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Selected aspects of generating short-term electricity demand forecasts, taking into account renewable energy sources

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Abstract: The risk of a decline in the quality of electricity demand forecasts in the short term increases due to the increase in the installed capacity of renewable energy sources (RES). This is mainly due to the high daily variability of electricity production from renewable sources, which is strongly dependent on local weather conditions. Production from renewable energy sources is a very complex time series, additionally reinforced by a significant increase in its share in total production. This applies in particular to photovoltaic sources in low-voltage networks. There is therefore an urgent need to improve the quality of forecasts in this area. The main goal of the research was to verify statistical models that often achieve good results in the complex problem of forecasting electricity demand. The main objective, regarding daily forecasts of consumers' demand for electricity, was achieved through the implementa-tion of intermediate objectives, including the development of a methodology for estimating electricity generated by photovoltaic installations.

Key words: photovoltaic, micro installation, prosumer, renewable source of energy

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Introduction

In the last 5 years, there has been an intensive development of small, distributed photovoltaic sources installed for home use (Machał, Remiorz i Bukowiec, 2022). In February 2023, the installed capacity in one of the electricity supplier amounted to 2.89 GW. Forecasting the power output of these PV systems has become critical to market and grid efficiency. In the last 7 years, peak summer demand has reached over 4.1 GW. The share of installed capacity is already 70% and is still growing. The increase in micro-installations is already significantly changing the load characteristics of the graphics unit of this electricity supplier. Micro PV installations, with a capacity up to 50 kW, connected to the Distribution System Operator (DSO), are scattered over the area of several provinces. For all micro installations from this area, the electricity supplier is obliged to make settlements in accordance with the rules set out in the Renewable Energy Sources Act.

Fig. 1. Distribution area where the electricity supplier has the largest number of customers with micro-installations (TAURON Dystrybucja S.A., 2023)

Source: TAURON Dystrybucja S.A., 2023.

Demand forecasts are typically based on statistical models (e.g., artificial neural networks) that can capture non-linear relationships between electricity load and a number of calendar variables, historical data, and weather. A significant number of PV installations in the distribution network changes these relationships through a strong correlation of photovoltaic generation with weather conditions and variability over time. Therefore, previous forecasting approaches that do not take into account the significant impact of PV, will generally show worse forecast performance.

Cloud cover is the main factor affecting the level of solar radiation intensity (Global Horizontal Irradiation - GHI) reaching the earth's surface. Clouds have very different characteristics. They arise, move, change and dissipate within hours and sometimes even minutes. So when cloud cover moves or changes quickly, forecasting solutions should also be fast (Paul, De Michele, Najafi i Avesani, 2022). The current electricity contracting process assumes forecasting demand for a horizon of 18 to 42 hours. In this case, the intensity of solar radiation (explanatory variable) is not sufficient to correctly forecast energy demand, because its forecasts are characterized by high uncertainty.

GHI forecasting methods

GHI forecasting has been developed in recent years using a wide range of methods. The most commonly used forecast models in this field are statistical models, models based on the sky images from ground-based cameras, satellite image models and numerical models (NWP).

Statistical models are models based on time series prediction. The most popular of these are linear models such as autoregressive (AR) and autoregressive moving average (ARMA) and machine learning techniques such as artificial neural networks (ANN) (Heinemann, 2006) (Hontoria, Aguilera i Zufiria, 2002) (Lauret, David, Fock, Bastide i Riviere, 2006).

Forecasting from ground-based sky images: models based on sky images obtained with 180° cameras. Sky images lead to knowing cloud conditions a few minutes ahead (Paulescu i inni, 2023) (Lin, Zhang i Wang, 2023).

Satellite image models. Geostationary satellites take pictures of the atmosphere all over the Earth with a time resolution of less than an hour. The large development that has taken place in satellite data acquisition in recent years makes this technique a very useful tool to improve GHI forecasting (Hammer, Heinemann i Lorenz, 1999) (Liwei i inni, 2020).

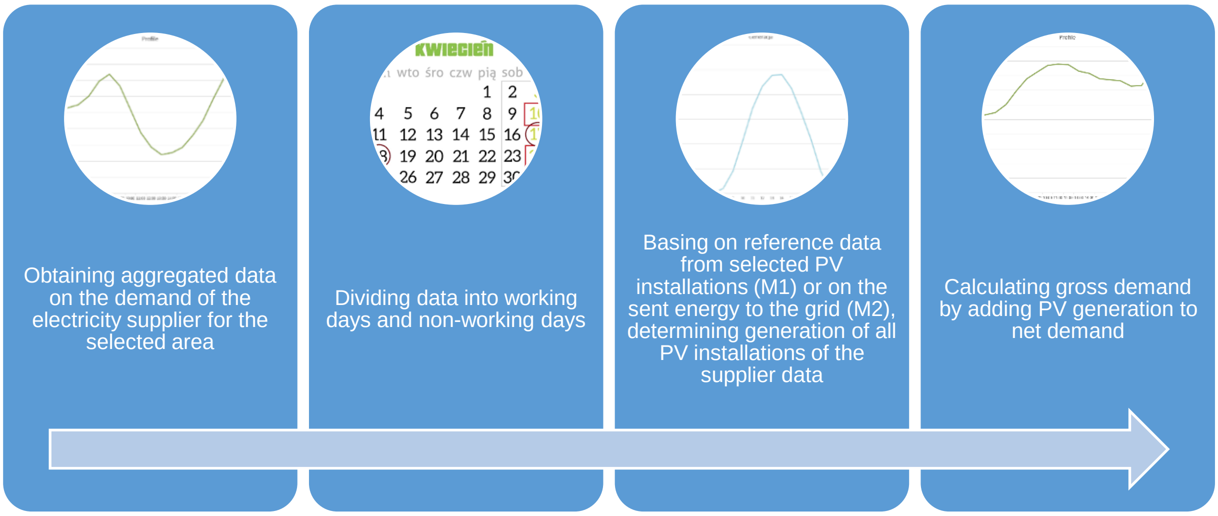
Numerical weather forecasting models (NWP) based on physical models to estimate atmospheric conditions, including cloud formation and dissolution. Physical models are described by differential equations solved by numerical methods. NWP models offer forecasting time horizons from a few hours to 15 days ahead (Heinemann, 2006) (Razagui, Abdeladim, Semaoui, Hadj Arab i S., 2020).

Despite continued advances in weather forecasting, there is a high risk of error in forecasting tomorrow's cloud sizes and paths (Deo i inni, 2023) (Lemos-Vinasco, Bacher i Møller, 2021). An additional factor of forecast uncertainty is the increasingly common use of energy storage, heat storage and electrical energy management systems in the facility (Lemos-Vinasco, Bacher i Møller, 2021) (Zhao, Gao, Qian i Ge, 2021) (Wu i inni, 2022). Due to the fact that the forecast of electricity demand carried out on day n for day n+1 is based mainly on the solar radiation intensity, which is an uncertain explanatory variable, increasing uncertainty in these forecasts can be expected.

Net demand, gross demand

The figure below shows a workflow diagram for generating the amount of electricity from photovoltaic sources and then generating a gross demand profile.

Fig. 2. Workflow diagram



Source:own work.

In accordance with the instructions of the distribution network (Instrukcja Ruchu i Eksploatacji Sieci Dystrybucyjnej, 2023), DSO determines the measurement data using the local measurement system. The DSO obtains this data in the form of:

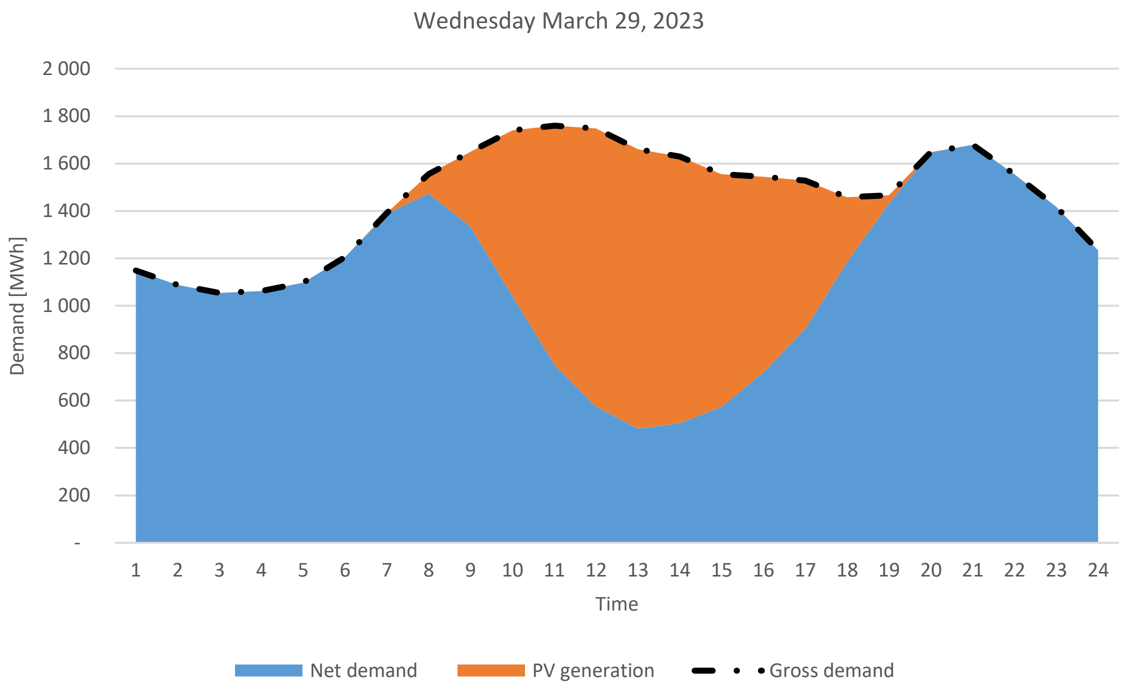
a) Hourly consumption/distribution of energy by the customer, determined on the basis of data from meters - hourly data

b) Periodic states (indications) of energy meter counters, and DSO uses standard profiles to determine hourly values.

For the purposes of Balancing Market settlements, the DSO designates and makes available hourly measurement and settlement data as aggregated Energy Delivery Sites (EDS). These data, due to their relatively quick acquisition time - 3 days after the end of the day, are used to forecast area demand. Correction of data by the DSO in accordance with the instructions of the distribution network is performed in month m and may apply to month's m-2, m-4 and m-15 (for example, October, August this year and September from the previous year may be adjusted in December).

Reconstruction of generating gross demand data are shown in the chart below (see fig. 3).

Fig. 3. Reconstruction of gross demand

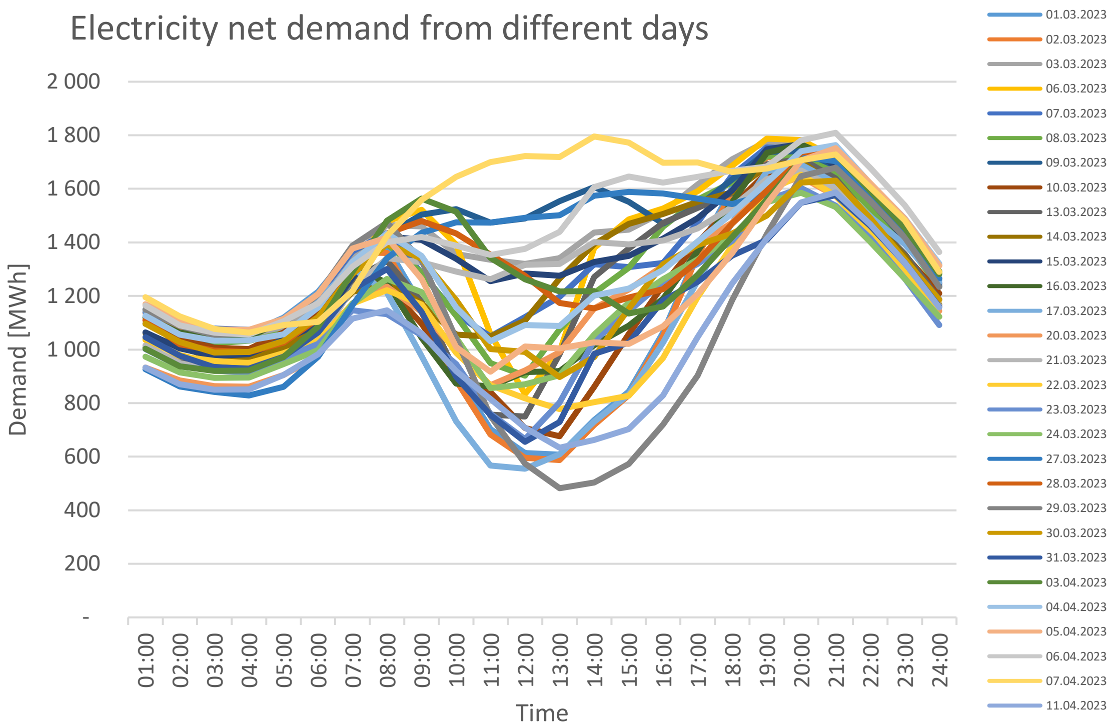


Source:own work.

The graph shows the demand profiles for March 29, 2023. It was sunny most of the day, with over 8 GWh of demand reduction due to PV generation. The dashed line in the graph shows the reconstructed gross demand , the orange area is the estimated demand reduction as a result of PV generation, and the blue area is the net demand. This approach to data analysis enables better forecasting of rapidly changing electricity demand. In addition to improved forecasting performance, the reconstructed gross demand profiles also provide important information for grid operators. They can identify the amount of electricity that can suddenly "appear" on a clear day or "disappear" during periods of heavy rain or snowfall (Power Grid, 2023).

Electricity net demand, which takes into account the impact of behind-the-meter generation by prosumers, is shown in the chart below (see fig. 4).

Fig. 4. Electricity net demand



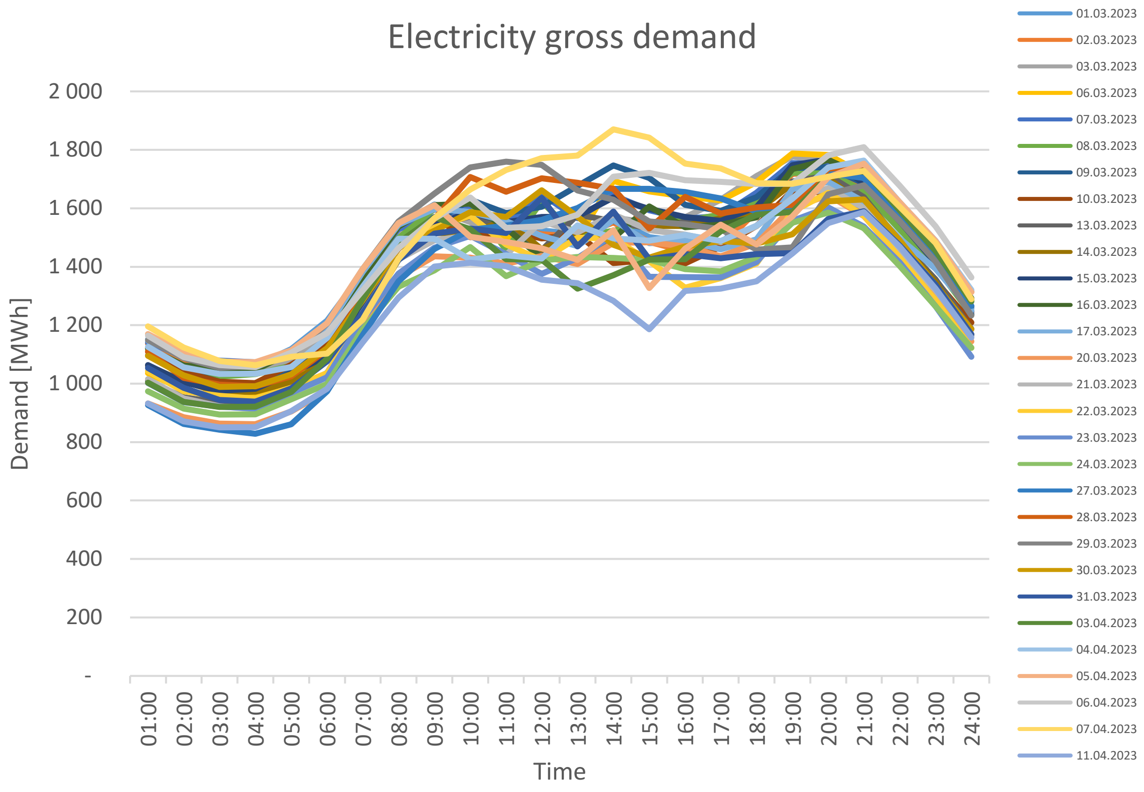
Source:own work.

The presented daily profiles contain data from March 1 to April 11, 2023 and include only working days. The previous characteristic profile with a night depression and a day peak was disturbed by the generation of PV installations. The current daily profiles in the literature are called the "duck curve" (Rubasinghe i inni, 2023) (Qingchun Hou a, Du, Miao, Peng i Kang, 2019). With generation data from these sources, it is possible to reconstruct the actual (Zap_{netto}) electricity demand profile (Zap_{brutto}) described with the formula:

$$Zap_{brutto_h} = Zap_{netto_h} + E_{Gen_h}$$

Photovoltaic generation (E_{Gen_h}) was determined indirectly, according to the method described in chapter 0. As a result of this work, a gross demand profile was created. It is shown in Figure 5.

Fig. 5. Electricity gross demand



Source:own work.

To compare the gross demand and net demand profiles, the coefficient of variation was used (Kolańska-Płuska i Gallus, 2022), which can be defined by the formula:

$$Cv = \frac{\sigma}{\bar{x}}$$

Cv is the coefficient of profile variation, $\bar{x}$ is the average demand in a day, σ is the sample standard deviation defined by the formula:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N}}$$

x_i –is the demand for i-hour

The interpretation of the coefficient Cv is based on comparing it with standard values. The coefficient is expressed as a percentage. Value below 25% means low volatility. Between 25% and 45% means average volatility and between 45% and 100% means strong volatility.

Autoregressive models (ARX - arima and mARX - arima with an independent variable (Nowotarski i Weron, 2016)) were used for the forecasts. An integrated seasonal auto-regression and moving average model ARIMA(p, d, q)×(P, D, Q)m were used to forecast the series (Koohi-Kamali, Abd. Rahim i Sobri, 2018):

$$\Phi(B^m)\phi(B)(1-B^m)^D(1-B)^d y_t = c + \Theta(B^m)\theta(B)\xi_t$$

y_t is the term of the time series, ξ_t is a white noise process with zero mean and variance σ 2, *m* is the length of the weekly cycle (168 h), *B* is the backshift operator, *d* and *D* are the orders of differentiation (ordinary and seasonal), φ(.), Φ(.), θ(.) and Θ(.) are polynomials of degree *p*, *q*, *P* and *Q*, respectively, and *c* is a constant.

Forecasts were compared on the basis of standard assessments: Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). MAPE is one of the most commonly used KPIs to measure forecast accuracy. It is calculated according to the formula:

$$MAPE = \frac{1}{n}\sum_{1}^{n}\frac{|y - y'|}{y}$$

y is actual data, *y'* is forecast

MAPE is the average of absolute errors divided by demand (each period separately). MAPE divides each error individually by the actual data, so it is skewed: high errors during periods of low demand significantly increase MAPE. For this reason, MAPE optimization will result in a forecast that will most likely be below demand.

RMSE is a very helpful indicator. It is defined as the square root of the mean squared error and can be calculated by the formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(y - y')^2}$$

y is actual data, *y'* is forecast

RMSE does not treat every error the same. Gives more weight to the most significant errors. This means that it only takes one big mistake to get a high RMSE.

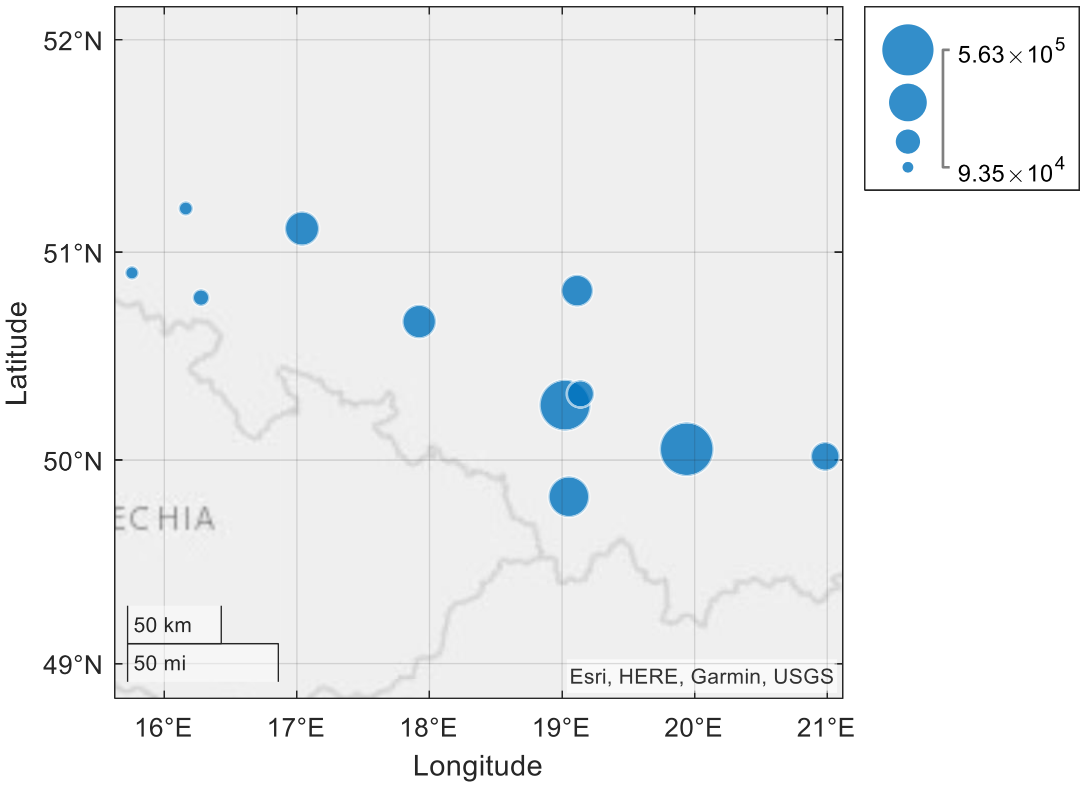
The calculations were performed on a computer with an Intel Core i5 processor (2 x 2.40GHz), 16 GB of installed RAM using Matlab software (Mathworks, 2021).

Generation behind the meter

A process of collecting data of the power installed in photovoltaic micro installations and their actual generation is proposed to take this factor into account in demand forecasts. This will enable monitoring geospatial trends in the growth of rooftop micro-installations.

Due to the high number of photovoltaic micro installations (hundreds of thousands), it is not possible to directly monitor the production of all PV installation (Gong, chen, Ji, Tang i Zhou, 2023). It is necessary to obtain data from a sufficient number of PV installation, which will be the basis for forecasting. In order to achieve this, data from several reference installations, were obtained. The data was divided geographically in the area of operation of the electricity supplier and hourly averaged in the next step. The spatial arrangement of the reference micro installations is shown on the map below (Figure 6). This method was marked as M1.

Fig. 6. Spatial distribution of reference photovoltaic installations with installed power



Source:own work.

Data on installed power and efficiency are scaled to determine the production of PV installations, taking into account the effects of local weather and the geographical heterogeneity of PV mirco installations. The estimated amount of energy produced by micro installations in the M1 method was determined in accordance with the following algorithm:

1. Obtaining data on hourly production from reference PV installations
2. Calculation of the coefficient of energy produced according to the formula:

$$W_{ER_{ih}} = \frac{ER_{ih}}{Pi}$$

ER_{ih}- Hourly actual production data from i - installation [kWh]

Pi- Installed power of i - installation [kWp]

3. Calculation of the average factor of energy produced in an hour:

$$W_{ER_h} = \frac{1}{n}\sum_{i}^{n} W_{ER_{ih}}$$

n - number of reference installations

4. Determination of the estimated generation of the area in an hour, according to the formula:

$$E_{Obsz_h} = P_{Obsz_h} W_{ER_h}$$

P_{Obsz_h} - power installed in a given period in the area [kWp][3]

An imperfection in this study is the relatively small number of PV installations with high installed power. It was therefore decided to use the data of electricity sent by prosumers to the distribution grid. The estimated amount of energy produced by micro-installations in the M2 method was determined in accordance with the following algorithm:

1. Obtaining data on the amount of electricity send to the distribution grid by micro-installations (E_{OD}).
2. Choosing of reference PV installations in the selected area. When choosing an installation, you should choose places where the density of installations is the highest and nontypical installations should be rejected (e.g. facing east or west, installations on trackers that achieve above-average performance).
3. Obtaining data on the amount of energy generated by reference installations. The data can be obtained, for example, from the website www.pvmonitor.pl .
4. Calculating the coefficient of energy produced according to the formula:

$$W_{ER_{it}} = \frac{ER_{it}}{P_i}$$

ER_{it}- actual data on production from i -installation in the period t [kWh], t – hour, day, week, month

P_i- Installed power of this installation [kWp]

5. Calculating the average coefficient of energy produced in period t:

$$W_{ER_t} = \frac{1}{n}\sum_{i}^{n} W_{ER_{it}}$$

n - number of reference installations

6. Determining the estimated PV generation of the area in period t, according to the formula:

$$E_{Gen_t} = P_{Obsz_t} W_{ER_t}$$

P_{Obsz_t} - power installed in period t in the studied area [kWp]

7. Determining the coefficient of energy sent to the distribution network:

$$W_{EO_t} = E_{OD_t} / E_{Gen_t}$$

8. Determining the hourly generation profile:

$$E_{Gen_h} = E_{OD_h} / W_{EO_t}$$

[3] Installed capacity varies over time and is currently on an upward trend.

Results

In the analyzed data, due to the impact of photovoltaic generation on the level of electricity demand, the variability at night is over 3 times lower than the variability during daytime hours. The averaged statistics are shown in the table below (see fig. 7).

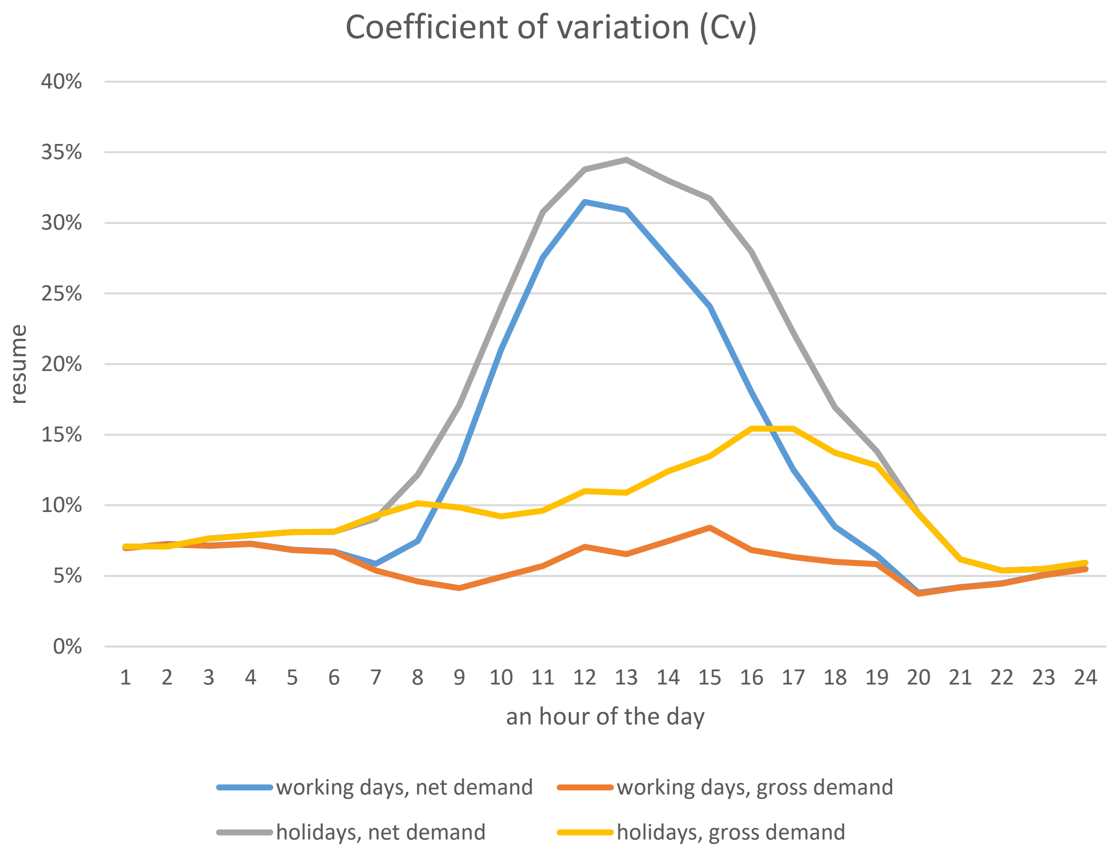
Fig. 7. Average statistics of daily profiles

Pointer – name	Working Net Demand	Working Gross Demand	Holiday Net Demand	Holiday Gross Demand
Minimum	958	1 222	806	1 012
Maximum	1 527	1,555	1 396	1 439
Mean	1 248	1 393	1 108	1 238
Standard deviation	146	82	174	122
Average coefficient volatility (Cv)	12%	6%	16%	10%

Source:own work.

For the net demand in analyzed period, average coefficient on working days was 12%, and 16% on holidays. After transforming the data into gross demand according to the M1 method, this coefficient was reduced to 6% on working days and 10% on holidays. For comparison, in the corresponding period of 2016, when the installed power in PV was approximately 0.2% of the currently installed power, the average coefficient of variation was 7.5%. Average hourly coefficients of variation are presented in the chart below (Figure 8).

Fig. 8. Average hourly coefficients of variation by working days and holidays



Source:own work.

The results of forecasting in the selected area are presented below. The data for learn models was 2022 year, and the test period was the data from January 1 to March 31, 2023. The data were presented in the following layout:

- Net demand - data unchanged.
- Gross Demand M1 - PV generation has been added to the net demand data. Generation estimated on the basis of the reference PV power plants.
- M2 Gross Demand - PV generation has been added to the net demand data. Generation has been estimated on the basis of the reference PV installations and the amount of electricity sent to the distribution network by prosumers.
- Demand 2016 - PV generation was omitted due to the little PV installed power.

Fig. 9. Results of comparing forecasts based on transformed demand data

Model	Input data	Average MAPE [%]	Average RMSE [MWh]
ARX	net demand	6.97	85.96
mARX	net demand	6.91	83.86
Naive	net demand	7.05	87.39
ARX	Gross demand M1	3.32	45.7
mARX	Gross demand M1	3.15	43.3
Naive	Gross demand M1	4.04	54.1
ARX	Gross demand M2	2.97	40.30
mARX	Gross demand M2	2.85	38.72
Naive	Gross demand M2	3.68	48.64
ARX	Demand 2016	3.20	39.9
mARX	Demand 2016	3.16	40.0
Naive	Demand 2016	4.55	54.77

Source:own work.

From the presented results (see fig. 9) we conclude that after transforming data from net value to gross value, electricity demand data is easier to forecast. The average absolute forecast error decreased from 6.9% to 2.9% and the RMSE error decreased from 84 MWh to 38 MWh. The deviations of forecasts based on transformed data are close to the deviations of forecasts based on data from 2016, in which the share of photovoltaics was negligible. The coefficient of variation for gross demand decreased from 12% to 6% for working days and from 16% to 10% for holidays.

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