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Application of Artificial Neural Networks for Forecasting the Dynamics of Growth in the Number of New Electric Vehicles in Poland

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Abstract

In recent years, the field of electromobility has been developing very dynamically in Poland and worldwide. Due to the necessity of adapting road and energy infrastructure, a forecast of the development of the electric vehicle market was required. The aim of this article is to develop a forecast of the number of electric vehicles in Poland for the years 2024–2030. For this purpose, an analysis of annual data on the number of electric vehicles in Poland was conducted. Selected neural network models were used for the forecast. The results of the study indicate that the number of electric vehicles in Poland is expected to continue growing. On one hand, this is influenced by European Union policies, and on the other, by the dynamic technological advancements in the field of electromobility. The choice of sample sizes (training, testing, and validation) significantly impacts the obtained results.

Keywords

artificial neural networks, forecasting, sustainable mobility, modeling, environmental impact

1 Introduction

This study tests the hypothesis that a multilayer perceptron (MLP) neural network trained on annual EV registration data for 2010–2023 can generate forecasts for 2024–2030 with acceptable accuracy, measured by MAPE. In addition, we hypothesize that the choice of training/testing/validation split affects forecast accuracy, with a higher training share leading to lower MAPE.

The development of electromobility is one of the key elements of sustainable transport as well as the energy transformation taking place in recent years. The growing popularity of electric vehicles (EVs) in Europe and Poland is largely driven by regulations introduced by the European Union regarding CO^2 emissions. From the perspective of planning charging infrastructure, developing power grids, and forecasting environmental changes, it is crucial to develop projections for the growth of the electric vehicle market.

Artificial Neural Networks (ANNs) are playing an increasingly significant role in modeling and forecasting phenomena related to electromobility. Their undeniable advantage lies in their ability to account for complex relationships and nonlinear trends. This makes artificial neural networks a useful and effective tool for predictive data analysis. This paper discusses Polish and international research on forecasting the number of electric vehicles using artificial intelligence, with a particular focus on artificial neural networks.

In the literature on sustainable mobility, increasing attention is paid to the role of so-called cognitive tools – approaches that combine modelling, simulation, data acquisition, and artificial intelligence to analyze and improve transport systems. Orynycz (2024) argues that this integrated perspective shortens technology development cycles, helps explain complex interdependencies, and supports the reduction of environmental impacts through more efficient design and more reliable performance prediction. These insights strengthen the case for using ML/ANN methods in forecasting the development of electromobility, where relationships are often nonlinear and shaped by many external factors.

Analyses of the global electric vehicle market have been conducted for quite some time. As early as 2012, a comprehensive methodology for forecasting demand for electric vehicles was presented (Shil et al., 2024). It incorporated stated preference (SP) analysis and a hybrid choice

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model (HCM). The study considered socioeconomic factors such as income, the number of vehicles in a household, and attitudinal variables such as preferences regarding leasing and vehicle utility.

Research conducted in Beijing (Glerum et al., 2013) highlighted the applicability of the Bass diffusion model for forecasting the number of electric vehicles. The cited study used the Analytic Hierarchy Process (AHP) and its fuzzy extensions (FAHP) to evaluate key factors influencing consumer decisions. The study predicted that by 2020, the number of electric vehicles in Beijing would grow significantly.

International researchers indicate that artificial neural networks are an effective tool for modeling the dynamics of EV market growth. Research conducted in the United States (Simsek et al., 2024) confirmed the validity of methods such as linear regression, Random Forest, and XG-Boost. The study incorporated factors such as economic indicators (household incomes, fuel prices, battery costs), environmental data (greenhouse gas emissions, air quality), and policy measures (tax incentives, rebates, and EV infrastructure). Results showed the superiority of Random Forest and Gradient Boosting in accuracy over linear regression.

In recent years, studies have also been conducted on the application of deep learning (Pelegov and Chanaron, 2022) for forecasting demand for different types of electric vehicles. The research included battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), and plug-in hybrid electric vehicles (PHEVs). The findings demonstrated the superiority of the Evs-PredNet model compared to others. Metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared were used to evaluate performance.

Artificial neural networks have also been applied to forecasting the demand for EV charging based on historical data. Indian researchers (Shanmuganathan et al., 2022) used a combination of LSTM with Empirical Mode Decomposition (EMD) to retain key signal features. Additionally, they employed the Arithmetic Optimization Algorithm (AOA) to tune model parameters, such as weights and thresholds, which improved its performance.

In Europe, studies on forecasting the growth of the electric vehicle market using ANNs have been conducted, among others, in Greece (Christidis et al., 2023). These studies utilized diverse data sources such as demographic statistics, car sales data, macroeconomic indicators (e.g., GDP per capita, price indices), and survey responses on perceptions of electric vehicles (EVs). The results also incorporated economic modeling. At the European level, EV market forecasts are additionally burdened by uncertainty resulting from macroeconomic and energy conditions (Taran, 2024). The article draws attention to the links between energy policy (including differences in energy and fuel prices) and electric vehicle market penetration, emphasizing that regulatory changes and geopolitical conditions may indirectly influence the pace of transport electrification in the EU. From a modeling perspective, this means the need to supplement classical forecasts with scenario analysis (e.g., scenarios of energy prices, the scale of support for RES/EVs, the pace of infrastructure expansion), as well as cautious interpretation of extrapolated historical trends.

In the Polish context, forecasting research focuses on the analysis of public policies that may influence the rate of EV adoption (Jankowska-Karpa and Wnuk, 2024). The article synthesizes health solutions, including emission and chemical regulations, efficiency criteria, taxes and subsidies, and measures implemented in cities (e.g., low-emission zones). The authors emphasize implementation in terms of emission reduction and promotion of electric vehicles, while simultaneously activating cost and infrastructure barriers. In practice, this means that in models forecasting the development of the EV market in Poland, it is justified to explicitly identify politicians who have access to financial/regulatory incentives and the development of public infrastructure, and also take into account public scenarios. Other research studies have been conducted to analyze and forecast the number of electric vehicles and the resulting energy demand up to 2025. The research was based on historical data from 2010–2018, which formed the foundation for estimations and forecasts. Methods such as logistic, polynomial, and exponential functions, as well as hybrid models, were used for modeling (Piotrowski et al., 2020).

The use of ANNs in scientific research in Poland also extends to forecasting electricity consumption in residential buildings, which can be analogous to modeling demand generated by electric vehicles. Researchers (Włas, 2016) used a multi-layer unidirectional neural network with a backpropagation algorithm, leveraging real measurement data from 41 days for training and 62 days for testing the model.

2 Data and methods

Currently, the field of electromobility is experiencing dynamic development worldwide. This poses numerous challenges, including the planning of not only road infrastructure but also energy infrastructure in many European countries, including Poland. In this context, artificial neural networks are proving to be an effective tool for forecasting trends in areas such as the electric vehicle market.

Therefore, efforts should be undertaken to forecast the development of the electric vehicle market in Poland. Fig. 1 presents the number of newly registered electric vehicles in Poland from 2010 to 2023.

A neural network can be described as a mathematical construct that uses the nervous system to function. They typically consist of multiple layers that make up the architecture of the network. The first layer contains information about images, numbers, text, or audio as a result of a process called training. This process may consist of thousands of inputs from which the network draws certain conclusions. The basic units of neural networks include artificial neurons, mathematical functions that emulate the behavior of biological neurons. Similar to biological neurons, artificial neurons have multiple inputs but send a single output value. This is similar to dendrites in the case of biological neurons. Neural networks are at the heart of the development of artificial intelligence. Instead, research in this area seeks to create models that employ intelligent behavior, such as the ability to generalize knowledge.

Neural networks often have a variety of applications. This includes, for example, services that allow viewers to watch on-demand online series that determine an individual's most similar movie preferences based on previous viewing history. In addition, neural networks can be used in online auctions to display customer-tailored products or to support the text translation process within the Google Translate platform. Neural networks are also used for forecasting, including the number of electrical vehicles. A neural network model is used to predict the number of electrical vehicles in the counties analyzed. The advantage of the method used is that it mimics the behavior of the human brain. A neural network consists of nodes with inputs, weights, variations, and outputs.

During testing, the optimal weights were corrected by the Statistica software and artificial neural network modules

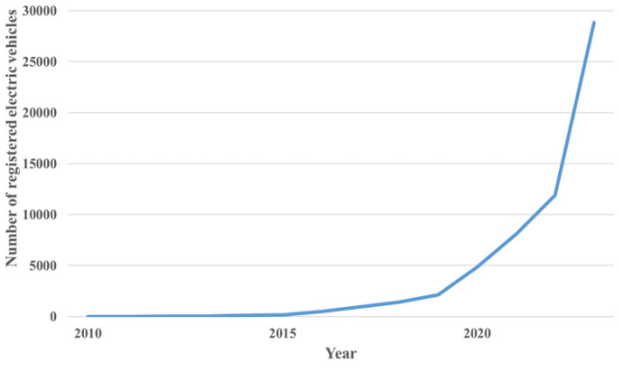


Fig. 1 The number of newly registered electric cars in Poland from 2010 to 2023 (Polskie Stowarzyszenie Nowej Mobilności, online)

available in that software. A multilayer perceptron (MLP) neural network with layers of hidden neurons was used for prediction (Cloud Software Group, online). The number of neurons in the middle layer ranged from 2 to 8 neurons in the analyzed cases, and the output layer was one neuron representing the time series output values of the number of electrical vehicles. Predictive results from the methods described depend on the choice of model and its parameters. The following prediction errors, determined from the Eqs. (1)–(6), were used to calculate the measure of predictive excellence.

ME – Mean error

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_p\right) \tag{1}$$

MAE – Mean absolute error

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - Y_p\right| \tag{2}$$

MPE – Mean percentage error

$$\mathrm{MPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{Y_i - Y_p}{Y_i} \tag{3}$$

MAPE - Mean absolute percentage error

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|Y_i - Y_p\right|}{Y_i} \tag{4}$$

SSE – Error Sum of Squares

$$\mathrm{SSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_p\right)^2} \tag{5}$$

M^2 – Theil's measure

$$M^2 = \frac{\sum_{i=1}^{N}\left(Y_i - Y_p\right)^2}{\sum_{i=1}^{N} Y_i^2} \tag{6}$$

where:

n – length of forecast horizon,

Y – observed value of electrical cars,

Y_p – projected value of electrical cars.

To forecast the number of electric vehicles, neural network models were utilized, for which the mean percentage error and the mean absolute percentage error were the smallest.

3 Results and discussion

For the annual forecast of the number electrical vehicles in Poland, data from the Polish EV Outlook Index from 2010–2023 were used. The research was conducted using the Statistica software, assuming two sample sizes for random sets:

- Training 70%, testing 15%, and validation 15%.
- Training 80%, testing 10%, and validation 10%.

The analysis included the following numbers of training networks: 20, 40, 60, 80, 100, 200, for which the MP error value was minimal (Tables 1 and 2). In Tables 1 and 2 the bold values indicate the minimum value in the corresponding comparison, while yellow highlighting indicates the lowest Mean Absolute Percentage Error (MAPE) among all evaluated models.

Table 1 Summary of neural network learning for the case of random sample size teaching 70%, testing 15% and validation 15%

Network number	Network name	Quality (learning)	Quality (testing)	Quality (validation)	Learning algorithm	Error function	Activation (hidden)	Activation (output)	Errors					
									ME	MAE	MPE	MAPE	SSE	Theil
20	MLP 1-3-1	0.99	1.00	1.00	BFGS 180	SOS	Logistic	Linear	846.97	1070.04	3.27%	17.53%	3375.79	3.45E-03
20	MLP 1-2-1	0.99	1.00	1.00	BFGS 4	SOS	Linear	Linear	537.52	903.61	4.49%	13.04%	2375.91	3.89E-03
20	MLP 1-8-1	1.00	1.00	1.00	BFGS 150	SOS	Exponential	Exponential	125.45	145.48	24.23%	24.98%	262.92	1.43E-01
20	MLP 1-5-1	1.00	1.00	1.00	BFGS 37	SOS	Tanh	Logistic	1432.80	1434.10	39.77%	39.83%	4546.44	1.49E-01
20	MLP 1-2-1	0.95	1.00	1.00	BFGS 4	SOS	Tanh	Exponential	601.24	1430.07	154.54%	168.34%	3049.32	4.39E-03
40	MLP 1-3-1	0.97	1.00	1.00	BFGS 4	SOS	Linear	Tanh	887.84	1850.50	80.53%	113.29%	4634.81	3.45E-03
40	MLP 1-3-1	0.99	1.00	1.00	BFGS 54	SOS	Tanh	Tanh	1189.59	1374.21	6.75%	16.80%	4531.64	3.89E-03
40	MLP 1-5-1	0.98	1.00	1.00	BFGS 3	SOS	Linear	Tanh	965.06	1607.76	9.57%	36.45%	4594.80	1.43E-01
40	MLP 1-8-1	1.00	1.00	1.00	BFGS 67	SOS	Logistic	Exponential	988.46	990.99	35.49%	35.55%	3029.88	1.49E-01
40	MLP 1-8-1	0.99	1.00	1.00	BFGS 34	SOS	Exponential	Logistic	1202.28	1393.04	21.94%	35.79%	4529.79	4.39E-03
60	MLP 1-3-1	0.99	1.00	1.00	BFGS 82	SOS	Tanh	Tanh	1176.38	1368.96	4.31%	16.06%	4531.31	3.45E-03
60	MLP 1-6-1	1.00	1.00	1.00	BFGS 285	SOS	Exponential	Exponential	121.70	144.00	23.74%	24.61%	259.07	3.89E-03
60	MLP 1-6-1	0.99	1.00	1.00	BFGS 2	SOS	Linear	Tanh	1143.31	1508.77	0.76%	20.32%	4611.40	1.43E-01
60	MLP 1-5-1	1.00	1.00	1.00	BFGS 251	SOS	Logistic	Logistic	1430.11	1430.11	39.73%	39.73%	4546.27	1.49E-01
60	MLP 1-7-1	1.00	1.00	1.00	BFGS 109	SOS	Logistic	Exponential	138.74	169.09	27.68%	28.30%	302.46	4.39E-03
80	MLP 1-4-1	0.99	1.00	1.00	BFGS 2	SOS	Linear	Tanh	1108.76	1514.23	5.99%	19.57%	4609.08	3.45E-03
80	MLP 1-4-1	0.99	1.00	1.00	BFGS 78	SOS	Logistic	Logistic	1265.12	1543.14	28.85%	43.85%	4728.23	3.89E-03
80	MLP 1-2-1	0.98	1.00	1.00	BFGS 4	SOS	Linear	Logistic	1043.39	1575.63	76.08%	88.39%	4567.89	1.43E-01
80	MLP 1-3-1	1.00	1.00	1.00	BFGS 53	SOS	Exponential	Exponential	1033.02	1034.30	37.01%	37.05%	3138.85	1.49E-01
80	MLP 1-6-1	0.98	1.00	1.00	BFGS 5	SOS	Linear	Logistic	1044.63	1565.74	69.27%	81.46%	4571.19	4.39E-03
100	MLP 1-5-1	1.00	1.00	1.00	BFGS 168	SOS	Tanh	Logistic	1430.66	1430.66	39.76%	39.76%	4546.43	3.45E-03
100	MLP 1-4-1	0.99	1.00	1.00	BFGS 46	SOS	Exponential	Tanh	1180.99	1369.97	4.80%	16.13%	4530.82	3.89E-03
100	MLP 1-5-1	0.99	1.00	1.00	BFGS 183	SOS	Tanh	Tanh	1176.38	1367.50	4.72%	16.45%	4531.25	1.43E-01
100	MLP 1-7-1	0.98	1.00	1.00	BFGS 4	SOS	Linear	Logistic	1081.92	1558.67	69.67%	82.50%	4567.31	1.49E-01
100	MLP 1-5-1	0.99	1.00	1.00	BFGS 84	SOS	Logistic	Tanh	1198.93	1373.10	19.29%	29.21%	4529.93	4.39E-03
200	MLP 1-8-1	1.00	1.00	1.00	BFGS 63	SOS	Tanh	Tanh	1212.86	1229.73	3.23%	13.05%	4521.68	3.45E-03
200	MLP 1-8-1	1.00	1.00	1.00	BFGS 148	SOS	Exponential	Exponential	115.54	148.53	23.51%	24.42%	258.73	3.89E-03
200	MLP 1-5-1	0.99	1.00	1.00	BFGS 3	SOS	Linear	Linear	672.10	963.22	19.71%	28.85%	2689.34	1.43E-01
200	MLP 1-6-1	1.00	1.00	1.00	BFGS 168	SOS	Logistic	Logistic	1429.62	1429.62	39.69%	39.69%	4546.12	1.49E-01
200	MLP 1-6-1	0.99	1.00	1.00	BFGS 3	SOS	Tanh	Linear	947.12	1125.34	3.91%	13.53%	3565.82	4.39E-03
								Minimal	**115.54**	**144.00**	**0.76%**	**13.04%**	**258.73**	**3.45E-03**

Table 2 Summary of neural network learning for the case of random sample size teaching 80%. testing 10% and validation 10% for Poland

Network number	Network name	Quality (learning)	Quality (testing)	Quality (validation)	Learning algorithm	Error function	Activation (hidden)	Activation (output)	Errors					
									ME	MAE	MPE	MAPE	SSE	Theil
20	MLP 1-5-1	0.88	0.00	0.00	BFGS 4	SOS	Exponential	Logistic	943.00	2102.86	46.91%	58.35%	3712.34	3.45E-03
20	MLP 1-7-1	0.94	0.00	0.00	BFGS 7	SOS	Exponential	Logistic	1059.16	1676.17	49.38%	54.57%	2705.30	3.89E-03
20	MLP 1-5-1	1.00	0.00	0.00	BFGS 132	SOS	Logistic	Exponential	15.37	139.56	1.36%	14.56%	220.57	1.43E-01
20	MLP 1-3-1	0.82	0.00	0.00	BFGS 4	SOS	Logistic	Logistic	493.83	2042.44	30.41%	49.78%	4252.30	1.49E-01
20	MLP 1-6-1	0.97	0.00	0.00	BFGS 9	SOS	Tanh	Linear	91.84	947.57	1.65%	19.31%	1888.03	4.39E-03
40	MLP 1-7-1	1.00	0.00	0.00	BFGS 51	SOS	Tanh	Linear	37.15	160.24	2.03%	13.42%	297.85	3.45E-03
40	MLP 1-7-1	0.98	0.00	0.00	BFGS 19	SOS	Logistic	Linear	95.31	599.20	11.81%	17.90%	1309.02	3.89E-03
40	MLP 1-7-1	0.99	0.00	0.00	BFGS 20	SOS	Tanh	Linear	250.45	513.94	9.14%	11.97%	900.41	1.43E-01
40	MLP 1-8-1	1.00	0.00	0.00	BFGS 60	SOS	Tanh	Exponential	40.38	90.28	6.77%	21.34%	153.27	1.49E-01
40	MLP 1-5-1	0.98	0.00	0.00	BFGS 15	SOS	Logistic	Linear	126.81	765.42	11.14%	23.48%	1493.87	4.39E-03
60	MLP 1-5-1	1.00	0.00	0.00	BFGS 48	SOS	Logistic	Tanh	48.12	211.64	8.95%	17.96%	323.44	3.45E-03
60	MLP 1-5-1	0.98	0.00	0.00	BFGS 15	SOS	Tanh	Tanh	451.78	950.59	21.36%	25.55%	1592.56	3.89E-03
60	MLP 1-2-1	0.99	0.00	0.00	BFGS 88	SOS	Exponential	Exponential	15.74	477.55	8.69%	28.31%	711.64	1.43E-01
60	MLP 1-5-1	0.95	0.00	0.00	BFGS 0	SOS	Linear	Tanh	48.71	1265.25	62.06%	81.61%	2415.27	1.49E-01
60	MLP 1-6-1	1.00	0.00	0.00	BFGS 102	SOS	Logistic	Exponential	29.98	395.44	15.00%	28.44%	558.63	4.39E-03
80	MLP 1-7-1	0.97	0.00	0.00	BFGS 4	SOS	Linear	Logistic	256.72	1078.93	59.46%	84.20%	1755.56	3.45E-03
80	MLP 1-5-1	1.00	0.00	0.00	BFGS 57	SOS	Tanh	Exponential	66.75	395.13	17.91%	27.51%	549.87	3.89E-03
80	MLP 1-6-1	0.97	0.00	0.00	BFGS 0	SOS	Linear	Linear	74.01	977.71	54.21%	68.68%	1770.30	1.43E-01
80	MLP 1-4-1	0.95	0.00	0.00	BFGS 5	SOS	Linear	Tanh	9.02	1256.38	52.47%	73.22%	2418.41	1.49E-01
80	MLP 1-5-1	1.00	0.00	0.00	BFGS 71	SOS	Exponential	Linear	43.61	167.36	0.99%	13.96%	310.16	4.39E-03
100	MLP 1-4-1	1.00	0.00	0.00	BFGS 323	SOS	Exponential	Linear	42.98	167.24	1.09%	13.91%	309.19	3.45E-03
100	MLP 1-2-1	0.91	0.00	0.00	BFGS 4	SOS	Exponential	Logistic	1089.22	1891.38	50.36%	57.10%	3218.46	3.89E-03
100	MLP 1-4-1	0.98	0.00	0.00	BFGS 6	SOS	Linear	Exponential	60.96	825.84	198.83%	210.60%	1194.93	1.43E-01
100	MLP 1-3-1	1.00	0.00	0.00	BFGS 212	SOS	Tanh	Logistic	19.68	248.13	37.91%	43.12%	411.81	1.49E-01
100	MLP 1-7-1	0.92	0.00	0.00	BFGS 4	SOS	Exponential	Logistic	747.49	1649.52	31.75%	40.20%	3092.91	4.39E-03
200	MLP 1-3-1	1.00	0.00	0.00	BFGS 31	SOS	Tanh	Tanh	140.77	235.96	16.93%	19.01%	349.68	3.45E-03
200	MLP 1-4-1	0.95	0.00	0.00	BFGS 14	SOS	Tanh	Tanh	224.02	1161.21	15.96%	20.60%	2318.11	3.89E-03
200	MLP 1-7-1	0.97	0.00	0.00	BFGS 7	SOS	Linear	Logistic	287.90	1058.07	80.60%	100.32%	1700.97	1.43E-01
200	MLP 1-3-1	0.98	0.00	0.00	BFGS 6	SOS	Linear	Exponential	49.59	827.10	195.87%	207.81%	1198.84	1.49E-01
200	MLP 1-6-1	0.97	0.00	0.00	BFGS 14	SOS	Tanh	Linear	188.36	889.23	16.63%	21.59%	1724.84	4.39E-03
								Minimal	**9.02**	**90.28**	**0.99%**	**11.97%**	**153.27**	**3.45E-03**

Based on the presented research results, it can be concluded that the number of electric vehicles in Poland will continue to grow. Depending on the adopted model, the development is predicted to be either highly dynamic or show a significant slowdown in its growth rate. The obtained results depend on the sample size selection. Increasing the percentage of the training group compared to the test and validation groups minimizes the Mean Absolute Percentage Error (MAPE).

For a 70% training group, 15% test group, and 15% validation group (70–15–15 proportions), the error was 13.04%, while for the second study (80–10–10), the error decreased to 11.94%. The results are influenced by both the significant pressure from the European Union to move away from internal combustion vehicles and the rapid advancements in electromobility technologies (Fig. 2).

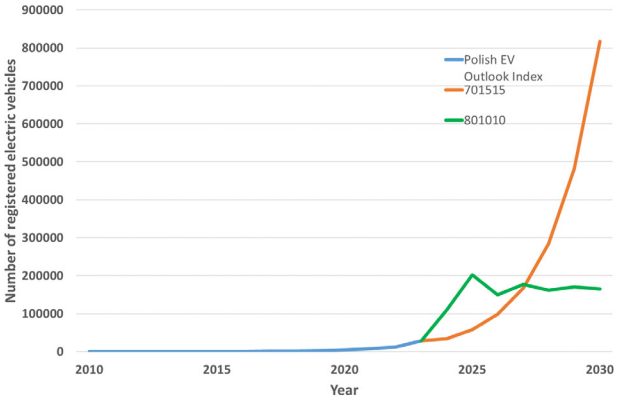


Fig. 2 The forecast number of electrical cars in Poland for the years 2024–2030

4 Conclusion

Artificial neural networks were used to forecast the number of electric vehicles in Poland, and the research was conducted in the Statistica environment. The weights used in the study were estimated by the program to minimize the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE).

Based on the obtained data, it can be concluded that further development of the electric vehicle market in Poland is to be expected. This is primarily influenced by the European Union's policies and advancements in electromobility technologies, including renewable energy sources (RES). The calculated forecast errors confirm the accuracy of the applied models.

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