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SPECIAL SECTION

Comprehensive forecast of electromobility mid-term development in Poland and its impacts on power system demand

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Abstract. This paper discusses three variants of how e-mobility development will affect the Polish Power System. Multivariate forecasts of annual new registrations of electric vehicles for up to seven years are developed. The forecasts use the direct trend extrapolation methods, methods based on the deterministic chaos theory, multiple regression models, and the Grey model. The number of electric vehicles in use was determined for 2019–2025 based on the forecast new registrations. The forecasts were conducted in three variants for the annual electric energy demand in 2019–2025, using the forecast number of electric vehicles and the forecast annual demand for electric energy excluding e-mobility. Forecasts were conducted in three variants for the daily load profile of power system for winter and summer seasons in the Polish Power system in 2019–2025 based on three variants of the forecast number of electric vehicles and forecast relative daily load profiles.

Key words: mid-term forecast, electromobility, electric vehicles (EV), power system demand, load profile.

1. Introduction

Depending on the point of view, e-mobility can be perceived as an opportunity for: creating demand for new products, reducing transport costs, reducing air pollution or increasing the share of renewable sources in the national energy mix. That is why the focus on e-mobility has soared in worldwide press in recent years [1]. The original plan adopted by the Polish Government in March 2017 provided for about 1 million electric vehicles (EVs), including Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs), by 2025 [2]. The "2030 Sustainable Transport Strategy" published in September 2019 assumes that the combined number of BEVs and hybrid vehicles of all types would be about 600 000 by 2030 [3]. Notably, at the end of 2018, about 2300 BEVs and 55 500 hybrid vehicles were used in Poland. Fig. 1 shows the magnitude of growth of new registrations and the cumulative number of BEVs and PHEVs in Poland from 2010 to 2018.

This paper brings the following novel contributions:

1. Comprehensive approach to how EVs affect the Polish Power System. This problem is addressed in steps. All the data processed in the subsequent steps result from our proprietary forecasts. Forecasts variants have been developed by using many prognostic methods (including hybrid models that stabilize forecast quality).
2. Unique approach to forecasts of daily energy demand profiles for two characteristic days, which deserves special attention. It uses both proprietary energy demand forecasts for the given year and forecasts of the shapes of relative profiles. Proprietary relative profiles are used to develop power demand profiles resulting from e-mobility, taking into account different EV categories. The diagram of research studies described in this paper is shown in Fig. 2.

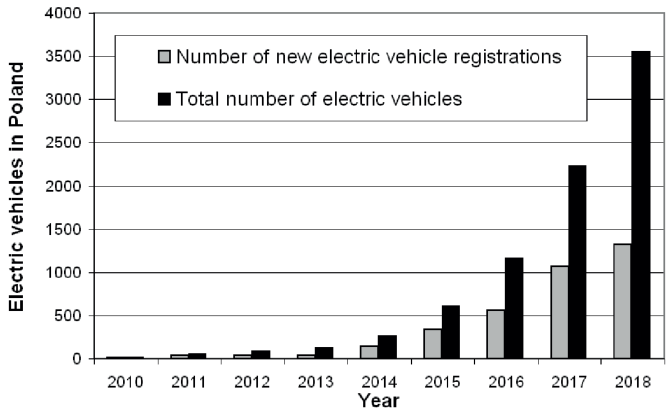

Fig. 1. Growth of new registrations and the cumulative number of BEVs and PHEVs in Poland

The paper is organized as follows. Section 2 describes the related studies. Section 3 analyses the drivers of e-mobility in various countries. Section 4 describes multivariate forecasts of the number of electric vehicles in Poland from 2019 through 2025 with a description of forecast methodology. Section 5 analyses the effect of e-mobility on annual electric energy demand in Poland in 2019–2025. Section 6 describes how e-mobility affects daily profiles of electric energy demand in 2019–2025. Section 7 discusses the results and their interpretation. Finally, Section 8 presents our conclusion.

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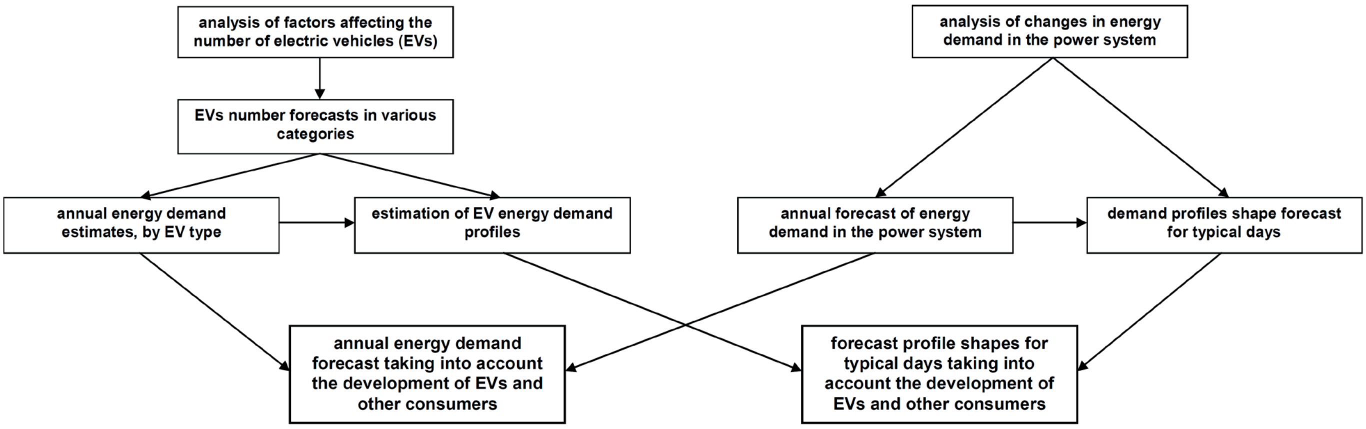

Fig. 2. Diagram of research studies described in this paper

2. Related works

Forecasting electromobility is a current issue. A large number of institutions, including university establishments, conduct research in this area. A broad review of current methodologies for forecasting long-term hourly national electric energy demand is conducted in [4].

The results of long-term analyses of how the increasing share of electric vehicles affects the power system in the EU are reported in [5]. As [5] points out, the integration of electric vehicles into the EU power system is a complex topic, with various aspects and scopes that can be analysed.

Electromobility topics are valid for the Polish Power System as well. Paper [6] discusses key legal and territorial conditions associated with the development of electromobility and presents basic information on electric vehicles in Poland and Europe. An analysis of the potential impact of EVs on the demand, supply, structure and costs of electric energy generation as well as CO_2 and air pollution as a result of bringing 1 million EVs to Polish roads by 2025 and tripling this number by 2035 is presented in [7]. Paper [8] describes the current state of development and future direction in the market for electric vehicles in Poland, and shows the results of the analysis of the influence of electric vehicle development, in part concerning the charging infrastructure, on the Polish Power System. Paper [9] includes a detailed concept and the possibilities which are gained by including electric cars in the electric energy economy (with the help of the Smart Grid infrastructure).

Preliminary research results regarding EV forecasts for Poland are presented in [1, 10]. However, [10] focuses on the impact of the operation of the EVCS infrastructure on the distribution grid, while [1] considers only a limited number of drivers of electromobility.

Parallel to the problem of forecasting, technical solutions are being developed for electromobility. Examples of research results in the field of engineering solutions for electromobility can be found in [11–13].

3. Drivers of e-mobility in various countries

Table 1 and Table 2 discusses selected potential drivers of e-mobility. In addition to the verified factors, a number of other potential threats to e-mobility development can be identified.

Table 1
Verified negative or unclear drivers of e-mobility

Name of driver	Description of the analysis
Price of electric energy	The following countries are selected for the analysis: Poland, the Czech Republic, Hungary, Japan, France, Germany, and the USA. Pearson correlation coefficient between the prices of electric energy and the number of EVs on the roads in 2018 in the seven countries of our analysis is -0.219 (statistically insignificant at 5% significance level).
Effect of average GDP per capita on the number of charging stations	The following countries are selected for the analysis: Poland, the Czech Republic, Hungary, Japan, France, Germany, and the USA. Pearson correlation coefficient between the average annual GDP per capita and the number of charging stations per EV in 2018 was 0.164 (statistically insignificant at 5% significance level).
Magnitude of change of the number of charging stations per EV in multi-annual period	The analysis of changes in the number of charging stations per EV in 2013–2018 identified no clear growing trend among the countries considered here. Depending on the country, the trend may be from growing to even slightly falling. It is therefore hard to conclude whether an increase in the number of charging stations drives new EV registrations or the number of EVs drives the construction of new charging stations. The relationship considered here is presented in Fig. 3.

Table 2
Verified positive drivers of e-mobility

Name of driver	Description of the analysis
Global trends, fashionable environment-friendly technologies	The following countries are selected for the analysis: Poland, Germany, France, Norway and the USA. Pearson correlation coefficient between the number of new registrations of electric vehicles in Poland and the number of new registrations in the other four countries in 2010–2018 varies from 0.909 (the USA) to 0.975 (Germany). For all five countries under analysis, there is a characteristic non-linear growing trend with increased magnitude in 2017–2018. Strong similarity across the shapes of the growing trend of the process provided an inspiration for choosing forecasting methods that use direct trend extrapolation. The relationships analysed here are presented in Fig. 4. The chart presents the percentage relative values on 2010 (100%).
E-mobility funding support	The effect of various funding schemes as a driver of the sale of electric vehicles is evident practically worldwide. The statistical analysis which successfully verifies the effect of that factor on EV sales is presented in paper [14]. The effect of funding support on increased EV demand can be observed in Fig. 4 (growing magnitude of new registrations in 2017–2018 in Germany). In May 2016, a subsidy for BEVs at 4000 euros and for PHEVs at 3000 euros has been introduced in Germany. In 2020 the subsidy will increase to 6000 euros.
Society wealth (average per-capita income)	The following countries are selected for the analysis: Poland, the Czech Republic, Hungary, Japan, France, Germany, and the USA. Pearson correlation coefficient between the average income per capita in the seven countries under analysis in 2018 and the combined number of EVs in 2018 per one million inhabitants is 0.914 (very high and positive correlation). The relationship considered here is presented in Fig. 5.
Availability of the charging station infrastructure (number of charging stations)	The following countries are selected for the analysis: Poland, the Czech Republic, Hungary, Japan, France, Germany, and the USA. Pearson correlation coefficient between the number of EVs operated in the seven countries and the number of charging stations (rapid and slow charging stations combined) in 2018 was 0.920 (very high and positive correlation).
Price of lithium-ion batteries used in EVs	Pearson correlation coefficient between the number of new registrations of electrical vehicles in Poland and the price of lithium-ion batteries used in electric vehicles in 2010–2018 was −0.815. The relationship considered here is presented in Fig. 6. Prices of batteries recorded a sharp (non-linear) fall over that period. Forecast prices for 2019–2030 according to paper [15] provide for a significant slow-down of the fall to about 18% per annum. In 2025, the price should approach 80 USD/kWh. Currently (2019), batteries account for about 33% of the overall cost of electric vehicles, and the forecast share until 2025 is about 20% [15]. In expert assessments, the forecast cuts of battery prices in the years to come will provide for quite a strong impulse to drive demand for electric vehicles. However, it should be noted that lithium-ion cells are responsible for less than 50% of the entire battery cost, the majority being the cost of cabling, protection and compartments.

These include, among others, low prices of petrol and diesel, the introduction of hydrogen driven cars, the cost of battery charging in public areas and other factors, such as the reduction of subsidies. These factors vary in time and are impossible to predict in several years' horizon (our forecasts look at seven consecutive years forward) and very difficult to take in to account in forecasting e-mobility development. A major problem

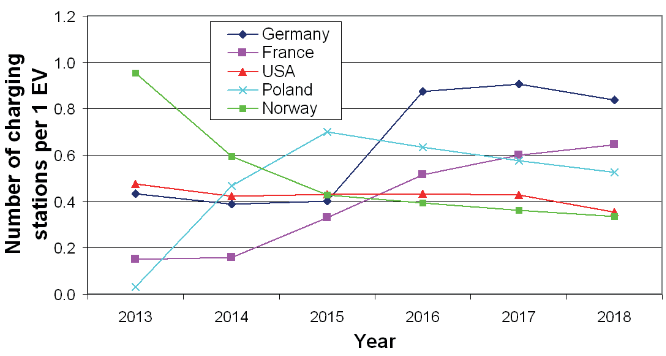

Fig. 3. Changes in the number of charging stations per EV in 2013–2018 in selected countries

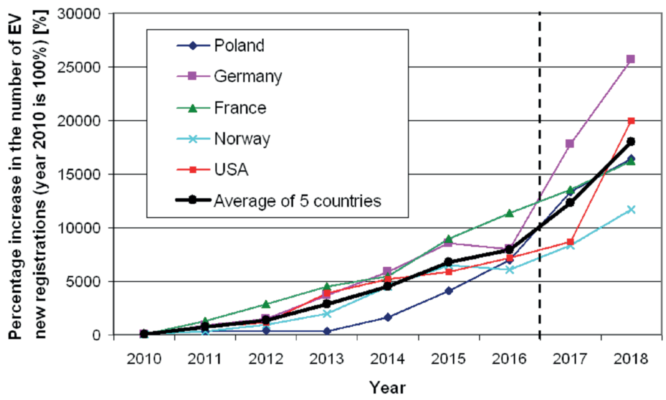

Fig. 4. Percentage increase in new registrations of electric vehicles in five countries and the average growth of new registrations

is also the lack of charging stations in some households (e.g. blocks of flats without underground parking places with charging stations), which makes it impossible to charge batteries with the cheapest electric energy. The problem of degraded battery capacity over several years of operation, costly replacement of batteries, difficulties with charging batteries at very low temperatures, quicker degradation of batteries frequently charged in quick-charge stations (high charging current) are some other examples of problems potentially discouraging from using electric vehicles. The environmental friendliness of electric vehicles, which is a potential incentive to buy an electric car, is far from obvious (environmentally harmful battery manufacturing and disposal process, power generation sources which are detrimental to the environment). Any factors affecting the development of e-mobility not adressed in this paper will be analysed in detail in further research.

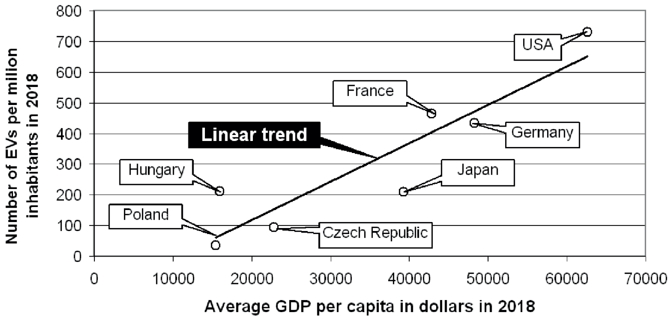

Fig. 5. Relationship between the number of EVs and wealth of the population

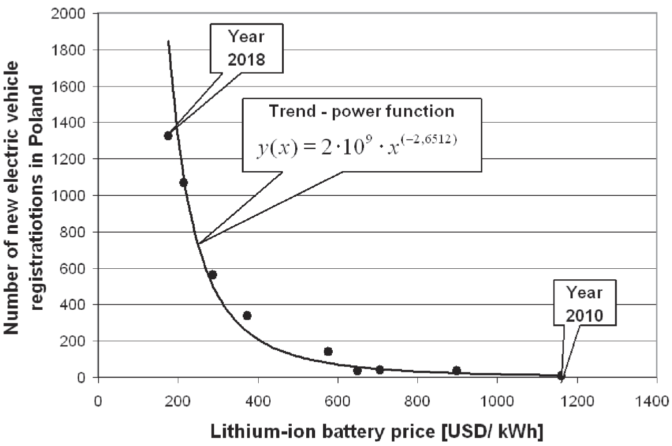

Fig. 6. Relationship between new registrations of electrical vehicles in Poland and the price of lithium-ion batteries used in electric vehicles in 2010–2018

4. Multivariate forecasts of the number of electric vehicles in Poland from 2019 through 2025

4.1. Methodology of forecasts. Methods used for medium-term and long-term forecasts were used for testing, while taking into account the variability of the time series of new registrations. A very short time series of new EV registrations in Poland (period 2010–2018) drives the uncertainty of forecasts and justifies the use of a hybrid model based on several models. The process is assumed to be in its initial development phase. The time series of the number of electric vehicles in other countries show that the growth dynamics and curve shapes are similar across countries (Fig. 4). The upward non-linear characteristcs of the process provided the basis for the selection of models. Table 3 presents a general comparison of twelve methods used for forecasting the number of electric vehicles in the given year and their grouping into four categories.

A vast majority of the methods presented in Table 3 use only information about the time series of the process. Econometric models use, in addition, real-world data (2010–2018) and forecasts (2019–2025) for the prices of lithium-ion batteries. The extrapolation of the trend of the power function is a function relationship between the number of new registrations in the year and the price of batteries.

The methods used here can be also grouped into:

- methods with the control of the process growth ceiling (logistic function and a Model according to Prigogine),
- methods without the control of the process growth ceiling (other methods).

If control of the development ceiling is impossible, there is a significant risk of degraded quality of forecasts with longer forecast horizons. The ability to control the process growth ceiling seems therefore very valuable due to the possibility of creating multiple forecast variants depending on the pre-determined maximum process growth.

The forecasts were verified by expert assessment of the magnitude of process variations in 2019–2025. Schuster's model was removed from further analysis due to a very small growing trend.

Reasons for the selection of forecasting models:

- The models described by equations (1), (2), (3), (4) and (5) use direct trend extrapolation methods. Functions whose shape is closest to the variability of the time series for the forecast process were selected. For 2010–2018 (parameter estimation range), SSE error was minimized for these functions and then the functions were extrapolated, i.e., forecasts were computed for 2019–2025.
- Methods based on deterministic chaos theory were selected due to their high effectiveness (demonstrated in many publications, including by authors of a peer-reviewed article [16]) in mid-term and long-term forecasting.
- Methods using time series are also typically applied in long-term forecasting. In particular, Grey model (7) is preferable, according to literature [17], where the process is in its initial phase and historical times series is short – our time series for the number of electric vehicles exactly fits this example.
- Econometric models use additional exogenous variables which do not belong to the forecast time series. These are popular and effective forecasting methods if other exogenous variables are known in addition to the forecast time series.
- The purpose of the hybrid model (10) is to average the forecast bundle obtained in previous steps. It is a popular and recommended approach if there are large differences between the outcomes from single forecasting models.

Table 3
Grouping of the methods used for forecasting the number of electric vehicles

Category of methods	Name of model	Equation number	Model parameter optimisation method	Minimised error	Step forecasts	Model acceptance after verification
Methods of direct trend extrapolation	Polynomial function of degree 2	(1)	MLS	SSE	No	Accepted
	Polynomial function of degree 3	(2)	MLS	SSE	No	Accepted
	Exponential function	(3)	MLS	SSE	No	Accepted
	Logistic function*	(4)	DEPS	SSE	No	Accepted
	Power function	(5)	DEPS	SSE	No	Accepted
Methods based on deterministic chaos theory	Model according to Prigogine*	(6)	DEPS	SSE	Yes	Accepted
	Schuster model	Description in [18]	DEPS	SSE	Yes	Rejected
Methods using time series	Grey model GM(1,1)	(7)	DEPS	SSE	Yes	Accepted
	Dynamic optimised Theta model	Description in [19]	N-M	SSE	Yes	Accepted
Econometric models	Multiple linear regression	(8)	DEPS	SSE	Yes	Accepted
	Multiple non-linear regression	(9)	DEPS	SSE	Yes	Accepted
Method using more than one model	Hybrid model	(10)	–	–	–	Accepted

Description: * – growth ceiling control models, DEPS – Differential Evolution and Particle Swarm Optimisation algorithm, MLS – Method of Least Squares, N-M – Nelder-Mead algorithm, SSE – Sum of Squared Errors.

Mathematical models of forecasting methods. The extrapolation model of polynomial function of degree 2 is described by formula (1).

$$y_{F\_P2}(t) = a \cdot t^2 + b \cdot t + c, \tag{1}$$

where t is the number in the time series of the process (2010 is the onset of the time series, or 1) and a, b, c are the parameters.

The parameter values after optimization are
$a = 33.573$, $b = -174.040$, $c = 201.860$.

The extrapolation model of polynomial function of degree 3 is described by formula (2).

$$y_{F\_P3}(t) = a \cdot t^3 + b \cdot t^2 + c \cdot t + d, \tag{2}$$

where a, b, c, d are the parameters.

The parameter values after optimization are
$a = 13.495$, $b = -107.050$, $c = 288.600$, $d = -193.400$.

The extrapolation model of the exponential function is described by formula (3).

$$y_{F\_E}(t) = a \cdot e^{b \cdot t}, \tag{3}$$

where a, b are the parameters.

The parameter values after optimization are
$a = 5.721$, $b = 0.634$.

The extrapolation model of the logistic function is described by formula (4).

$$y_{F\_L}(t) = \frac{a}{1 + b \cdot e^{-c \cdot t}}, \tag{4}$$

where $a > 0$ is the saturation level and $b > 0$, $c > 0$ are the parameters.

The parameter values after optimization are
$a = 1007141$, $b = 30424.126$, $c = 0.469$.

The extrapolation model of the power function is described by formula (5).

$$y_{F\_POW}(price) = a \cdot (price)^b, \tag{5}$$

where $price$ is the price of lithium-ion batteries [USD/kWh] in the year of forecast (actual values for 2010–2018, price forecasts for 2019–2025), $a > 0$, $b < 0$ are the parameters.

The parameter values after optimization are
$a = 10^9$, $b = -2.6512$.

The Model according to Prigogine is described by formula (6) [18].

$$y_{M\_P}(t) = y(t-1) \cdot \left[1 + r \cdot \left(1 - \frac{y(t-1)}{K}\right)\right], \tag{6}$$

where $y_{M\_P}(t)$ is the population size in period t, $r > 0$ is the population growth rate, $K > 0$ is the development ceiling (forecast population growth in the future).

The parameter values after optimization are
$r = 0.3$, $K = 1000000$.

Grey model GM(1,1) is described by formula (7). In this model, the order of the grey differential equation and the number of variables equal 1. This model is recommended by literature [17] especially for very short time series (more than 3 data items) and where the process evolution is in its initial phase.

$$\begin{aligned}
&\hat{y}(t) = \hat{y}^{(1)}(t) - \hat{y}^{(1)}(t-1),\\
&\hat{y}^{(1)}(t) = \left[y^{(1)}(1) - \frac{u}{a}\right] \cdot e^{(-a(t-1))} + \frac{u}{a},\\
&\hat{y}^{(1)}(t) = \sum_{i=1}^{t} y(i), \quad t = 1,2,\ldots,n
\end{aligned} \tag{7}$$

where $n \geq 4$ is the length of time series, a is the evolution parameter, u is grey variable and $\hat{y}(t)$ is forecast in period t.

The parameter values after optimization are
$a = -0.554$, $u = 19.676$.

A variety of the Theta model, called dynamic optimised Theta model, was selected for forecasting. This model is presented in detail in [19]. This model is nonlinear. In general, the Theta model is a univariate forecasting method consisting, in a modification of the local curvature, of the time series through "Theta" coefficient applied to the second differences of the data. As a result of the modification, new lines are created with the mean and slope of the original time series [19].

A linear model of the multiple regression is described by formula (8).

$$\hat{y}_t = a_0 + a_1 \cdot price_{t-1} + a_2 \cdot new\_vehicle_{t-1} + \varepsilon, \tag{8}$$

where $\hat{y}_t$ is forecast in period t, a_0 is the constant, a_1, a_2 are the parameters, $price_{t-1}$ is the price of lithium-ion batteries in period $t-1$ (for the forecast range these are known price forecasts), $new\_vehicle_{t-1}$ is the number of new registrations of electric vehicles in period $t-1$ and ε is random disturbance or error.

The parameter values after optimization are
$a_0 = 378.561$, $a_1 = 1.051$, $a_2 = -0.375$.

A non-linear model of the multiple regression is described by formula (9).

$$\hat{y}_t = a_0 + a_1 \cdot new\_vehicle_{t-1} + \frac{a_2}{price_{t-1}} + \varepsilon, \tag{9}$$

The parameter values after optimization are
$a_0 = -343.960$, $a_1 = 0.101$, $a_2 = 347173$.

The hybrid model presented in [20] is described by formula (10). The forecast in the hybrid model is an arithmetic weighted average of forecasts from several models.

$$\hat{y}_t = \frac{\sum_{i=1}^{k} \hat{y}_t^i \cdot w_i}{\sum_{i=1}^{k} w_i}, \tag{10}$$

where k is the number of forecasting models and $\hat{y}_t^i$ is forecast in period t generated by the model number i.

4.2. Forecast number of new registrations of electric vehicles from 2019 to 2025. In the first step, model parameters were optimised. Table 4 presents the statistics of errors for the selected methods from the model parameter estimation range (2010–2018). Note that the model with the smallest fitting errors will not always be the best forecasting model. For instance, the creeping trend model used in [21] generated significantly overstated forecasts despite the smallest fitting errors among the seven forecasting methods tested. Nevertheless, the size of the fitting errors of the models is a valuable selection hint. SSE is more important than MAPE due to the dynamic process growing in a non-linear fashion. In our task, a small SSE means better fitting of the most recent, big values from the time series (2015–2018).

Table 4
Fitting error statistics for selected methods

Name of model	MAPE [%]	SSE	Pearson correlation coefficient
Polynomial function of degree 2 – equation (1)	43.23	**25 038**	**0.9931**
Polynomial function of degree 3 – equation (2)	113.20	6 782 303	**0.9848**
Exponential function – equation (3)	**27.87**	199 427	0.9669
Logistic function (saturation level – 1 million) – equation (4)	62.08	**59 306**	**0.9847**
Power function (uses the time series for lithium-ion battery prices) – equation (5)	**35.37**	888 433	0.9775
Model according to Prigogine (development ceiling – 1 million) – equation (6)	**36.75**	166 912	0.9672
Multiple linear regression model – equation (8)	88.12	**77 826**	**0.9778**
Multiple non-linear regression model – equation (9)	77.57	**56 150**	**0.9841**
Grey model GM(1,1) – equation (7)	**35.40**	**92 077**	0.9769
Dynamic optimised Theta model	**35.77**	264 447	0.9697

Notes: – five best fitting results for each fitting measure are printed in bold.

The only model with small (printed in bold) MAPE and SSE errors is the Grey model. Following the optimisation of the parameters of the Models according to Prigogine, the initial values of the development ceiling (initial values were tested: 0.5 million, 1 million, 5 million, 10 million and 20 million), recorded almost no discernible change. Similar stability of the initial values of the saturation level occurred when optimising the parameters of the logistic function (the same initial values as in the Model according to Prigogine were tested). For the Model according to Prigogine and forecasts using the logistic function, forecast values would grow very insignificantly with the increase of the development ceiling.

In the next step, using the models from Table 4, the number of EV new registrations for 2019–2025 was forecast. Then, using historical data from 2010–2018 and forecasts results, cumulative values of the time series of new registrations were calculated for 2019–2025. The cumulative values represent forecasts of the number of electric vehicles on the roads in 2019–2025. Due to a short forecast horizon, the calculations do not take into account the natural process of some electric vehicles being withdrawn from operation. Fig. 7 presents the results of forecasts for all methods from Table 4. The most optimistic forecasts for 2025 were obtained from the method of extrapolation of the exponential function. The most pessimistic forecasts were obtained from the dynamic optimised Theta model. The Grey model obtained a value closest to the average of both of those forecasts. The value closest to the average calculated from all 10 forecasts was obtained from the method of extrapolation of the logistic function. Forecasts values obtained from the different models are highly dispersed. Therefore, three variants of forecasts were selected for further analysis.

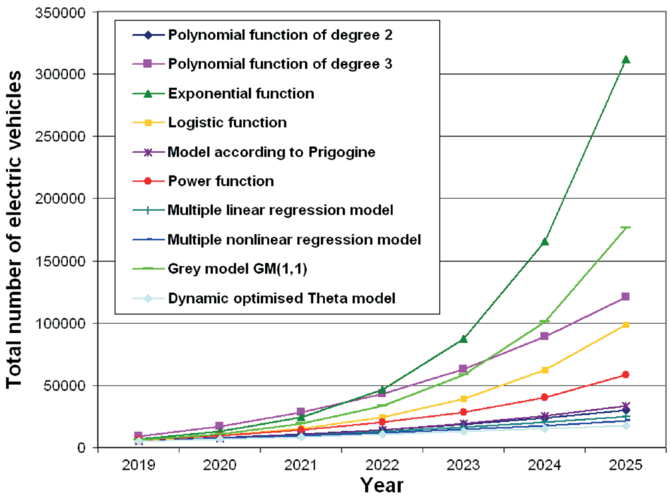

Fig. 7. Results of forecasts of the total number of EV in Poland obtained by 10 methods

4.3. Selection of three forecast variants. Models based on time series only provide no extra information on the external environment of the forecast process. Such forecasts result solely from the interpretation of historical information on the process. Extreme forecasts may be less realistic. Therefore, extreme forecasts (model of extrapolation of the exponential function and the dynamic optimised Theta model) were removed from the process of selection of the three variants. This is an approach frequently used when generating a bundle of forecasts. Finally, the following three variants were chosen for further analysis based on expert assessment:

- optimistic variant (176,216 EVs operated in 2025) – forecasts of the Grey model described by equation (7),
- pessimistic variant (21,523 EVs operated in 2025) – forecasts of the multiple non-linear regression model described by equation (9),
- balanced variant (70,516 EVs operated in 2025) – forecasts using the hybrid model described by equation (10) – weighted arithmetic average from the forecasts obtained from eight models described by equations (1), (2), (4), (5), (6), (7), (8) and (9) with equal weights.

5. Effect of e-mobility on annual electric energy demand in Poland in 2019–2025

5.1. Methodology of forecasts. Forecasts of annual demand for electric energy excluding e-mobility were conducted by six methods.

Method I. The Model according to Prigogine is described by formula (6).

The parameter values after optimization are
$r = 0.0088999$, $K = 11549684067$.

Method II. Modified Holt's model as presented in detail in [16].

The parameter values after optimization are
$\alpha = 1.176$, $\beta = 0.189$, $\gamma = 0.2$.

For method I and method II, forecasts for 2020–2025 are conducted by a stepwise method. Model parameters for the data from the estimation range are selected using optimisation by DEPS method. The minimum SSE was sought.

Method III. The model of extrapolation of the linear function is described by formula (11). Parameters A, B are selected by the Least Squares Method.

$$y(t) = A \cdot t + B \tag{11}$$

where t is the number of the data point in the time series of the process (1990 is the onset of the time series, or 1).

The parameter values after selection by the Least Squares Method are $A = 1362.301$, $B = 126165$.

Method IV. Method of constant annual growth – model 1 is described by formula (12). Annual growth is the average annual growth calculated based on historical data of the forecast process.

$$\hat{y}_t = y_{t-1} + \frac{\sum\limits_{j=2}^{k}(y_j - y_{j-1})}{k-1}, \tag{12}$$

where k is the number of the data point in the time series and y_{t-1} is the previous value (or forecast) from the time series.

Method V. Method of constant annual growth – model 2 is described by formula (13). The annual growth is equal to the slope A from the linear function described by formula (11) used for trend line extrapolation forecasting.

$$\hat{y}_t = y_{t-1} + A, \tag{13}$$

The parameter value is $A = 1362.301$.

Method VI. Hybrid model is described by formula (10). The following methods are selected for the hybrid model: Model according to Prigogine (6), modified Holt's model, constant annual growth method – model 1 (12) and constant annual growth method – model 2 (13).

5.2. Forecast annual electric energy demand in Poland until 2025 excluding the development of e-mobility in Poland.

Table 5 presents the statistics of fitting errors for the estimation of the parameters of six forecasting methods (2010–2018). Fig. 8 presents historical data for annual electric energy demand, being a range of estimations of method parameters (from 1990 to 2018) and forecasts obtained by six methods (from 2019 to 2025). The linear function extrapolation model generated less realistic forecasts (significantly understated forecasts for 2019–2022 relative to the actual energy consumption in 2018). The largest forecast values were obtained from the modified Holt's model. Forecasts obtained from the hybrid model described by equation (10) were selected by expert assessment as the most probable ones for further analysis.

Table 5
Fitting error statistics for tested methods

Name of model	MAPE [%]	SSE [TWh]	Pearson correlation coefficient
Model according to Prigogine – equation (6)	**1.52**	**205.05**	0.9723
The method of constant annual growth – model 1 – equation (12)	1.53	206.37	0.9723
The method of constant annual growth – model 1 – equation (13)	1.53	205.76	0.9723
Modified Holt's model	1.63	274.53	0.9699
Linear function – equation (11)	1.73	265.57	0.9665
Hybrid model – equation (10)	1.53	206.66	**0.9724**

Note: best fitting results for each fitting measure are printed in bold

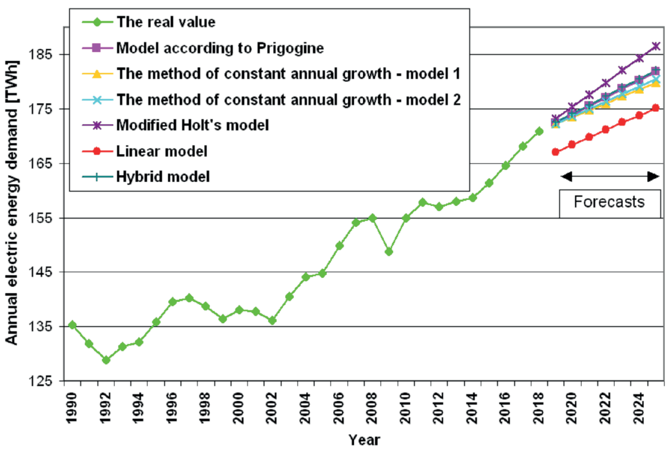

Fig. 8. Historical data for annual demand for electric energy in Poland and results of forecasts obtained by six methods

5.3. Forecast annual demand for electric energy in Poland in 2019–2025 resulting only from the operation of the forecast number of electric vehicles.

The algorithm has four steps.

Step 1. Calculation of the average annual number of EV charges.

Step 2. Calculation of the average annual energy consumption by a single EV.

Step 3. Calculation of three variants of the number of various EV types based on the results of forecasts (see section 4.3) of the number of EVs operated in 2019–2025.

Step 4. Calculation of annual demand for electric energy based on the number of EVs.

Table 6 presents summary calculation results for 2025. Fig. 9 presents, in three variants, forecast annual demand for electric energy in Poland in 2019–2025 resulting only from the operation of the forecast number of electric vehicles.

Table 6
Input data and results of calculations for 2025

	Type of electric vehicle			
	BHEV	PHEV	Electric buses	Electric trucks and electric-delivery vans
Input data for calculation				
Percentage share of the overall number of EVs of all types [%]	57.50	34.32	2.84	5.34
Average annual mileage [km]	15 000	15 000	80 000	80 000
Battery capacity in a single EV [kWh]	26.28	12.60	167.50	276.56
Average EV range [km]	233	74.1	175.00	252.20
Results of calculation of average values				
Average annual number of charges	65	203	458	318
Average annual energy consumption by a single EV [kWh]	1709	2562	76 715	87 949
Results of calculation of the number of EVs in 2025				
Pessimistic variant [pcs]	12 376	7387	611	1149
Balanced variant [pcs]	40 547	40 547	2003	3766
Optimistic variant [pcs]	101 324	60 477	5005	9410
Results of calculation of electric energy demand for charging the forecast number of EVs in 2025				
Pessimistic variant [GWh]	21.14	18.93	46.81	101.08
Balanced variant [GWh]	69.28	62.02	153.37	331.16
Optimistic variant [GWh]	173.13	154.98	383.26	827.56

The three forecast variants differ significantly from each other. The optimistic variant forecasts more than eight times higher values than the pessimistic one. Electric buses, electric trucks and electric delivery vans have significantly higher share of electric energy demand than BHEVs and PHEVs.

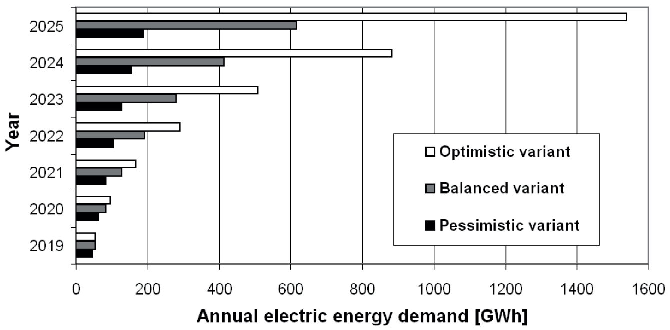

Fig. 9. Forecast annual demand for electric energy in Poland in 2019–2025 resulting only from the operation of the forecast number of electric vehicles

5.4. Forecast annual electric energy demand in Poland until 2025 including the development of e-mobility in Poland. The forecast for the year is the sum of the forecast electric energy demand excluding e-mobility for the year (for the result obtained by the hybrid model, see Section 5.2) and the forecast electric energy demand resulting from the operation of electric vehicles in the year (for the result, see Section 5.3). Detailed results are presented in Table 7. Fig. 10 presents, in three variants, the percentage effect of the forecast electric energy demand resulting from e-mobility development on the forecast annual electric energy demand in Poland. Fig. 10 shows that in the optimistic variant, in 2025 demand for electric energy resulting from e-mobility will grow to just under 1% and this growth is ten times as much as in the pessimistic variant.

Table 7
Forecast annual electric energy demand in Poland until 2025 including the development of e-mobility in Poland

Year	Pessimistic variant [TWh]	Balanced variant [TWh]	Optimistic variant [TWh]
2019	172.591	172.597	172.599
2020	174.206	174.226	174.238
2021	175.826	175.871	175.910
2022	177.452	177.539	177.639
2023	179.084	179.237	179.464
2024	180.724	180.982	181.452
2025	182.371	182.799	183.722

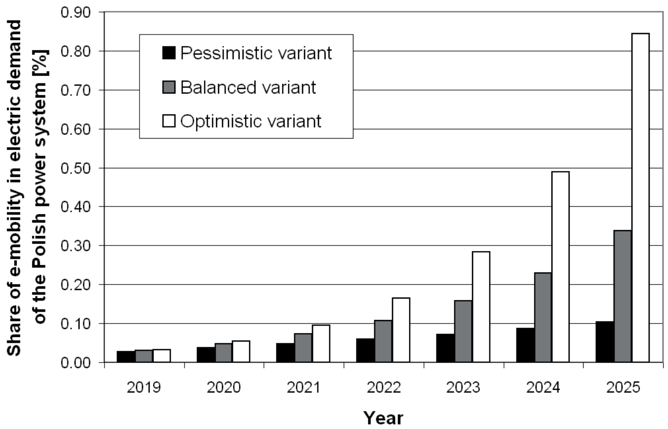

Fig. 10. Percentage effect of the forecast electric energy demand resulting from e-mobility development on the forecast annual electric energy demand in Poland

6. Effect of e-mobility on daily profiles of electric energy demand in 2019–2025

6.1. Methodology of forecasts. Forecasts of relative values of the profiles in the subsequent years separately for each hour were conducted using the linear function extrapolation model described by formula (11). Parameters A, B are selected by the Least Squares Method.

6.2. Forecast shapes of daily profiles of characteristic days in 2019–2025 excluding e-mobility. The third Wednesday of January and the third Wednesday of July are "characteristic days" in the Polish Power System, representing the winter and the summer working days, respectively, with their anticipated peak powers. The task was conducted in five steps.

Step 1. For each year of the 2009–2018 period, two daily profiles of characteristic days were calculated. The value of each hour of the profile was calculated as arithmetic average of hourly values from five working Wednesdays. The five working Wednesdays are: the characteristic day (the third Wednesday of January or the third Wednesday of July), two preceding and two following working Wednesdays. This treatment evened out the profiles and reduced the random component resulting from a single day such as working Wednesday.

Step 2. Hourly values of both profiles, in each year separately, were normalized. Normalization is the division of the value of profiles from each hour by average hourly electric energy demand in the year. The normalization made it possible to track changes in the shape of the profiles in 2009–2018 ignoring any profile shape changes resulting from the multi-annual growing trend of energy demand over the subsequent years.

Step 3. Based on the data from 2009–2018 for each of 24 hours of both profiles, independent parameters of the linear trend functions described by formula (11) were determined (a total of 48 functions). Table 8 presents the statistics (average values from 24 functions) concerning the linear trend functions ob-

Table 8
Statistics of linear trend functions – average values of 24 functions

Slope of straight line S	MAPE [%]	SSE [p.u.]	Pearson correlation coefficient
24 linear functions for the winter profile			
−0.0068	1.24	0.0027	0.7522
24 linear functions for the summer profile			
0.00510	0.818	0.0010	0.7817

tained (2010–2018). Fitting errors are slightly larger for the average error measures for 24 functions of the winter profile, similarly as the magnitude of change (average slope of the straight lines).

Step 4. Relative values of both profiles were forecast by extrapolating the function onto seven subsequent periods (from 2019 to 2025). Historical hourly values and forecast relative electric energy demand from the daily profile of the winter and summer days in the subsequent years are presented in Fig. 11 and Fig. 12, respectively.

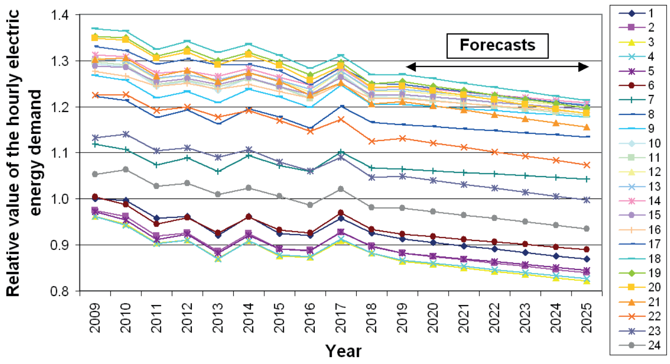

Fig. 11. Hourly relative values of electric energy demand in Poland from the daily profile of the winter and summer days in the subsequent years

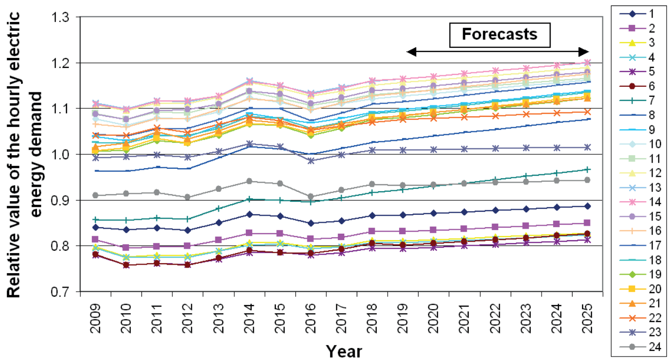

Fig. 12. Hourly relative values of electric energy demand in Poland from the daily profile of the summer day in the subsequent years

A clearly growing trend for the hourly values of the summer profile in Fig. 12 represents a growing share of summer days in annual energy demand in the subsequent years. The average growth from 2018 to 2025 calculated based on forecasts for all hours is 3.23%. Depending on the hour of the day, the growth was from 0.73% to 5.43% (the smallest changes are between 09:00 p.m. and 06:00 a.m.). A clearly falling trend for the hourly values of the winter profile in Fig. 11 represents a falling share of that day in annual energy demand in the subsequent years. The average fall from 2018 to 2025 calculated based on forecasts for all hours is 4.03%. Depending on the hour of the day, the fall was from 2.21% to 6.86% (the least changes are between 06:00 a.m. and 05:00 p.m.).

Step 5. Relative forecast values of both profiles (2019–2025) are recalculated to actual values [GWh]. Forecast annual electric energy demand in Poland (2019–2025), as described in Section 5.2, recalculated as average hourly values of energy demand in the year are used. This extensive, stepwise method for the generation of forecast hourly values of the profiles increases the accuracy of forecasting. This method incorporates both the growing trend of the annual energy demand and how relative profiles evolve over the subsequent years. Fig. 13 and Fig. 14 present the shapes of the profiles of the characteristic summer and winter days, respectively, in 2009 (the first profile of historical data), in 2018 (the last known profile from historical data) and in 2025 (forecast profile within a 7 years' horizon).

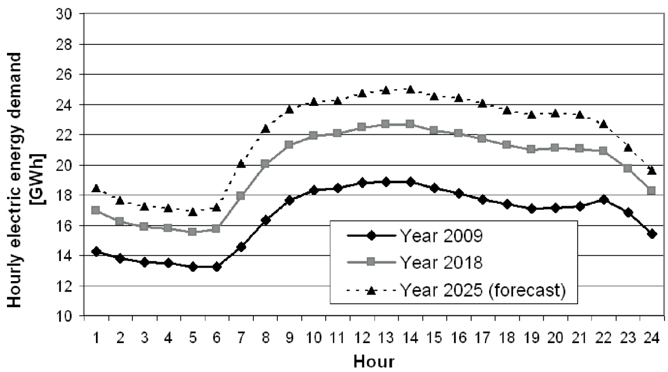

Fig. 13. Daily profiles of electric energy demand for the characteristic summer day in Poland for three selected years

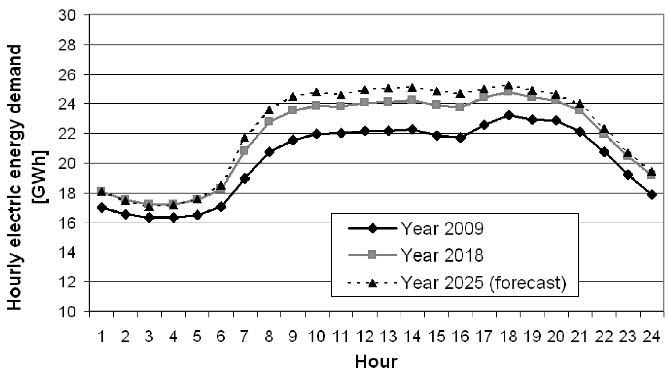

Fig. 14. Daily profiles of electric energy demand for the characteristic winter day in Poland for three selected years

For the winter day profile, two opposing trends overlap – natural growth of annual energy demand and the falling share of that day in the overall annual energy demand. As a result, changes (growth) of the profile value between 2018 and 2025 were very slight (but most evident) from 6:00 a.m. to 17:00 p.m.

6.3. Forecast shapes of daily profiles of characteristic days in 2019–2025 including e-mobility. Calculation of the hourly values of daily profiles of electric energy demand resulting from e-mobility only used the relative profiles developed for a working day for EVs and the daily electric energy demand from four EV categories calculated based on annual values. The subsequent calculations assumed that BEVs and PHEVs form a single category – cars with the same relative profiles. The methodology of the construction of relative hourly profiles for EV electric energy demand and the relative profiles alone are described in detail in [22]. A total of 6 relative profiles were used. Each of the three EV categories has two profiles – electric energy drawn from rapid charging stations and from slow charging stations. Slow charging was assumed to be: 70% for electric cars, 20% for electric buses and 35% for electric trucks and electric delivery vans, and the remaining electric energy is drawn from rapid charging.

Calculations were performed for the three variants of forecast EV number in each EV category, separately for 2019–2025. In the next step, combined daily electric energy demand due to charging EVs of any type was calculated. Fig. 15 presents the results of calculations for the optimistic variant of the forecast number of EVs in 2025. The biggest electric energy demand for EV charging is between 05:00 a.m. and 06:00 p.m. For the balanced and pessimistic variants, hourly profiles are 40% and 12%, respectively, of the value from the optimistic variant.

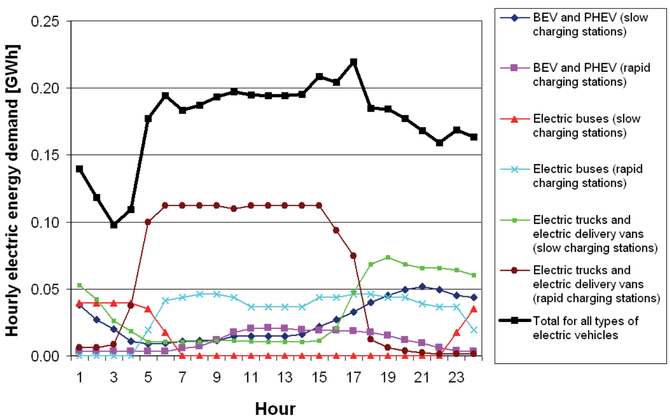

Fig. 15. Daily profile of electric energy demand due to EV charging – optimistic variant of the forecast number of EVs in 2025

There is a fairly clear similarity between the characteristic winter and summer days and the energy demand profile resulting from e-mobility. Linear correlation coefficients are statistically significant (5% significance level) and are 0.7810 and 0.7260, respectively.

Fig. 16 presents the magnitude of growth of electric energy demand due to EV charging for all categories in 2019–2025 for the optimistic variant of the forecast number of EVs. The largest growth is in 2023–2025. Fig. 17 presents daily electric energy demand profiles for the characteristic winter and summer days with and without e-mobility for the optimistic variant of the number of EVs in 2025. Percentage growth of energy demand due to e-mobility for the optimistic variant varies, depending on the time of the day, from 0.57% (from 2:00 a.m. to 3:00 a.m.) to 1.13% (from 5:00 a.m. to 6:00 a.m.).

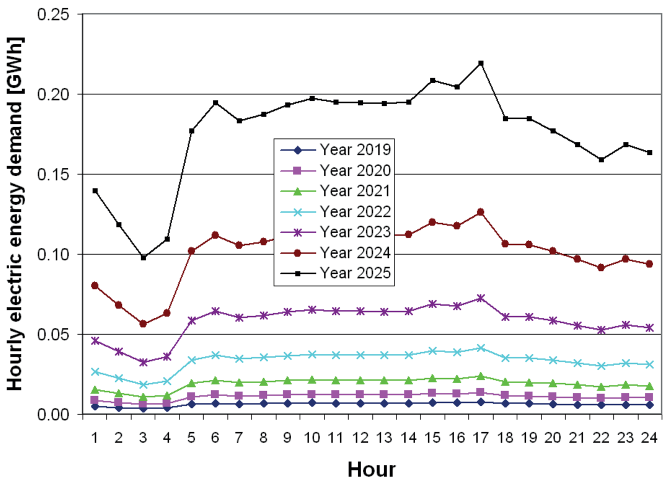

Fig. 16. Daily electric energy demand profiles resulting from charging EVs of all categories in 2019–2025 for the optimistic variant of the forecast number of EVs

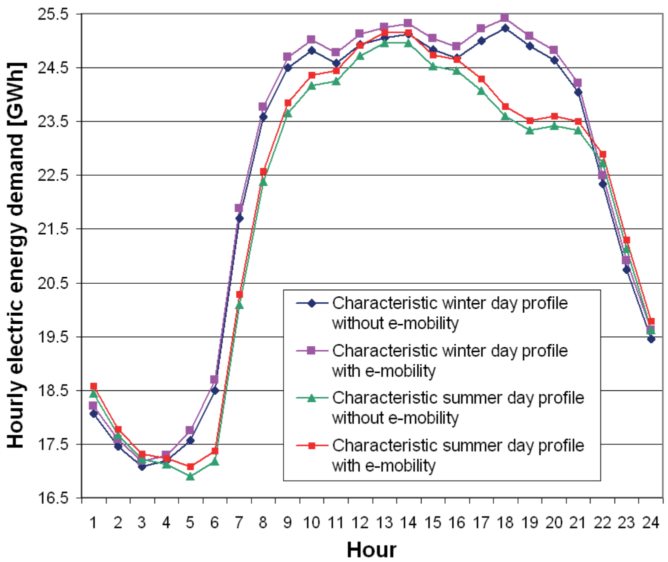

Fig. 17. Daily electric energy demand profiles for the characteristic winter and summer days with and without e-mobility for the optimistic variant of the number of EVs in 2025

7. Discussion

This paper presents detailed analysis of electromobility, which at the end of the day affects the national power system. The analysis involves the following steps:

- determination of the factors affecting the magnitude of e-mobility development,
- development of variant forecasts of the number of electric vehicles,
- development of variant forecasts of the changes in electric energy demand due to operation of electric vehicles and other causes,
- development of forecasts of the changes in daily profiles of electric energy demand due to operation of electric vehicles and other causes.

We forecast that the electric energy demand due to e-mobility will grow by less than 1% by 2025, which is our forecast horizon. The effect of e-mobility on daily profiles of electric energy demand for both characteristic days is no more than 1.13% for the total number of 176,216 EVs (optimistic variant for the forecast number of EVs).

Such values are not expected to bring any significant adverse effect system-wide. However, peak demand due to charging electric vehicles occurs at similar times as the load peaks in the power system. With a larger number of vehicles, this buildup (concurrency) of peaks needs to be alleviated by various measures (e.g. special tariffs, energy storage).

It is worth noting that if the number of electric vehicles was 1 million in 2025 (as originally planned by the government), the increase in energy demand would be 3.23% to 6.42%, depending on the time of the day. This would be a challenge to the national power system – especially in hot summer days in peak demand.

8. Conclusions

Electromobility is currently in its initial development phase. The final level of this development is unknown. Currently, BEVs and PHEVs are also regarded as electric vehicles. But it cannot be ruled out that electric vehicles using hydrogen fuel or hybrid battery-hydrogen EVs will grow more popular. In terms of the power system, these vehicles can be to some extent treated as contributing to a change of how the power system operates (storage of excess electric energy from RES in hydrogen). In a longer time scale, the price of fossil fuels, technology changes and the effect of political trends on economic processes also remain unknown. In this perspective, the horizon of research presented in this paper does not seem to be long. Hence, the conclusion that the limited forecast number of EVs will have a small effect on the transmission system are obviously real. It should be noted, however, that despite a small effect on the transmission sub-system, electromobility can have a significant effect on certain sections of the distribution subsystem.

An interesting aspect is the possibility to use electric vehicles as distributed power storage. Vehicle-to-Grid (V2G) systems provide for the two-way flow of power between electric vehicles and the power grid, which allows us to use the power stored in batteries to stabilize the operation of the power grid. Another aspect of e-mobility is the source of power used for charging electric vehicles. The use of RES significantly increases environmental friendliness of electric vehicles. What is also important is the availability of high-quality wind speed and solar radiation forecasts to be able to fully control and tap the RES potential in a short time horizon. Extensive research on spatial wind speed forecasts is presented in [23].

A novelty of this paper is a comprehensive approach to how EVs affect the Polish Power System. The paper proposes a unique approach to forecasts of daily energy demand profiles for two characteristic days, which deserves special attention. It uses both proprietary power demand forecasts for the given year and forecasts of the shapes of the relative profiles. Proprietary relative profiles are used to develop energy demand profiles resulting from e-mobility, taking into account different EV categories.

Any factors affecting the development of e-mobility not adressed in this paper will be analysed in detail in further research.

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