100 % renewable energy system. The study suggests that existing energy-only markets may require capacity mechanisms to avoid underinvestment [18]. Meanwhile, Nordic countries, as assessed by Pursiheimo et al., are actively studying the feasibility of a 100 % renewable energy supply by 2050, with power-to-gas technologies playing a role in scenarios with high wind and solar power [19].

Pakistan's energy transition roadmap, outlined by Sadiqa et al., focuses on solar photovoltaic (PV) as the dominant source in integrated scenarios, leading to cost-competitive 100 % renewable energy [20]. Europe envisions a 100 % renewable energy power sector by 2050, with storage technologies like batteries, pumped hydro, and power-to-gas playing a vital role in decreasing the levelized cost of electricity, as studied by Child et al. [21]. Germany, as explored by Hansen et al., actively investigates the feasibility of transitioning its energy system to 100 % renewable energy by 2050, considering technical and economic aspects across various sectors [22].

In Kazakhstan Bogdanov et al. showed that transitioning to 100 % renewable power and heat supply by 2050 is technically and economically feasible despite challenging conditions [23]. Ireland's exploration of optimal pathways for achieving 100 % renewable energy by 2050, as emphasized by Xue et al., highlighted the importance of carbon capture options and power generation variability [24]. Cuba's aim to achieve 24 % renewable energy in electricity production by 2030, with research by Korkeakoski outlined scenarios that assess technical and cost feasibility across various renewable energy levels [25].

Studies of city-sized energy systems with hourly resolution are also well established. In 2010, Østergaard and Lund modeled the Danish city of Frederikshavn's electricity, heating, and transportation system to pave the way for the city to become 100 % renewable [26]. Kiss simulated the proposed energy strategy of the Hungarian city of Pécs to understand the potential impact of their policy [27]. Zhao et al. modeled the energy system of Beijing to potentially shift the city to 100 % renewable energy by 2030 [28]. Other studies include the work of Bačeković and Østergaard, who modeled Zagreb, Croatia, and compared different 100 % renewable energy scenarios [29], as well as the work of Yazdaine et al. on the cost-optimal approach to energy strategy based on the city of Basel, Switzerland [30].

To underscore the prevalence of hourly or even larger temporal resolutions in energy systems modeling literature, it is noteworthy that Østergaard et al. [31] compiled and analyzed 315 peer-reviewed articles on energy systems analysis using EnergyPLAN, a software that does not employ resolutions finer than 60 min.

### 2.2. Studies on temporal resolution in energy system models

Studies exploring the effect of different temporal resolutions in energy system modeling are scarce. The most notable studies related to this topic include the works of Haydt et al. [32], Bistline [33], and Shirizadeh and Quirion [34], discussed below.

Haydt et al.'s research underscores the critical role of temporal resolution in energy planning models, especially in systems heavily reliant on intermittent renewable energy sources. Their analysis convincingly demonstrated that models with higher time resolution yield more precise results in terms of dispatched renewable sources and CO2 emissions compared to conventional balance approaches. This insight highlights the importance of considering finer temporal resolutions for accurate energy system modeling.

Bistline's study explored the consequences of temporal resolution on decarbonization pathways within the power sector. The research indicates that simplified approaches (i.e.: low granularity time resolution) to handling temporal variability can lead to substantial deviations from more comprehensive models, impacting cost assessments, technology

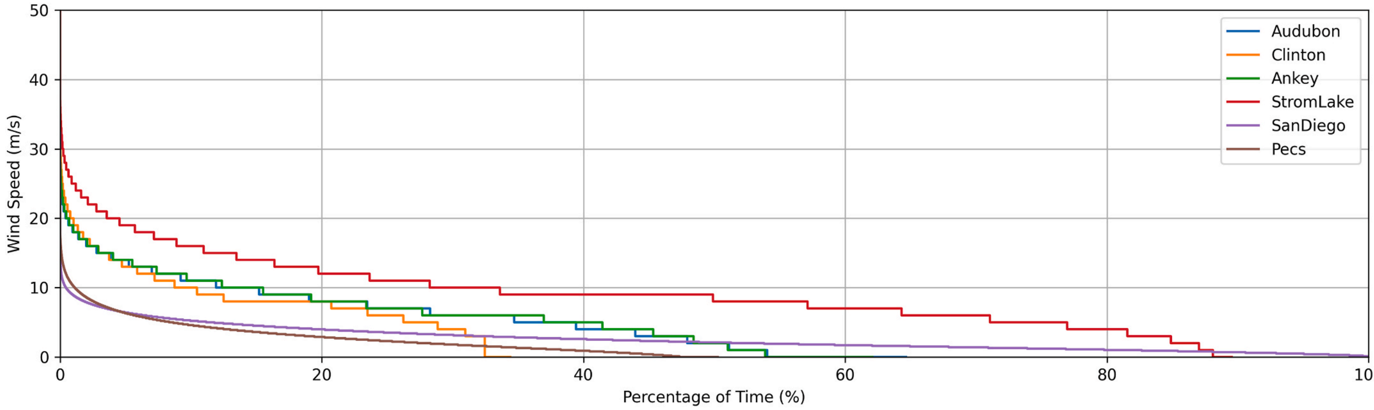


**Fig. 3.** Wind speed duration curves for different locations.

selection, and emissions reduction strategies. This finding underscores the growing significance of finer temporal resolution, particularly in scenarios aiming for deep decarbonization.

Shirizadeh and Quirion's work investigated the impact of time-series aggregation methods in multi-sector energy system optimization models. Their findings reveal that reducing temporal resolution results in smaller deviations concerning key output variables such as the energy mix, system cost, and CO2 emissions.

However, all three of these analyses share a common limitation: they focus on time resolutions *60 min or larger* and do not examine the potential effects and advantages of employing finer time intervals.

It is important to note that the impact of using 60-min resolution data compared to 1-min resolutions in other energy-related areas has been studied. For instance, Simolin et al. [35] investigated electric vehicle charging loads and found that employing excessively coarse temporal resolutions, like 1-h intervals, could result in modeling inaccuracies as high as 80 % in certain cases. In another study conducted by Beck et al. [36] which focused on the influence of high-resolution electrical load and PV generation profiles on the optimal sizing of PV-battery systems, it was recommended to use a finer temporal resolution of at least 300 s for sizing decisions that heavily rely on the load profile characteristics. When using hourly (3600-s) data, some of the relative errors for optimal power in the system increased by up to 50 %. Time resolution in household power consumption models was analyzed by Jimenez-Castillo et al. [37] in a study exploring recording intervals of monitored energy data from 1 to 60 min. Their findings suggested that using data with resolutions of 60 min could distort results compared to 1-min data by as much as 32 % in some households.

The inclusion of the above literature aims to point out that the problem of time resolution is not trivial and there are instances in energy systems where using more coarse data for modelling purposes can significantly distort results.

Since the three studies dealing with energy planning models [32–34] did not address these potential issues, this current study aims to fill this gap by investigating whether the widely used hourly time resolution is adequate for such analyses or if it distorts results when compared to more detailed data inputs, such as 1-min intervals.

## 3. Methodology

In this section, the data collection and analysis processes for solar, wind, and electricity data from Pécs, Hungary, as well as wind data from five locations in the United States, are outlined. The description covers data collection methods, processing, and transformation steps, with a focus on factors such as solar radiation, wind power generation and model building. Additionally, an individual analysis of wind speed data from diverse locations reveals significant variations in wind formation characteristics which will be the basis of a better generalization of our results.

### *3.1. Data collection*

#### *3.1.1. Solar, wind and electricity data from pécs*

Pécs, located in southern Hungary, is the fifth-largest city in the country. It is a historic city with a substantial population with approximately 140,000 residents. Minute-by-minute data was collected from a weather station operated by the University of Pécs. The central component of the automated weather station originates from the Finnish company VAISALA, while additional equipment hails from Lambrecht GmbH and OTT GmbH. Situated within the University of Pécs' Ifjúság Street campus, this station has been gathering meteorological information since November 2008 and collects a wide range of information, such as air and soil temperature, humidity, precipitation, wind speed, air pressure and both direct and diffuse solar radiation, for which the

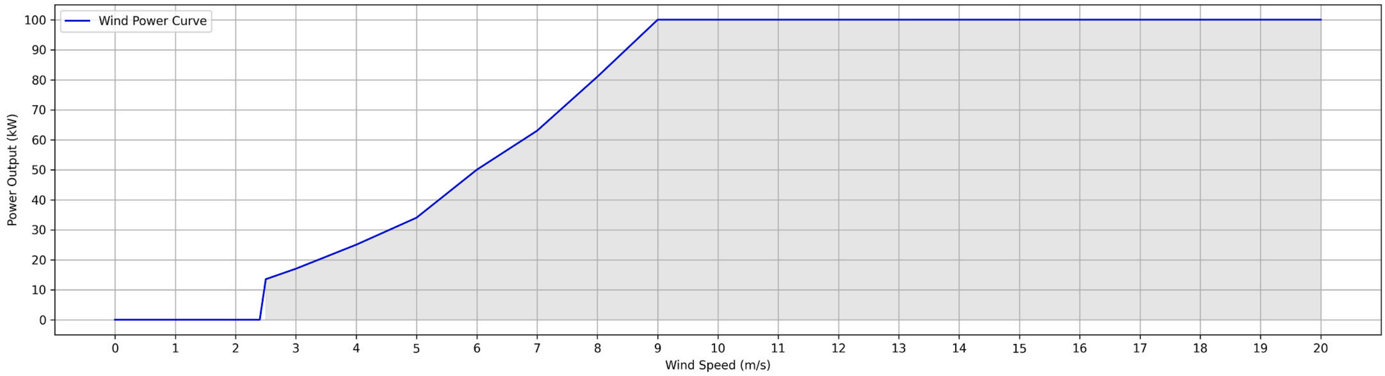


**Fig. 4.** Wind power curve used in the models.

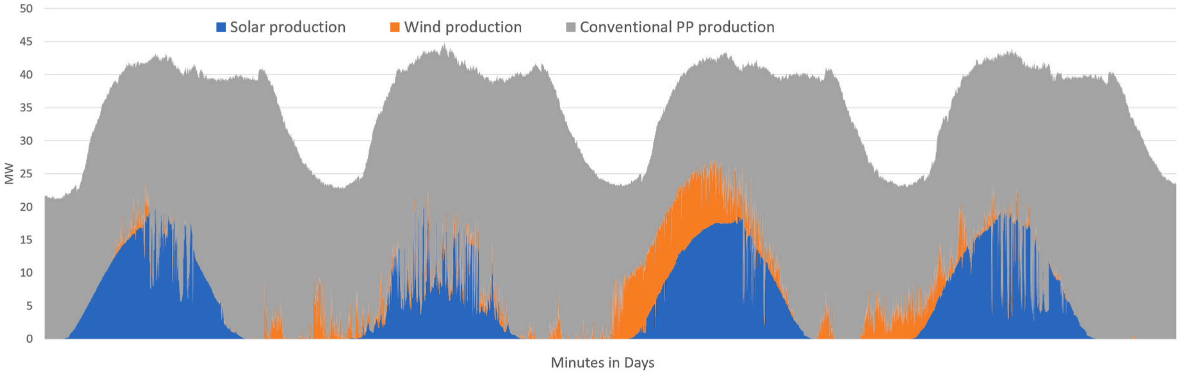


**Fig. 5.** Visualization of the operation of the model from May 23 to May 26.

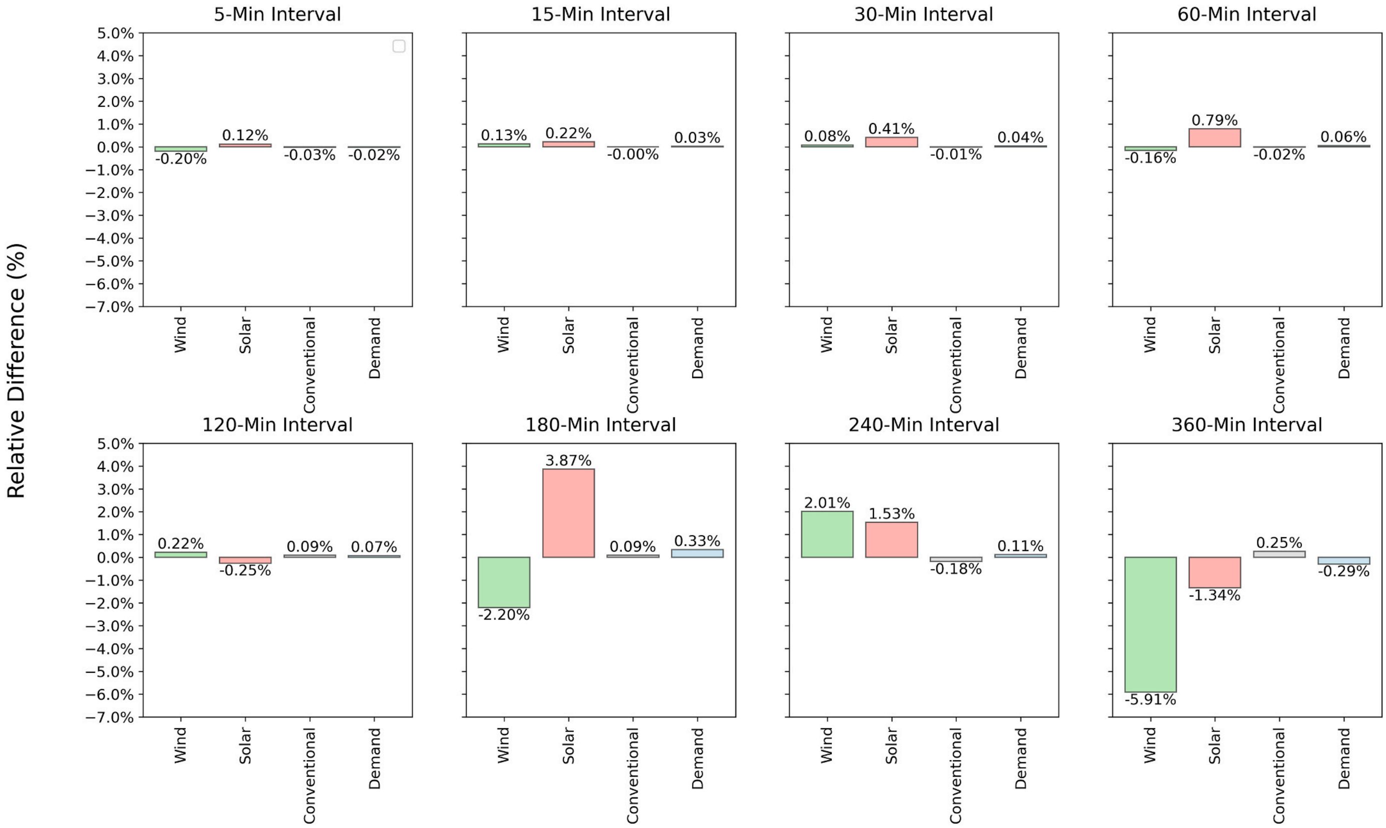


**Fig. 6.** Relative difference of model outputs to 1-min resolution (2015).

station employs a horizontally oriented pyranometer which gives the Global Horizontal Solar Irradiance (GHI) for the location. Detailed information about the weather station can be found at [38]. The data used by this study were air temperature, global solar radiation (direct + diffused) and wind gust.

Authors also obtained the minute resolution Extraterrestrial Global Horizontal Solar Irradiance (EGHI) and the solar elevation angle for the location of Pécs using the Solar Position and Intensity (SOLPOS) calculator provided by the National Renewable Energy Laboratory (NREL) [39].

EGHI varies in intensity for a given latitude throughout the day, forming a symmetrical, bell-shaped curve. In contrast, the GHI indicates the actual solar irradiance received at a specific time and location on Earth, since it considers the effects of Earth's atmosphere, weather conditions, and the local environment. Fig. 2 demonstrates this difference using data from a summer day in 2016 in Pécs, Hungary.

For the models developed in Section 3.3 the authors were provided minute-by-minute data for the electricity demand for the city of Pécs by the local energy supply company, EON [40].

### 3.1.2. *Wind data from other locations*

In order to generalize the results later in the study, 1-min resolution wind data from different geographical locations were obtained for 5 locations in the United States: San Diego, (California), Audubon, Ankeny, Clinton and Storm Lake (all Iowa). They were downloaded from the Automated Surface Observing System (ASOS), which is considered to be the flagship automated observing network [41]. To ensure distinct wind patterns and strengthen the basis for generalizing the results, a brief investigation was conducted regarding the wind formation characteristics of these locations:

The most important of the surface processes involved in wind formation is shear. The surface of the Earth is virtually at rest, and the air

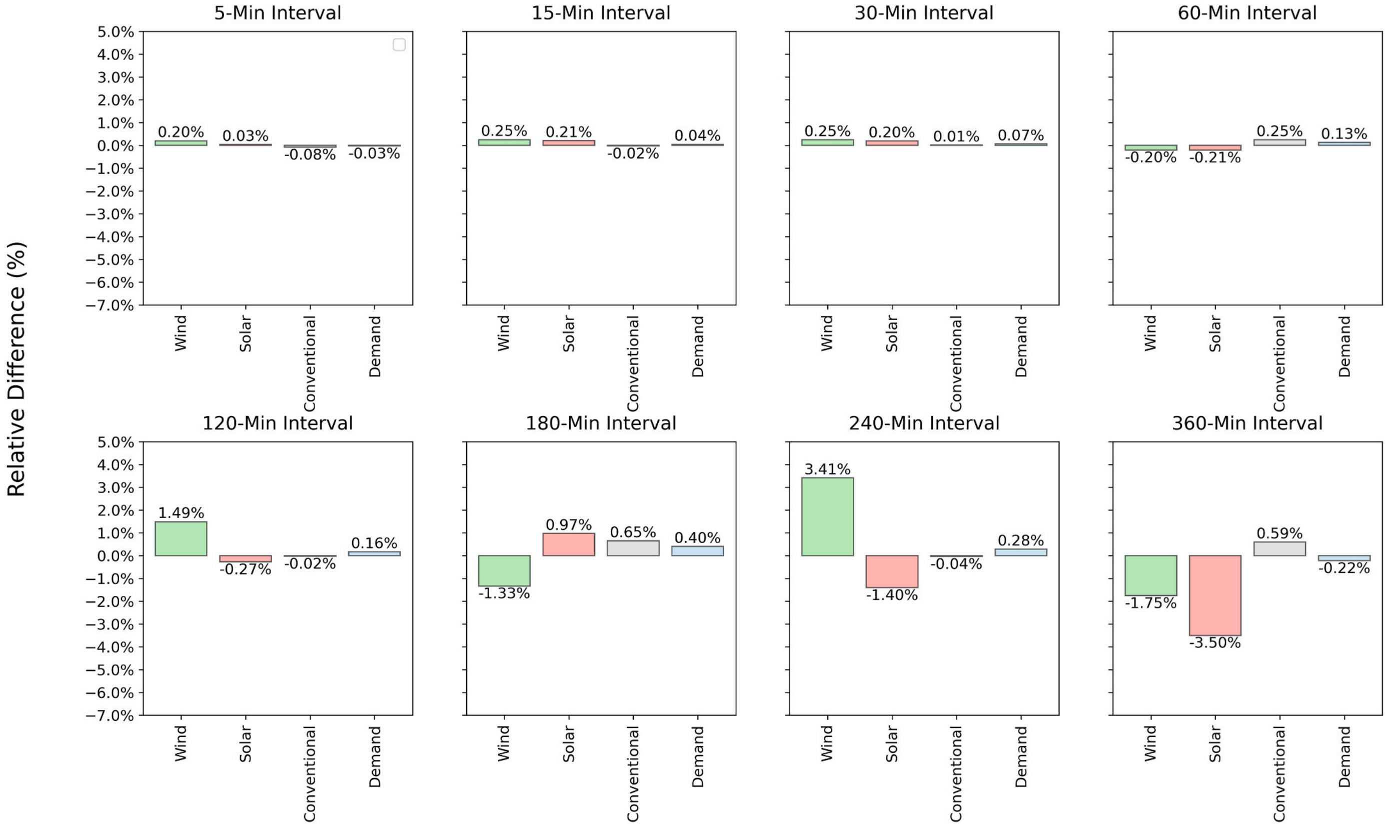


**Fig. 7.** Relative difference of model outputs to 1-min resolution (2016).

particles directly above the surface do not move. The higher the air particles are from the surface, the faster their movement. Shear and air density are the two most important factors that shape the wind phenomenon near the surface. The tangential rate (i.e., between two layers of air parallel to the surface) is denoted by τ and the density by ρ to form the shear rate (u):

$$u = \sqrt{\tau/\rho}$$

The shear rate logarithmically increases with height and effectively describes wind speeds at altitudes of around one hundred meters. Wind speed characteristics are influenced by the geographical conditions of the study area. In continental regions, wind speed and direction result from the combined effects of topography and local climate. In most areas, a prevailing wind direction and average wind speed can be identified with statistically verifiable deviations.

The six selected locations exhibit significant geographical diversity, resulting in variations in wind generation and strength. In Iowa, prevailing winds typically originate from the south, originating from the Gulf of Mexico. The region's topography consists of river valleys and plains forming part of the Great Plains, as well as a mountain range reaching heights of 1000–2000 m in the western part of the state, which serves as a foothill of the Rocky Mountains. Average wind speed data reveal that wind speeds measured in the plains are 1–2 m/s lower than those measured in the mountains. Interestingly, the substantial differences in the selected stations' characteristics, which should significantly impact wind formation, have a limited influence on the statistical properties of the resulting wind patterns, which are crucial for energy production.

While Ankeny sits at an elevation of approximately 800 m above sea level, Audubon, located 100 km away, is situated at an altitude of 1400 m. Although wind speed and other data do not differ significantly, the mechanisms of wind formation vary between the two locations. In the case of Ankeny, the plains in the western half of the state dominate the topography, whereas Audubon is positioned in the foreground of the Rocky Mountains at an elevation of 600 m above sea level. Shearing, a key factor in determining wind direction and speed, differs in both cases. While the layering of the wind on the plains remains unaffected by topography, elevations due to hills or mountains cause wind streamlines to thicken under topographical influence, altering the source of wind formation.

The data from Storm Lake Station substantiate the impact of topography on wind formation. The station's name and altitude indicate the topographic acceleration of the wind. It is noteworthy that, despite Audubon's similar altitude, its average wind speed is significantly lower compared to Storm Lake Station, where the average wind speed is approximately 3 m/s higher.

In the case of San Diego, the ocean plays a pivotal role in wind formation, making it a justified location for the study. Coastal areas often exhibit unique weather patterns, resulting in the development of coastal winds due to the presence of the ocean. Coastal winds primarily form due to differences in the heat capacities of water and soil. During the day, the ocean and the air above it are cooler, while the reverse is true at night. Consequently, local winds in San Diego differ from those in locations like Iowa.

Pécs, Hungary, presents a unique situation. Despite being located in the foothills of the Mecsek Mountain range, the mountain's presence reduces average wind speed due to shading by the prevailing wind direction (NW).

The differences are further evident from the distinct wind speed duration curves plotted in Fig. 3, which graphically represent the distribution of wind speeds over time. Duration curves provide a comprehensive view of how frequently different wind speeds occur, helping us understand the temporal patterns and variability in wind behavior at each location.

In conclusion, the individual analysis of wind speed data from six diverse locations, including Pécs and five U.S. locations, confirms their

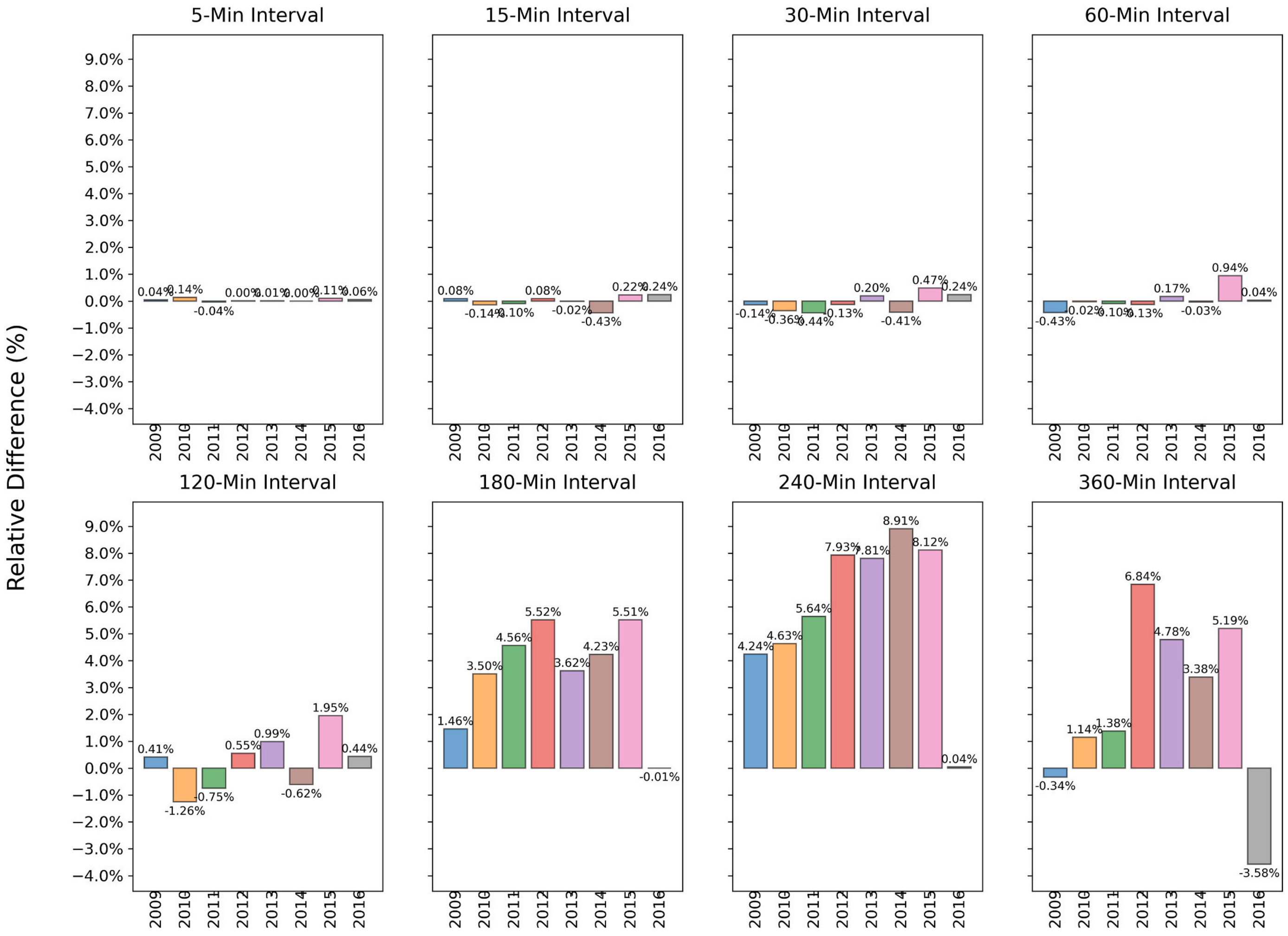


**Fig. 8.** Relative difference to 1-min resolution in solar production for different dime intervals (2009–16).

significant differences. This knowledge enforces the foundation for generalizing our results and provides insights into the broader applicability of our findings.

### 3.2. Data processing/transformation

To make raw meteorological station data compatible with energy system models, the same transformations are required as those used in energy modeling.

#### 3.2.1. Photovoltaic (solar) power generation

The following section outlines the calculations employed to determine solar power production. Solar panels are typically oriented at specific angles, depending on their location on Earth. For Pécs, the recommended tilt angle corresponds with the city's latitude, which is 46°. Since the data provided by the meteorological station was for the Global Horizontal Solar Irradiance (GHI), a transformation was performed to convert it into the irradiance on a tilted panel. This transformation was executed using 'pvlib', a well-documented Python library, recognized for its benchmark implementations of photovoltaic (PV) system models [42]. The Global Horizontal Irradiance was split into the estimated Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI) which were subsequently used to compute the total irradiance $(I_{s-tilted})$ on a south-facing panel tilted at 46°, situated in Pécs.

The resultant effective solar irradiance was then converted into photovoltaic energy. To achieve this, the authors utilized the calculation method for electricity production $(P_{pv})$ from a photovoltaic module as outlined in the documentation of a leading energy modeling software, EnergyPRO. The following information is directly sourced from Ref. [43]:

$$P_{pv} = P_{Max} \cdot \frac{I_s}{I_{STC}} \cdot [1 - \gamma_s \cdot (T_{cell} - T_{STC})]$$

Where: $P_{Max}$: Installed capacity (W), $I_s$: Solar irradiance (in this case: $I_{s-tilted}$, $W/m^2$), $I_{STC}$: Irradiation at standard conditions (1000 $W/m^2$), $\gamma_s$: Temperature coefficient for module efficiency (0.4 %/°C), $T_{STC}$: The cell temperature at standard conditions (25 °C) and $T_{cell}$ (cell temperature):

$$T_{cell} = T_\alpha + I_s \cdot \left( \frac{\text{NOCT} - 20^\circ\text{C}}{800 W/m^2} \right)$$

Where: $T_\alpha$: ambient temperature and NOCT: Nominal Operating Cell Temperature (46 °C).

These calculations simulated an actual tilted solar panel's behavior and output $(P_{pv})$ very closely and were used in the models built in Section 3.3.

#### 3.2.2. Wind power generation

For wind production, the power curve (see Fig. 4) of a well-established 100 kW turbine was employed, sourced from a database that collects data from various manufacturers and models of wind

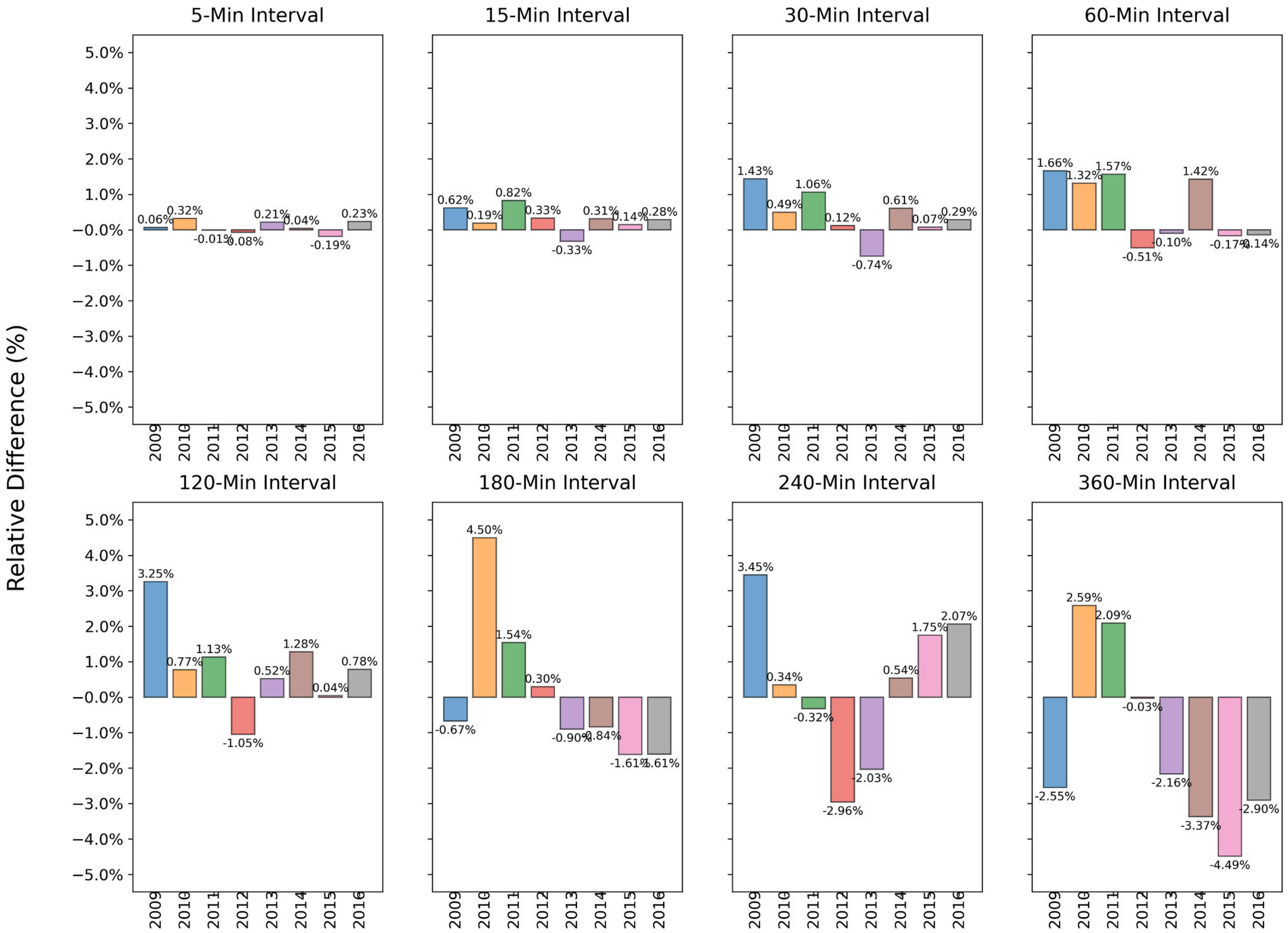


**Fig. 9.** Relative difference to 1-min resolution in wind production for different time intervals (2009–16).

turbines [44]. The power curve serves as a crucial conversion tool, translating wind gusts measured in meters per second (m/s) into corresponding electric power outputs. To ensure the accuracy of the generated wind power data, the turbine model was calibrated by configuring the cut-in and cut-out wind speeds to 2.5 m/s and 20 m/s, respectively, as specified by the manufacturer's documentation.

The objective of this process was to align the simulated wind power generation with the data that an actual energy system model would receive in real-world scenarios, thus ensuring that the generated wind power data is not only representative but also suitable to gain accurate insights into the behavior of wind power both individually and as a part of an energy system.

### 3.3. Model building

To be able to assess the differences between 60-min resolution model outputs and finer resolutions, a model was run for the city of Pécs for the years 2015 and 2016. The models operate as the models described in the Introduction section, allocating input available from solar power, wind power and a conventional power plant to meet the city's electricity demand. The order of priority for energy use was: 1. Wind, 2. Solar, 3. Conventional PP. In case of overproduction, they were curtailed in reverse order. Running this model where the renewable sources are built into a system allows us to obtain outputs that are consistent with "in-system" behavior of energy sources. Please see Fig. 5 for a visualization of the distribution of available power supplying the demand curve for a 4-day period.

Once the model was constructed, it underwent simulations using nine distinct sampling intervals (time resolutions): 1-min, 5-min, 30-min, 60-min, 120-min, 180-min, 240-min, and 360-min, spanning two different years, 2015 and 2016, and the results were saved for further analysis detailed in the following section.

## 4. Results and discussion

In this section, the performance of the models detailed in the methodology section is analyzed. The primary objective was to assess their accuracy in relation to the 1-min benchmark. This was primarily accomplished by calculating the ratio between the outputs obtained from lower resolution models and those from their corresponding 1-min models.

To assess the robustness of these models, various dimensions were explored: Section 4.1 investigates how results deviate when data are integrated into an energy system model; Section 4.2 examines how results differ across seven years, assessing the models' consistency over time; Section 4.3 analyzes how results vary when applied to diverse geographical locations, seeking to understand regional variations; Section 4.4 explores how results change when starting times are lagged for coarser resolution observations and Section 4.5 examines the trend effect and its potential implications.

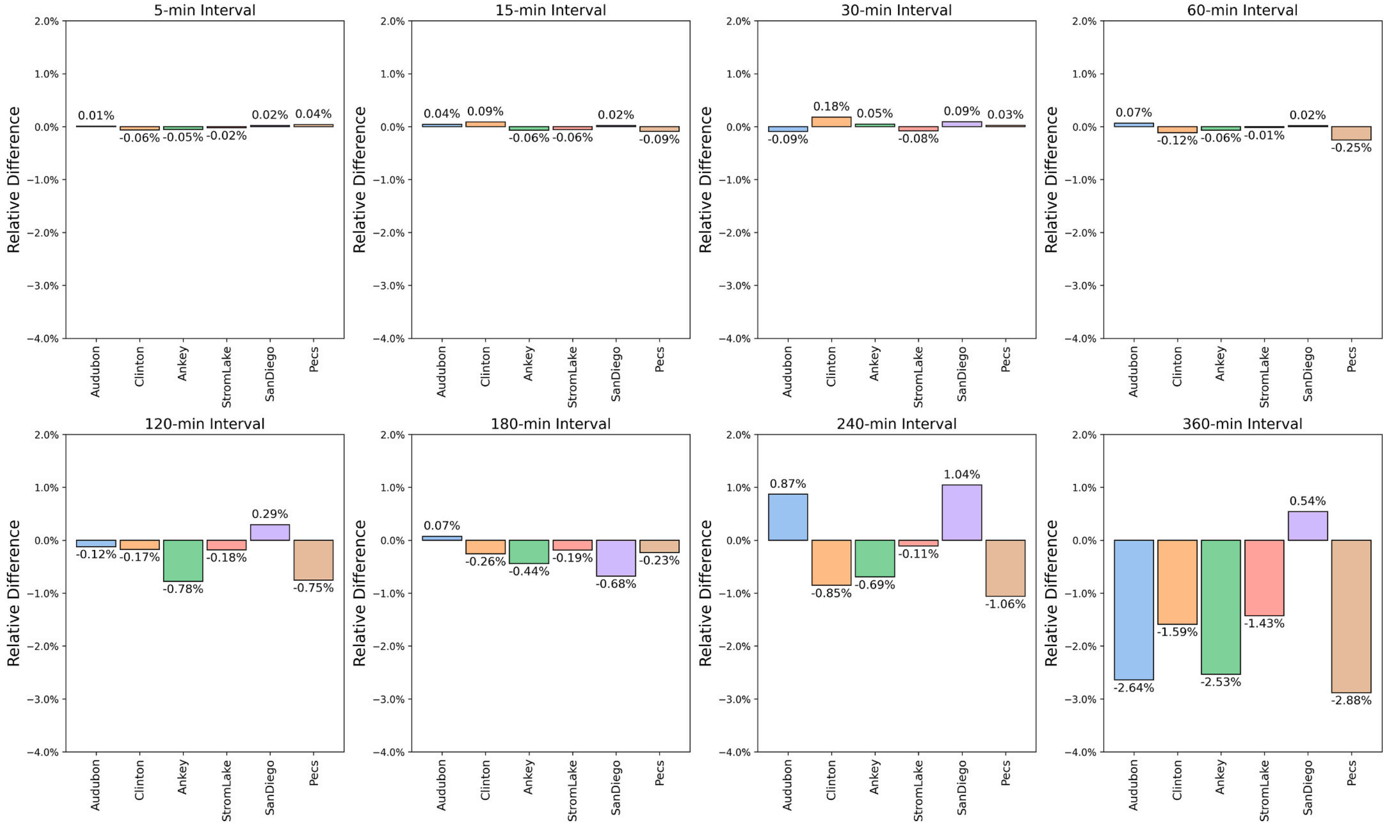


**Fig. 10.** Relative difference wind power generation compared to 1-min resolution.

**Table 1**
The quotient of the highest and lowest averages using lagged start timed sampling.

| Frequencies | Pécs | San Diego | Audubon | Ankeny | Clinton | Storm-Lake |
|---|---|---|---|---|---|---|
| Frequencies 1 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Frequencies 5 | 1.0033 | 1.0019 | 1.0015 | 1.0008 | 1.0014 | 1.0006 |
| Frequencies 10 | 1.0065 | 1.0041 | 1.0035 | 1.0015 | 1.0035 | 1.0015 |
| Frequencies 15 | 1.0103 | 1.0068 | 1.0036 | 1.0024 | 1.0042 | 1.0021 |
| Frequencies 30 | 1.0147 | 1.0099 | 1.0071 | 1.0050 | 1.0060 | 1.0041 |
| Frequencies 60 | 1.0247 | 1.0181 | 1.0123 | 1.0112 | 1.0088 | 1.0071 |

### *4.1. Stability of outputs for energy systems*

This part of the analysis focuses on evaluating the performance of the energy system model at varying time resolutions. Key variables such as power generation by wind turbines, solar panels, conventional power plants, and electricity demand are examined. This investigation aims to understand how temporal granularity influences the model's accuracy. The primary objective was to assess the relative deviation of results obtained at lower time resolutions from the reference benchmark, represented by the 1-min resolution model run. This benchmark is known for its precision and serves as a standard for accuracy. By comparing the outputs - namely Wind, Solar and Conventional PP production and Electricity Demand - of coarser time resolution models to this benchmark, the impact of reduced temporal granularity on the model's performance can be evaluated.

The relative differences in model outputs are visually depicted in Figs. 6 and 7, providing a clear representation of variable behavior across different time resolutions. These visual representations aid in comprehending trends and patterns within the data. As an example, the first value in Fig. 6 (−0.20 %) means that when running a model that uses data sampled at every 5 min, the deviation in the model's wind generation output differed by −0.20 % compared to the model using 1-min data. Please note that results are also plotted for more than 60-min intervals so the trend can be observed.

The results show that, as a general rule, when the time resolution becomes coarser, the variables exhibit greater deviations from the 1-min resolution benchmark. This trend aligns with the expectation that finer temporal resolutions capture more subtle changes in the energy system.

However, the relative deviations seem to be minor, especially when focusing on the 60-min models, where none of the measured outputs deviate by more than 1 % from the benchmark. This indicates that, even with a 60-min resolution, which is considerably coarser than the 1-min benchmark, the models maintain a high level of accuracy. These findings underscore the model's robustness and its ability to effectively represent the overall dynamics of the energy system.

### *4.2. Model performance across time*

This section dives deeper into analyzing intermittent renewable sources (solar and wind power) in isolation over several years to determine whether the results maintain robustness when examining data spanning multiple years. Both solar and wind power generation were calculated (as described in Sections 3.2.1 and 3.2.2) for the years 2009–2016 for the city of Pécs. As before, the objective is to assess the relative deviation of results obtained at coarser time resolutions from the reference benchmark, represented by the 1-min resolution model run.

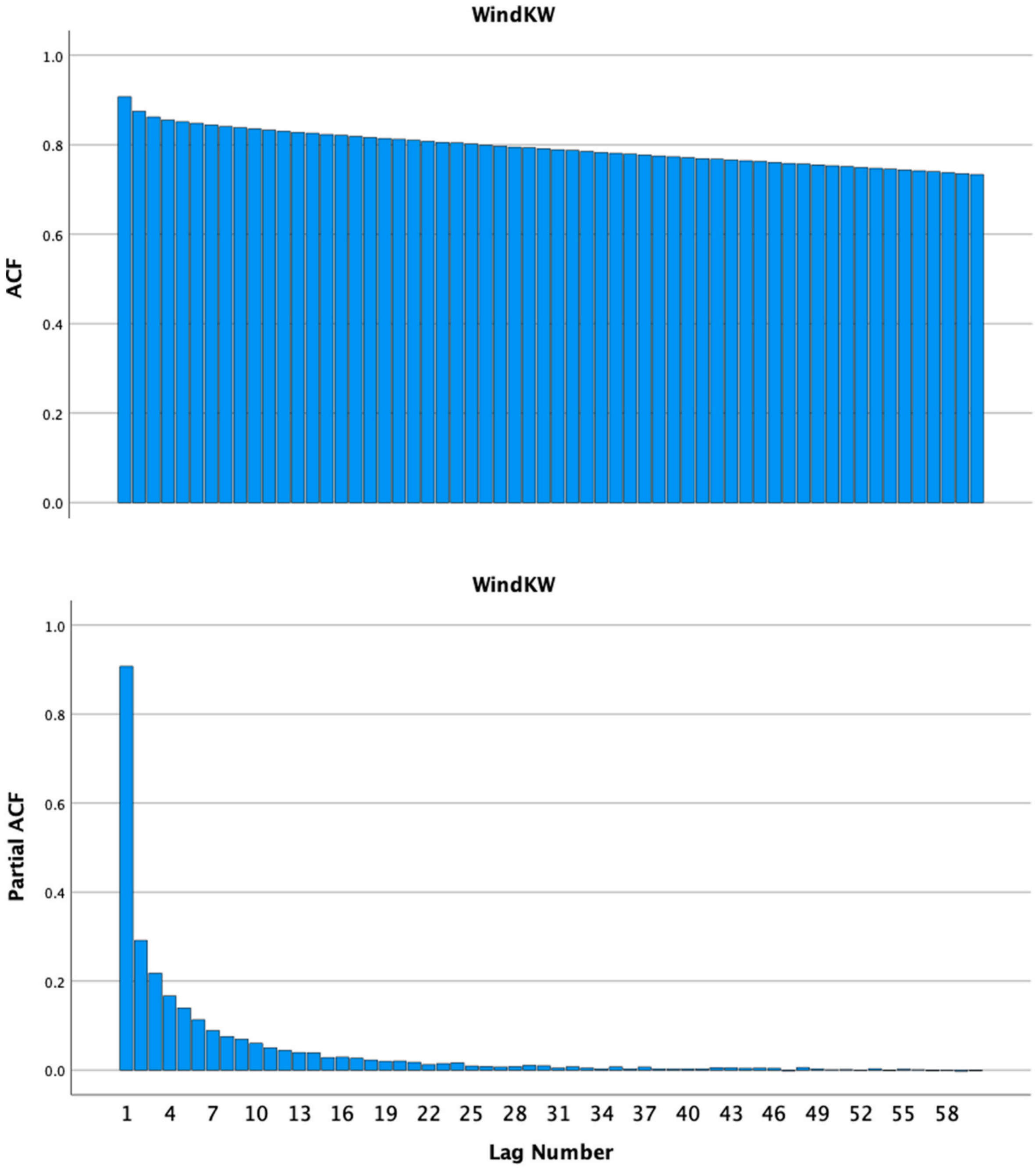


**Fig. 11.** AFC and PAFC of wind data 2016, Pécs.

The results for solar power generation are plotted in Fig. 8. For each of the 8 time intervals (5–360 min), bars represent the relative difference to the 1-min resolution solar outputs for each of the 7 years. For example, when using a 180-min time resolution model in 2011, there was a 4.56 % deviation from the 1-min model in solar output.

The results show that for none of the 7 years studies did the relative difference deviate for the 60-min model significantly. In fact, the biggest difference was 0.94 % for the 2015 model. It can be seen that as temporal resolutions get lower (2-h plus), the relative deviations do get larger, but the results give us no reason to question the accuracy of the 60-min model.

The same can be said for the results for wind power plotted in Fig. 9, which works similarly as Fig. 8, but for wind data. The coarser time resolution seems to affect the aggregated energy production of wind turbines, as there is an increasing trend in the deviation for all years. Due to the high intermittency and no apparent periodicity of when the wind speed is increasing or decreasing, a relatively high difference (even up to 5 %) from the minute-by-minute time resolution can be observed, but only with time resolutions such as 180 min or more. However, similarly to previous cases, the relative deviation remains modest (around 2 % at most) for the widely used 60-min resolution.

### 4.3. *Model performance across geographic locations*

In this section, the robustness of different time resolutions of the energy system model is examined when applied to various geographic locations. An examination of the model's behavior provides insights into whether the observed pattern of minimal relative deviation for models up to 60-min resolutions is consistent across distinct geographic settings. As described in Section 3.1.2, data was obtained for 6 locations with

**Table 2**
The within-hour tests for all the hours for all the geographic areas (60 min).

| | Pécs | San Diego | Audubon | Ankeny | Clinton | Storm-Lake |
|---|---|---|---|---|---|---|
| No. of Hours | 8784 | 17472 | 11280 | 10824 | 6000 | 15648 |
| Valid No. of Hours | 7381 | 17369 | 6216 | 6218 | 4014 | 10444 |
| With sign. trend | 3748 | 9571 | 3580 | 3752 | 2678 | 6669 |
| No. of the negative trend | 1876 | 4700 | 1853 | 1940 | 1315 | 3384 |
| No. of the positive trend | 1872 | 4871 | 1727 | 1812 | 1363 | 3285 |
| Mean of neg. parameter | −0.2712 | −0.1777 | −0.4748 | −0.4342 | −0.591 | −0.479 |
| The mean of pos. parameter | 0.2776 | 0.1715 | 0.4887 | 0.4421 | 0.4873 | 0.4757 |
| Ratio, No. of −/+ trends | 1.0021 | 0.9649 | 1.073 | 1.0751 | 0.9648 | 1.0301 |
| Ratio. mean of −/+ trends | −0.9769 | −1.0362 | −0.9716 | −0.9821 | −1.2128 | −1.0069 |

distinctively different wind profiles. Wind power generation models were run in accordance with the description in Section 3.2.2, and the resulting data was analyzed. The same time resolutions were applied as in the previous sections and compared to the benchmark 1-min resolution model run with the same data.

As depicted in Fig. 10, the findings align closely with those from earlier sections of the study. The chart illustrates the relative difference compared to the 1-min model outputs across all 8 time resolutions, with distinct color bars representing each of the 6 study locations. Regardless which of the diverse wind profiles of the 6 locations the data is coming from, the production of wind power from wind turbines do not deviate significantly when using time resolutions up to 60 min, and it can be argued that even larger temporal resolutions, such as 2–3 h yield acceptable results/deviations.

### 4.4. The effect of lagged starting time of sampling

Examining the potential impacts of varying starting points for periodic sampling is essential to check whether the small differences observed are starting time specific variations, or if they consistently demonstrate that every periodic sample - regardless of the starting time - exhibits very little deviation from the 1-min resolution result. For instance, it examines whether outcomes would differ if the hourly sample point were not taken at the top of the hour (e.g., 2:00, 3:00, 4:00) but were shifted by 30 min (e.g., 2:30, 3:30, 4:30). This was conducted for every possible starting point and for every time resolution up to 60 min for wind power generation across all six locations, yielding the results summarized in Table 1.

As an example, the 1.0068 in the Frequencies 15 row of the San Diego column means that among the 15 different starting points for sampling every 15 min, the ratio of the highest to the lowest average wind power generated by the simulation was 1.0068, i.e., there was less than a 1 % difference. The modest values displayed in Table 1 collectively indicate that the results remain stable, and the minimal relative differences between coarser resolution outputs and the 1-min resolution outputs are not contingent on the starting time of sampling.

### 4.5. Exploration of trend effect

Fig. 1 in the Introduction section shows how periodical sampling, such as the classical 60-min time interval samples, can lead to consistent under- or overestimation of actual values. Since this phenomenon is inherent and inevitable with periodical sampling, it is important to examine whether there is a significant imbalance between under-overestimations.

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are statistical methods that address the question of relationships between a time series and its lags. ACF measures both direct and indirect correlation between the time series and its lags, while PACF isolates the correlation at specific lags by controlling for other intervening lags. Both ACF and PACF were applied to the wind power production datasets from all 6 locations; Fig. 11 illustrates the results from Pécs in 2016.

In the figure, the y-axis denotes the relative difference, measuring correlation strength, with values between −1.0 (perfect negative correlation) and 1.0 (perfect positive correlation). The x-axis displays the lag number, indicating intervals between compared data points. The functions reveal significant relationships and trends within the 60-min data. The ACF shows consistent correlation values for all lags, while the PACF has a strong correlation at the first lag (0.9) which quickly drops off, suggesting that the time series might be best described by a first-order autoregressive model. In contrast, the correlation values in the ACF function suggest a consistent trend throughout the 60-min period, maintaining a correlation exceeding 0.7 even with a 59-min lag between data points. These observed patterns suggest systematic variations within each hour, indicating that periodic sampling might lead to systematic under- or overestimations. Given the indications from both the ACF and PACF analyses pointing towards potential underlying trends in the time series data, our subsequent examination looks into understanding these patterns across all six locations using trend analysis. Trend analysis is a statistical method that identifies and assesses patterns in data over time, revealing the direction a variable is moving, whether up, down, or consistently. It highlights significant trends not immediately evident in raw data. The results are presented in Table 2.

The Number of Hours row signifies the total hours considered for analysis. Hours characterized by zero variance (e.g., 60 consecutive zero values) are excluded when calculating the "Valid No. of Hours." The number of hours exhibiting significant trends is presented in the third row. Subsequent rows show the count of negative and positive trends, along with the average estimated trend parameters, which allow us to observe the "cancelling effect" of these trends. Finally, the ratio of negative to positive trends and the average mean values are provided for further analysis.

It is evident that strong autocorrelation exists, but with an equal occurrence of negative and positive cases with virtually identical magnitudes. This means that despite notable autocorrelation in 60-min time series data, since it is characterized by equal occurrences of both negative and positive trends that effectively cancel each other out, there is no reason to believe that hourly sampling causes consistent under- or overestimation and thus is suitable for capacity planning purposes.

## 5. Conclusion and policy implications

This research provides valuable insights into the impact of time resolution in capacity planning simulations for energy systems with intermittent renewables. Firstly, it demonstrates that hour-based data is nearly as effective as minute-based data, thus, minute-level time resolution may not be necessary for accurate capacity planning of intermittent renewables. This conclusion is significant for policy formulation, as it ensures the continued validity of the plethora of existing hour-based resolution models in the face of increasing renewable energy integration. It is likely that the behavior of intermittent renewables in most parts of the world is similar to the diverse geographical areas discussed here, so the result is not limited to a specific geography. As a result, the research emphasizes the dependability of established software applications that employ hourly time resolution to simulate upcoming power plant systems featuring intermittent capabilities. These software tools retain their relevance for capacity planning objectives.

While some studies discussed in the literature review have raised concerns about coarser time resolutions in systems such as electric car charging, household energy systems, or PV-battery modules, our research suggests that these concerns may not be as relevant in the context of energy system planning. The characteristics of energy systems, even those with intermittent renewables, allow for greater flexibility in time resolution without resulting in significant modeling inaccuracies. This is because they are typically applied to urban or larger-scale systems, whereas the cited articles focused on systems with a non-negligible storage capacity relative to the system, and occasionally or exclusively relied on photovoltaic input as their sole energy source. Future research could collect data and run analyses for an even more diverse set of geographical locations, where the simulations could further validate the effects of different time resolutions.

In conclusion, this study reassures that a time resolution of up to 60 min is suitable for capacity planning in energy systems and can aid in policy formulation without introducing systematic errors.

## Author contribution

Kiss Viktor: Conceptualization, Methodology, Software, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization; Kiss Tibor: Conceptualization, Methodology, Software, Validation, Formal analysis, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration; Hetesi Zsolt: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing.

## 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.

## Data availability

Data will be made available on request.

## References

[1] Wierzbowski M, Filipiak I, Lyzwa W. Polish energy policy 2050 – an instrument to develop a diversified and sustainable electricity generation mix in a coal-based energy system. Renew Sustain Energy Rev 2017;74:51–70. https://doi.org/10.1016/j.rser.2017.02.046.

[2] Sluisveld van AE, Hof A, Vuuren van DP, Boot P, Criqui P, Matthes FC, Notenboom J, Pedersen SL, Pfluger B, Watson J. Low-carbon strategies towards 2050: comparing ex-ante policy evaluation studies and national planning processes in Europe. Environ Sci Pol 2017;78:89–96. https://doi.org/10.1016/j.envsci.2017.08.022.

[3] Mulholland E, Rogan F, O Gallachoir BP. From technology pathways to policy roadmaps to enabling measures – a multi-model approach. Energy 2017;138:1030–41. https://doi.org/10.1016/j.energy.2017.07.116.

[4] Hache E, Palle A. Renewable energy source integration into power networks, research trends and policy implications: a bibliometric and research actors survey analysis. Energy Pol 2019;124:23–35. https://doi.org/10.1016/j.enpol.2018.09.036.

[5] Sasanpour S, Cao KK, Gils HC, Jochem P. Strategic policy targets and the contribution of hydrogen in a 100% renewable European power system. Energy Rep 2021;7:4595–608. https://doi.org/10.1016/j.egyr.2021.07.005.

[6] Zhou W, Hagos DA, Stikbakke S, Huang L, Cheng X, Onstein E. Assessment of the impacts of different policy instruments on achieving the deep decarbonization targets of island energy systems in Norway – the case of Hinnøya. Energy 2022;246:123249. https://doi.org/10.1016/j.energy.2022.123249.

[7] Paardekooper S, Lund H, Thellufsen JZ, Bertelsen N, Mathiesen BV. Heat Roadmap Europe: strategic heating transition typology as a basis for policy recommendations. Energy Efficiency 2022;15:32. https://doi.org/10.1007/s12053-022-10030-3.

[8] Lund H, Mathiesen BV. Energy system analysis of 100% renewable energy systems - the case of Denmark in years 2030 and 2050. Energy 2009;34:524–31. https://doi.org/10.1016/j.energy.2008.04.003.

[9] Connolly D, Lund H, Mathiesen BV, Leahy M. The first step towards a 100% renewable energy-system for Ireland. Appl Energy 2011;88:502–7. https://doi.org/10.1016/j.apenergy.2010.03.006.

[10] Krajačić G, Duić N, Carvalho M da G. How to achieve a 100% RES electricity supply for Portugal? Appl Energy 2011;88:508–17. https://doi.org/10.1016/j.apenergy.2010.09.006.

[11] Doepfert M, Castro R. Techno-economic optimization of a 100% renewable energy system in 2050 for countries with high shares of hydropower: the case of Portugal. Renew Energy 2021;165:491–503. https://doi.org/10.1016/j.renene.2020.11.061.

[12] Elliston B, MacGill I, Diesendorf M. Comparing least cost scenarios for 100% renewable electricity with low emission fossil fuel scenarios in the Australian National Electricity Market. Renew Energy 2014;66:196–204. https://doi.org/10.1016/j.renene.2013.12.010.

[13] Morel J, Obara S, Morizane Y. Operation strategy for a power grid supplied by 100% renewable energy at a cold region in Japan. J Sustain Develop Energy, Water and Environ Syst 2014;2:270–83. https://doi.org/10.13044/j.sdewes.2014.02.0022.

[14] Sáfián F. Modelling the Hungarian energy system – the first step towards sustainable energy planning. Energy 2014;69:58–66. https://doi.org/10.1016/j.energy.2014.02.067.

[15] Kiss VM, Hetesi Z, Kiss T. Issues and solutions relating to Hungary's electricity system. Energy 2016;116:329–40. https://doi.org/10.1016/j.energy.2016.09.121.

[16] Campos J, Csontos C, Munkacsy B. Electricity scenarios for Hungary: possible role of wind and solar resources in the energy transition. Energy 2023;278:127971. https://doi.org/10.1016/j.energy.2023.127971.

[17] Krakowski V, Assoumou E, Mazauric V, Maïzi N. Feasible path toward 40–100% renewable energy shares for power supply in France by 2050: a prospective analysis. Appl Energy 2016;184:501–22. https://doi.org/10.1016/j.apenergy.2016.03.094.

[18] Weiss O, Bogdanov D, Salovaara K, Honkapuro S. Market designs for a 100% renewable energy system: case isolated power system of Israel. Energy 2017;119:266–77. https://doi.org/10.1016/j.energy.2016.12.055.

[19] Pursiheimo E, Holttinen H, Koljonen T. Path toward 100% renewable energy future and feasibility of power-to-gas technology in Nordic countries. IET Renew Power Gener 2017;11:1695–706. https://doi.org/10.1049/iet-rpg.2017.0021.

[20] Sadiqa A, Gulagi A, Breyer C. Energy transition roadmap towards 100% renewable energy and role of storage technologies for Pakistan by 2050. Energy 2018;147:518–33. https://doi.org/10.1016/j.energy.2018.01.027.

[21] Child M, Bogdanov D, Breyer C. The role of storage technologies for the transition to a 100% renewable energy system in Europe. Energy Proc 2018;155:44–60. https://doi.org/10.1016/j.egypro.2018.11.067.

[22] Hansen K, Mathiesen BV, Skov IR. Full energy system transition towards 100% renewable energy in Germany in 2050. Renew Sustain Energy Rev 2019;102:1–13. https://doi.org/10.1016/J.RSER.2018.11.038.

[23] Bogdanov D, Toktarova A, Breyer C. Transition towards 100% renewable power and heat supply for energy intensive economies and severe continental climate conditions: case for Kazakhstan. Appl Energy 2019;253:113606. https://doi.org/10.1016/j.apenergy.2019.113606.

[24] Yue X, Patankar N, Decarolis J, Chiodi A, Rogan F, Deane JP, O'Gallachoir B. Least cost energy system pathways towards 100% renewable energy in Ireland by 2050. Energy 2020;207:118264. https://doi.org/10.1016/j.energy.2020.118264.

[25] Korkeakoski M. Towards 100% renewables by 2030: transition alternatives for a sustainable electricity sector in Isla de la Juventud, Cuba. Energies 2021;14:2862. https://doi.org/10.3390/en14102862.

[26] Østergaard PA, Lund H. A renewable energy system in Frederikshavn using low-temperature geothermal energy for district heating. Appl Energy 2011;88(2):479–87. https://doi.org/10.1016/j.apenergy.2010.03.018.

[27] Kiss VM. Modelling the energy system of Pécs – the first step towards a sustainable city. Energy 2015;80:373–87. https://doi.org/10.1016/j.energy.2014.11.079.

[28] Z Zhao G, Guerrero JM, Jiang K, Chen S. Energy modelling towards low carbon development of Beijing in 2030. Energy 2017;121:107–13. https://doi.org/10.1016/j.energy.2017.01.019.

[29] Bačeković I, Østergaard PA. A smart energy system approach vs a non-integrated renewable energy system approach to designing a future energy system in Zagreb. Energy 2018;155:824–37. https://doi.org/10.1016/j.energy.2018.05.075.

[30] Yazdanie M, Densing M, Wokaun A. Cost optimal urban energy systems planning in the context of national energy policies: a case study for the city of Basel. Energy Pol 2017;110:176–90. https://doi.org/10.1016/j.enpol.2017.08.009.

[31] Østergaard PA, Lund H, Thellufsen JZ, Sorknæs P, Mathiesen BV. Review and validation of EnergyPLAN. Renew Sustain Energy Rev 2022;168:112724. https://doi.org/10.1016/j.rser.2022.112724.

[32] Haydt G, Leal V, Pina A, Silva CA. The relevance of the energy resource dynamics in the mid/long-term energy planning models. Renew Energy 2011;36(11):3068–74. https://doi.org/10.1016/j.renene.2011.03.028.

[33] Bistline JE. The importance of temporal resolution in modeling deep decarbonization of the electric power sector. Environ Res Lett 2021;16(8):084005. https://doi.org/10.1088/1748-9326/ac10df.

[34] Shirizadeh B, Quirion P. Do multi-sector energy system optimization models need hourly temporal resolution? A case study with an investment and dispatch model applied to France. Appl Energy 2022;305:117951. https://doi.org/10.1016/j.apenergy.2021.117951.

[35] Simolin T, Rauma K, Rautiainen A, Järventausta P, Rehtanz C. Assessing the influence of the temporal resolution on the electric vehicle charging load modeling accuracy. Elec Power Syst Res 2022;208:107913. https://doi.org/10.1016/j.epsr.2022.107913.

[36] Beck T, Kondziella H, Huard G, Bruckner T. Assessing the influence of the temporal resolution of electrical load and PV generation profiles on self-consumption and sizing of PV-battery systems. Appl Energy 2016;173:331–42. https://doi.org/10.1016/j.apenergy.2016.04.050.

[37] Jiménez-Castillo G, Rus-Casas C, Tina GM, Muñoz-Rodriguez FJ. Effects of smart meter time resolution when analyzing photovoltaic self-consumption system on a daily and annual basis. Renew Energy 2021;164:889–96. https://doi.org/10.1016/j.renene.2020.09.096.

[38] Metrological station dataset, university of pecs, faculty of sciences, Hungary Retrieved from http://joido.ttk.pte.hu/en/. [Accessed 18 August 2018].

[39] Solar Position and Intensity (SOLPOS) Calculator, National Renewable Energy Laboratory (NREL), Retrieved from https://midcdmz.nrel.gov/solpos/solpos.html [accessed 25 September 2023].

[40] EON Hungary, Hungarian Subsidy of E.ON Group, https://www.eon.hu/hu.

[41] The Iowa Environmental Mesonet (IEM). Environmental data collection and storage. Retrieved from https://mesonet.agron.iastate.edu/[accessed 18 August 2018].

[42] Holmgren WF, Hansen CW, Mikofski MA. Pvlib python: a python package for modeling solar energy systems. J Open Source Softw 2018;3(29):884. https://doi.org/10.21105/joss.00884.

[43] Solar Collectors and Photovoltaic in energyPRO with array shading. EMD International A/S, Niels Jernesvej 10, 9220 Aalborg Ø, PP: 22. Retrieved from: https://www.emd-international.com/files/energypro/Solar%20Collector%20and%20Photovoltaic%20in%20energyPRO.pdf [accessed 23 September 2023].

[44] Wind turbine models. Hummer H25.0-100KW. Retrieved from, https://en.wind-turbine-models.com/turbines/1682-hummer-h25.0-100kw. [Accessed 23 September 2023].