Review

A Review of Auto-Regressive Methods Applications to Short-Term Demand Forecasting in Power Systems

Rafał Czapaj 1,*, Jacek Kamiński 2,*, and Maciej Sołtysik 3

1 PSE Innowacje Sp.z o.o., Al. Jerozolimskie 132 a, 02-305 Warsaw, Poland
2 Mineral and Energy Economy Research Institute of the Polish Academy of Sciences, The Department of Policy and Strategic Research, The Division of Energy Economics, Wybickiego 7A, 31-261 Kraków, Poland
3 Faculty of Electrical Engineering, Czestochowa University of Technology, Armii Krajowej 17, 42-200 Częstochowa, Poland
* Correspondence: rafal.czapaj@wp.pl (R.C.); kaminski@min-pan.krakow.pl (J.K.)

Abstract: The paper conducts a literature review of applications of autoregressive methods to short-term forecasting of power demand. This need is dictated by the advancement of modern forecasting methods and their achievement in good forecasting efficiency in particular. The annual effectiveness of forecasting power demand for the Polish National Power Grid for the next day is approx. 1%; therefore, the main objective of the review is to verify whether it is possible to improve efficiency while maintaining the minimum financial outlays and time-consuming efforts. The methods that fulfill these conditions are autoregressive methods; therefore, the paper focuses on autoregressive methods, which are less time-consuming and, as a result, cheaper in development and applications. The prepared review ranks the forecasting models in terms of the forecasting effectiveness achieved in the literature on the subject, which enables the selection of models that may improve the currently achieved effectiveness of the transmission system operator. Due to the applied approach, a transparent set of forecasting methods and models was obtained, in addition to knowledge about their potential in the context of the needs for short-term forecasting of electricity demand in the national power system. The articles in which the MAPE error was used to assess the quality of short-term forecasts were analyzed. The investigation included 47 articles, several dozen forecasting methods, and 264 forecasting models. The articles date from 1997 and, apart from the autoregressive methods, also include the methods and models that use explanatory variables (non-autoregressive ones). The input data used come from the period 1998–2014. The analysis included 25 power systems located on four continents (Asia, Europe, North America, and Australia) that were published by 44 different research teams. The results of the review show that in the autoregressive methods applied to forecasting short-term power demand, there is a potential to improve forecasting effectiveness in power systems. The most promising prognostic models using the autoregressive approach, based on the review, include Fuzzy Logic, Artificial Neural Networks, Wavelet Artificial Neural Networks, Adaptive Neurofuzzy Inference Systems, Genetic Algorithms, Fuzzy Regression, and Data Envelope Analysis. These methods make it possible to achieve the efficiency of short-term forecasting of electricity demand with hourly resolution at the level below 1%, which confirms the assumption made by the authors about the potential of autoregressive methods. Other forecasting models, the effectiveness of which is high, may also prove useful in forecasting by electricity system operators. The paper also discusses the classical methods of Artificial Intelligence, Data Mining, Big Data, and the state of research in short-term power demand forecasting in power systems using autoregressive and non-autoregressive methods and models.

Keywords: short-term forecasting; electrical power demand; power systems; autoregressive forecasting methods; classical forecasting methods; artificial intelligence methods; Big Data; machine learning; Data Mining
1. Introduction

1.1. Overview

The economic development of countries is inextricably linked with the functioning of their power systems. Due to the development of power grids and the growing access to them, electricity is now indispensable for the proper functioning of the economy and the population, and the demand for it is systematically growing. Rising electricity prices in recent years and their fluctuations, in addition to insufficient development of the manufacturing sector, make it difficult to optimally meet the growing demand for electricity. Unfortunately, storage of electricity on a large scale and in the long term is a complex and very expensive issue. Thus, at any time in the operation of power systems, it is necessary to maintain a balance between the generation of electricity and its consumption, taking into account the technical limitations of electricity networks, in order to maintain continuity and security of power and electricity supplies while maintaining the optimal operating costs of the power system. In this context, forecasting the load of power systems is an essential element of planning their work in the short, medium, and long term, and is one of the greatest challenges faced by the power industry in every country. Electricity demand forecasting is a basic element of planning electricity generation, participation in electricity markets, and the development of the power grid. Short-term forecasting of the power system load, performed, inter alia, by operators of power systems, requires ensuring the highest possible accuracy for each hour of the day while maintaining the lowest computational cost at an appropriate time. Forecasting the load on systems with the use of prognostic models using explanatory variables is costly and time-consuming, in contrast to autoregressive methods which use only information about the earlier development of the analyzed parameter in the forecasting process. Thus, along with the observed trend indicating the reduction in forecast horizons from hours to minutes, and even seconds, it is necessary to search for cheap and quick forecasting methods that will allow the current forecasting effectiveness to be maintained at lower costs of their development and with a comparable or shorter development time.

1.2. Literature Survey

In short-term electrical power demand forecasting, both autoregressive methods using the properties of moving averages and exponential smoothing, and methods using machine learning [1–6]. Support Vector Machines and Particle Swarms, and artificial intelligence [7], including Artificial Neural Networks, have been used for years. Many research centers worldwide have developed more accurate forecasting methods and models, especially for short-term forecasting. Several teams have conducted research at the academic level, perfecting the methods and models they have developed. For the conducted analyses and simulations, usually, STATISTICA®, SAS/ETS, and SPSS environments [8], GRETL [9,10], and the R and Python programming languages are used, among others.

The demand for electrical power is characterized by large fluctuations [11]. In this case, the key factors exhibit daily, weekly, annual, and multi-year variability [12]. Moreover, the seasonal variability (which results in annual variability), quarterly variability (seasons), and monthly variability (part of the seasons) are distinguished. Continuity of power demand and the still “insufficient” (in the sense of high power/capacity) development of energy storage results in the inability to store it in large quantities, which makes it necessary to cover the demand for power at the time of the occurrence of this demand [13].

Other factors, apart from the passage of time (consecutive days, weeks, etc.), that influence the variability in the power system load [14,15] are the variability in weather conditions and the resulting variability in the ambient temperature, in addition to the transition from winter to summer time [16,17] and from summer to winter time (introduced to flatten the evening peak of power demand in the summer half of the year) [12]. Other weather factors influencing the level of demand in the power system include, among others, cloudiness, air humidity, and wind speed [12]. The ambient temperature significantly affects the load in the power system. The change in weather conditions directly impacts
consumer behavior (municipal and industrial), consisting of increasing power consumption from lighting and heating devices (convector heating and electric heating).

1.3. Motivation and Incitement

Individual areas of the Polish Power System have a different share in shaping the domestic demand for electrical power. Naturally, areas with significant industrialization and, therefore, a significant population in Poland, translate into greater demand for electrical power (and, consequently, electrical power consumption), and thus, to a greater extent, changes in the weather (atmospheric conditions) affect these areas. The yearly demand forecasting error for the Polish National Power System is approximately 1%, which shows a high level of accuracy; thus, there is a need to search for the potential in well-known methods and models, including autoregressive models, to reduce the error below this level. In this context, this paper aims to review auto-regressive methods applied to short-term power demand forecasting in power systems.

1.4. Research Gaps

The conducted review of articles describing the methods and forecasting models used in short-term forecasting of electric power demand shows a great variety. Autoregressive methods are still an attractive and effective tool for forecasting. Their unquestionable advantage is low financial outlay and quickly obtaining forecast results. The current observation of scientific reports in the form of literature reviews is time-consuming. Therefore, it is important to develop rankings of forecasting models, taking into account their forecasting effectiveness. While preparing this review, the authors identified a gap in presenting the results of valuable research in this aspect, and thus attempted to develop such a ranking. The Mean Average Percentage Error was adopted as a measure for assessing the quality of forecasts developed with autoregressive methods. From the prepared ranking of 264 autoregressive models, a set of Top 10 models was distinguished, which can be a significant aid for researchers and scientists dealing with short-term forecasting of electricity demand in power systems.

1.5. Major Contributions

The main contribution of the authors is to present an overview of methods in the field of artificial intelligence, Data Mining (now often associated with Big Data issues), and Big Data. In addition, the state of research in short-term power demand forecasting for power systems using autoregressive and non-autoregressive methods and models is presented, along with a detailed table that describes the results of the review of 47 articles describing 264 forecasting models (Table 1, where MAPE is an ex post, and MAPE(ea) is an ex ante approach). Additionally, the authors present a new way to develop literature reviews in the context of selecting the most prospective prognostic models. In the proposed new approach (explained in the flowchart—Figure 1), ranking of forecasting models (Tables 2 and 3 and Figure 2) was used due to the selected measure of forecast quality (Mean Average Percentage Error). The applied new approach to the development of the results of literature reviews is an excellent source of knowledge for scientists, experts, and analysts, supporting the preparation of forecasts for power system operators, with particular emphasis on transmission system operators.
Table 1. The publications’ preview results in short-term power demand forecasting methods and models used for power systems.

| No. | Authors/Title/Publicizing House | Year | Analysis Scope | Country | Method, Model | Effectiveness | Model No. |
|-----|--------------------------------|------|----------------|---------|--------------|--------------|-----------|
| 1.  | Al-Fuhaid A.S. et al. | 1997 | 1994 | Kuwait | ANN(ea)—Artificial neural network | MAPE(ea) | 1.84 4.84 | 1 |
| 2.  | Al Meshaiei E., Soltan H. | 2011 | 2006–2008 | Kuwait | MA(ea7,30)—Moving Average (7, 30) | MAPE(ea) | 3.84 | 2 |
| 3.  | Al-Shobaki S., Mohsen M. | 2008 | 2002–2007 | Jordan | ARIMA(ea) | MAPE(ea) | 5.25 | 3 |
| 4.  | Badran S.M., Abouelatta O.B. | 2013 | 1988–2006 | Saudi Arabia | MR—Multiple Regression, MAPE | MAPE | 11.58 14.35 | 4 |
| 5.  | Badran S.M., Abouelatta O.B. | 2017 | 2013, 2015 | Poland (NPS) | HA + MR—Hierarchical Approximator + Multiple Regression | MAPE | 1.08 2.26 | 6 |
| 6.  | Buttrigo J., Asfour S. | 2017 | 2005–2015 | USA (New England) | ANN—Artificial Neural Network | MAPE | 0.85 | 7 |
| 7.  | Ceperic E., Ceperic V. | 2013 | 2006 | USA | ANN—Artificial Neural Network | MAPE | 1.50 3.72 | 8 |
| 8.  | Chakkoutahi F., Kharei M. | 2017 | 2011.05.02–2011.07.03 | Australia | ARIMA | MAPE | 0.76 1.07 | 11 |
| 9.  | Chapagain K., Kittipiyakul S. | 2016 | 2013–2015 | Thailand | MR—Multiple Regression, MAPE | MAPE | 1.75 33.45 | 15 |
| 10. | Chen H. et al. | 2001 | 1999 | Canada | ANN—Artificial Neural Network | MAPE | 0.48 3.00 | 17 |
| 11. | Chheepa T.K., Mangani T. | 2017 | 1996–1997, 2000 | Iran | ARIMA | MAPE | 1.48 1.99 | 18 |
| 12. | Clements A.A. et al. | 2015 | 1999.07.12–2013.11.27 | Australia | ARIMA | MAPE | 1.36 2.89 | 19 |
Table 1. Cont.

| No. | Authors/Title/Publishing House                                                                 | Year       | Analysis Scope | Country    | Method, Model                                                                 | Effectiveness | Model No. |
|-----|-----------------------------------------------------------------------------------------------|------------|----------------|------------|--------------------------------------------------------------------------------|---------------|-----------|
| 13  | Czapaj R. Typowanie zmiennych objaśniających przy wykorzystaniu zautomatyzowanych metod statystycznych jako sposób optimizacji wyboru metody estymacji szczytowego dobowego obciążenia KSE Przegląd Elektrotechniczny 4(93) [30] | 2016       | 2010–2014 Poland (NPS) | -         | MARSplines                                                                    | MAPE 1.86    | 20        |
|     |                                                                                               |            |                |            | C&RT—Classification and Regression Trees                                       | MAPE 2.57    | 21        |
|     |                                                                                               |            |                |            | C&RT—Classification and Regression Trees                                       | MAPE 2.56    | 22        |
|     |                                                                                               |            |                |            | Chi²—Automatic interaction detector using Chi²                                  | MAPE 4.06    | 23        |
|     |                                                                                               |            |                |            | CHAID—Chi² Automatic Interaction Detector                                         | MAPE 3.69    | 24        |
| 14  | Czapaj R., Kamiński J., Benalcazar P. Dobór zmiennych objaśniających z wykorzystaniem metody MARSplines Politechnika Częstochowska, XIV Konferencja PE [31] | 2018       | 2009–2014 Poland (NPS) | -         | MARSplines                                                                    | MAPE 1.86    | 25        |
| 15  | Czapaj R., Kamiński J., Benalcazar P. Prognozowanie krótkoterminowe z wykorzystaniem metody MARSplines Politechnika Częstochowska, XIV Konferencja PE [32] | 2018       | 2009–2014 Poland (NPS) | -         | MARSplines(ea)                                                                | MAPE(ea) 6.57| 27        |
| 16  | Dąsak K. Dobór zmiennych wejściowych do Modelu Rozkładu Kanonicznego Politechnika Częstochowska, VI Konferencja PE [33] | 2002       | 1993–1995 Poland (NPS) | -         | MRK(Mo-Fr)—Canonical Vector Decomposition Method from Monday till Friday       | MAPE(Mo-Fr) 0.64| 28        |
| 17  | Dudek G. Short-Term Load Forecasting Based on Kernel Conditional Density Estimation Przegląd Elektrotechniczny 8(86) [34] | 2010       | 1997–2000 Poland (NPS) | -         | SFS(5 years)—Sequential Forward Selection Methods                              | MAPE 1.84    | 29        |
|     |                                                                                               |            |                |            | SBS(5 years)—Sequential Backward Selection Methods                               | MAPE 1.77    | 30        |
|     |                                                                                               |            |                |            | NS(5 years)—Nearest Neighbors                                                    | MAPE 1.94    | 31        |
|     |                                                                                               |            |                |            | ANN(5 years)—Artificial Neural Network                                            | MAPE 2.02    | 32        |
|     |                                                                                               |            |                |            | FE(5 years)—Fuzzy Estimators                                                     | MAPE 1.76    | 33        |
|     |                                                                                               |            |                |            | SFS(4 years)—Sequential Forward Selection Methods                                | MAPE 2.19    | 34        |
|     |                                                                                               |            |                |            | SBS(4 years)—Sequential Backward Selection Methods                               | MAPE 2.06    | 35        |
|     |                                                                                               |            |                |            | NS(4 years)—Nearest Neighbors                                                    | MAPE 2.55    | 36        |
|     |                                                                                               |            |                |            | ANN(4 years)—Artificial Neural Network                                            | MAPE 2.24    | 37        |
|     |                                                                                               |            |                |            | FE(4 years)—Fuzzy Estimators                                                     | MAPE 2.14    | 38        |
| 18  | Dudek G., Janicki M. Nearest Neighbor Model with Weather Inputs for Pattern-based Electricity Demand Forecasting Przegląd Elektrotechniczny 3(93) [35] | 2017       | 2011–2014 Poland (NPS) | -         | MAPE (working days)                                                            | 1.55 1.67    | 39        |
|     |                                                                                               |            |                |            | MAPE (working days)                                                            | 2.82 2.88    | 40        |
|     |                                                                                               |            |                |            | MAPE (working days)                                                            | 2.41 3.26    | 41        |
|     |                                                                                               |            |                |            | MAPE (working days)                                                            | 3.43 4.82    | 42        |
| No. | Authors/Title/Publishing House | Year | Analysis Scope | Country | Method, Model | Effectiveness | Model No. |
|-----|---------------------------------|------|----------------|---------|--------------|--------------|-----------|
| 18. | Dudek G., Janicki M.  
Nearest Neighbor Model with Weather Inputs for 
Pattern-based Electricity Demand Forecasting  
Przeglad Elektrotechniczny 3(93) [35] | 2011–2014 | Poland (NPS) | Belgium | NNWISA(weekends)  
—Nearest Neighbors with Weather Inputs for Similarity Analysis | MAPE(weekends) 1.75 1.76 | 43 |
|     | | 2017 | New England | USA | MAPE(weekends) 2.92 3.16 | 45 |
|     | | | | | MAPE(weekends) 4.31 4.99 | 46 |
|     | | 2011–2014 | Poland (NPS) | Belgium | NNWISA(Holidays)  
—Nearest Neighbors with Weather Inputs for Similarity Analysis | MAPE(Holidays) 4.36 16.17 | 47 |
|     | | | | | MAPE(Holidays) 4.05 12.61 | 48 |
|     | | | | | MAPE(Holidays) 6.35 7.03 | 49 |
|     | | 2002–2004 | Poland (NPS) | Poland | PCR—Principal Component Regression | MAPE(January) 2.37 | 51 |
|     | | | | | MAPE(January) 1.52 | 52 |
|     | | 2016 | | | MAPE(January) 1.59 | 53 |
|     | | | | | MAPE(January) 1.51 | 54 |
|     | | 2002–2004 | Poland (NPS) | New England | PCR—Principal Component Regression | MAPE(January) 1.36 | 55 |
|     | | | | | MAPE(January) 1.18 | 56 |
|     | | | | | MAPE(July) 2.63 | 57 |
|     | | | | | MAPE(July) 1.14 | 58 |
|     | | | | | MAPE(July) 1.23 | 59 |
|     | | | | | MAPE(July) 1.06 | 60 |
|     | | | | | MAPE(July) 0.94 | 61 |
|     | | | | | MAPE(July) 1.00 | 62 |
|     | | | | | MAPE—Exponential Smoothing | 1.35 | 63 |
|     | | | | | MAPE—Partial Least Squares Regression | 1.34 | 64 |
|     | | | | | ARIMA—Artificial Neural Network (Multilayer Perceptron) | MAPE 1.82 | 65 |
|     | | | | | NWE—Nadaraya—Watson Estimator | MAPE 1.66 | 66 |
|     | | | | | NM—Naive Method | MAPE 1.44 | 67 |
|     | | | | | MAPE 1.30 | 38 |
|     | | | | | MAPE 3.43 | 39 |
| No. | Authors/Title/Publishing House | Year Scope | Country | Method, Model | Effectiveness | Model No. |
|-----|--------------------------------|------------|---------|--------------|--------------|----------|
| 19. | Dudek G. Pattern-Based Local Linear Regression Models for Short-Term Load Forecasting Elsevier, Electric Power System Research (130) [36] | 2007–2009 | France  | PCR—Principal Component Regression | MAPE 1.71 | 70 |
|    |                                |            |         | PLSR—Partial Least Squares Regression | MAPE 1.57 | 71 |
|    |                                |            |         | ARIMA        | MAPE 2.32 | 72 |
|    |                                |            |         | ES—Exponential Smoothing | MAPE 2.10 | 73 |
|    |                                |            |         | ANN(MLP)—Artificial Neural Network (Multilayer Perceptron) | MAPE 1.64 | 74 |
|    |                                |            |         | NWE—Nadaraya—Watson Estimator | MAPE 1.66 | 75 |
|    |                                |            |         | NM—Naive Method | MAPE 5.05 | 76 |
| 20. | Dudek G. Drzewa regresyjne i lasy losowe jako narzędzia predykcji szeregów czasowych z wahańiami sezonowymi Politechnika Częstochowska [37] | 2006–2008 | Australia | PCR—Principal Component Regression | MAPE 3.00 | 84 |
|    |                                |            |         | PLSR—Partial Least Squares Regression | MAPE 2.83 | 85 |
|    |                                |            |         | ARIMA        | MAPE 3.67 | 86 |
|    |                                |            |         | ES—Exponential Smoothing | MAPE 3.52 | 87 |
|    |                                |            |         | ANN(MLP)—Artificial Neural Network (Multilayer Perceptron) | MAPE 2.92 | 88 |
|    |                                |            |         | NWE—Nadaraya—Watson Estimator | MAPE 2.82 | 89 |
|    |                                |            |         | NM—Naive Method | MAPE 4.88 | 90 |
|    |                                | 2002–2004 | Poland (NPS) | RF(January)—Random Forest | MAPE(January) 1.42 | 91 |
|    |                                |            |         | C&RT(January)—Classification and Regression Trees | MAPE(January) 1.70 | 92 |
|    |                                |            |         | C&RTR(January)—Fuzzy Classification and Regression Trees | MAPE(January) 1.62 | 93 |
|    |                                |            |         | ARIMA(January) | MAPE(January) 2.64 | 94 |
|    |                                |            |         | ES(January)—Exponential Smoothing | MAPE(January) 2.35 | 95 |
|    |                                |            |         | ANN(January)—Artificial Neural Network | MAPE(January) 1.32 | 96 |
|    |                                |            |         | NM(January)—Naive Method | MAPE(January) 6.37 | 97 |
|    |                                |            |         | RF(July)—Random Forest | MAPE(July) 0.92 | 98 |
|    |                                |            |         | C&RT(July)—Classification and Regression Trees | MAPE(July) 1.16 | 99 |
| No. | Authors/Title/Publishing House | Year | Analysis Scope | Country | Method, Model | Effectiveness | Model No. |
|-----|--------------------------------|------|----------------|---------|---------------|--------------|----------|
| 20. | Dudek G. Drzewa regresyjne i lasy losowe jako narzędzia predykcji szeregów czasowych z wahańiami sezonowymi Politechnika Częstochowska [37] | 2016 | 2002–2004 Poland (NPS) | C&RTR(July)—Fuzzy Classification and Regression Trees | MAPE(July) | 1.13 | 100 |
|     |                               |      |                |         | ARIMA(July)   | MAPE(July)   | 1.21 | 101 |
|     |                               |      |                |         | ES(July)—Exponential Smoothing | MAPE(July) | 1.19 | 102 |
|     |                               |      |                |         | ANN(July)—Artificial Neural Network | MAPE(July) | 0.97 | 103 |
|     |                               |      |                |         | NM(July)—Naive Method | MAPE(July) | 1.29 | 104 |
| 21. | Esener I.I., Yuskel T., Kurban M. Short-Term Load Forecasting Without Meteorological Data Using AI-Based Structures Turkish Journal of Electrical Engineering & Computer Sciences (23) [38] | 2015 | Turkey | ANN—Artificial Neural Network | MAPE 3.67 | 105 |
|     |                               |      |                |         | WM+ANN—WM—Wavelet Method + ANN—Artificial Neural Network | MAPE 3.73 | 106 |
|     |                               |      |                |         | WM+ANN(RBF)—WM—Wavelet Method + ANN—Artificial Neural Network (Radial Basis Functions) | MAPE 2.89 | 107 |
|     |                               | 2009 |                |         | ED—Empirical Decomposition | MAPE 3.52 | 108 |
|     |                               |      |                |         | ANN—Artificial Neural Network | MAPE 3.81 | 109 |
|     |                               | 2010 |                |         | WM+ANN—WM—Wavelet Method + ANN—Artificial Neural Network | MAPE 4.18 | 110 |
|     |                               |      |                |         | WM+ANN(RBF)—WM—Wavelet Method + ANN—Artificial Neural Network (Radial Basis Functions) | MAPE 2.99 | 111 |
|     |                               |      |                |         | ED—Empirical Decomposition | MAPE 3.63 | 112 |
| 22. | Fan S. Short-Term Load Forecasting Based on a Semi-Parametric Additive Model IEEE Transactions on Power Systems [39] | 2010 | 1997–2009 (training) 2009.01.01–2009.01.31 (test) Australia | SPAM—Semi-Parametric Additive Model | MAPE 1.41 | 113 |
|     |                               |      |                |         | ANN—Artificial Neural Network | MAPE 1.82 | 114 |
|     |                               |      |                |         | SPAM+ANN—Hybrid Model (Semi-Parametric Additive Model + Artificial Neural Network) | MAPE 1.58 | 115 |
| 23. | Farahat M.A. Short Term Load Forecasting Using Neural Networks and Particle Swarm Optimization Journal of Electrical Engineering [40] | 2018 | 2011.07.01–2011.08.10 (training) 2011.08.11–2011.08.17 (test) Egypt | ANN(BP)—Artificial Neural Network (Back Propagation Training) | MAPE 4.60 | 116 |
|     |                               |      |                |         | ANN(BP)+PSO—ANN(BP)—Artificial Neural Network (Back Propagation Training) + PSO—Particle Swarm Optimization | MAPE 1.90 | 117 |
| 24. | Gorwar M. Short Term Load Forecasting Using Time Series Analysis: A Case Study for Karnataka, India ResearchGate, IJESIT Conference [41] | 2012 | 2011–2012 India | AR(ea)—Autoregression | MAPE 13.03 | 118 |
|     |                               |      |                |         | ARMA(ea) | MAPE 11.73 | 119 |
|     |                               |      |                |         | ARIMA(ea) | MAPE 6.15 | 120 |
| No. | Authors/Title/Publishing House | Year | Analysis Scope | Country | Method, Model | Effectiveness | Model No. |
|-----|--------------------------------|------|----------------|---------|--------------|--------------|-----------|
| 25. | Hassan S., Khosravi A., Jaafar J. Examining Performance of Aggregation Algorithms for Neural Network-Based Electricity Demand Forecasting ScienceDirect, Electrical Power and Energy Systems (64) [42] | 2015 | 2011 (30-min Intervals) | Malaysia, Australia, Pakistan | ANN(I)—Artificial Neural Network (Integration) | MAPE(I 30 min.) 7.16 | 121 |
|     |                               |      |                |         | ANN(TI)—Sztuczna sieć neuronowa (Trimmed Integration) | MAPE(I 30 min.) 10.13 | 122 |
|     |                               |      |                |         | ANN(BA)—Artificial Neural Network (Bayesian Averaging) | MAPE(I 30 min.) 4.34 | 123 |
|     |                               |      |                |         | NM—Metoda naiwna | MAPE(I 30 min.) 6.41 | 124 |
| 26. | He W. Deep Neural Network Based Load Forecast Computer Modelling & New Technologies 18(3) [43] | 2014 | 2000.02.10–2012.11.30 | China | ANN—Artificial Neural Network | MAPE 1.90 2.08 | 125 |
|     |                               |      |                |         | FR(ea)—Fuzzy Regression without Interaction | MAPE(ea) 14.21 | 126 |
|     |                               |      |                |         | FRICV(ea)—Fuzzy Regression without Interaction with Categorical Variables | MAPE(ea) 5.16 | 127 |
|     |                               |      |                |         | FR(ea)+MR—FR(ea)—Fuzzy Regression without Interaction + MR—Multiple Regression | MAPE(ea) 4.63 | 128 |
|     |                               |      |                |         | FR(ea)+TV—FR(ea)—Fuzzy Regression without Interaction + TV—Temperature Variables | MAPE(ea) 3.68 | 129 |
| 27. | Hong T., Wang P. Fuzzy Interaction Regression for Short Term Load Forecasting University of North Carolina at Charlotte 13(1) [44] | 2014 | 2005–2007 | USA | IS+TC(USA 2013)—IS—Image Similarities + TC—Temperature Correction (USA 2013) | MAPE 4.50 | 130 |
|     |                               |      |                |         | IS(USA 2013)—Naive Method (USA 2013) | MAPE 10.78 | 131 |
|     |                               |      |                |         | IS+TC(USA 2014)—IS—Image Similarities + TC—Temperature Correction (USA 2014) | MAPE 4.68 | 132 |
|     |                               |      |                |         | IS(USA 2014)—Naive Method (USA 2014) | MAPE 10.94 | 133 |
| 28. | Janicki M. Temperature Correction Method for Pattern Similarity-Based Short-term Electricity Demand Forecasting Models Przegląd Elektrotechniczny 3(93) [45] | 2017 | 2013–2014 | Belgium | IS+TC(BEL 2013)—IS—Image Similarities + TC—Temperature Correction (Belgium 2013) | MAPE 3.80 | 134 |
|     |                               |      |                |         | IS+TC(BEL 2014)—IS—Image Similarities + TC—Temperature Correction (Belgium 2014) | MAPE 3.66 | 136 |
|     |                               |      |                |         | IS+TC(BEL 2014)—IS—Image Similarities + TC—Temperature Correction (Belgium 2014) | MAPE 3.66 | 136 |
|     |                               |      |                |         | IS+TC(BEL 2014)—IS—Image Similarities + TC—Temperature Correction (Belgium 2014) | MAPE 3.66 | 136 |
| No. | Authors/Title/Publishing House | Year | Analysis Scope | Country | Method, Model | Effectiveness | Model No. |
|-----|--------------------------------|------|----------------|---------|--------------|--------------|----------|
| 29. | Kheirkhah A. et al. Improved Estimation of Electricity Demand Function by Using of Artificial Neural Network, Principal Component Analysis and Data Envelopment Analysis Elsevier Ltd. Computers & Industrial Engineering (64) [46] | 2013 | 1992.04.01–2003.02.28 | Iran, Ireland, Turkey | GA—Genetic Algorithm | MAPE 0.14 | 138 |
|     |                               |      |                |         | FR—Fuzzy Regression | MAPE 0.08 | 139 |
|     |                               |      |                |         | ANN—Artificial Neural Network | MAPE 0.16 | 140 |
|     |                               |      |                |         | ANFIS—Adaptive Neuron Fuzzy Inference System | MAPE 0.15 | 141 |
|     |                               |      |                |         | DEA—Data Envelopment Analysis | MAPE 0.01 | 142 |
| 30. | Kolcun M., Holka L. Daily Load Diagram Prediction of Eastern Slovakia Politechnika Cz˛ estochowska, VI Konferencja PE [47] | 2002 | 1997–1998 | Slovakia | ANN(Koh)—Kohonen’s Artificial Neural Network | MAPE 3.50 | 143 |
| 31. | Lin Y. An Ensemble Model Based on Machine Learning Methods and Data Preprocessing for Short-Term Electric Load Forecasting Energies 10(1186) [48] | 2017 | 2010.08.01–2011.07.31 | Australia | EML—Extreme Machine Learning | MAPE 0.83 | 144 |
|     |                               |      |                |         | EMLDE—Extreme Machine Learning (optimized by Differential Evolution | MAPE 0.77 | 145 |
|     |                               |      |                |         | ARIMA | MAPE 0.73 | 146 |
| 32. | Liu N., Babushkin V., Afshari A. Short-Term Forecasting of Temperature Driven Electricity Load Using Time Series and Neural Network Model Journal of Clean Energy Technologies 2(4) [49] | 2014 | 2010.01.01–2011.06.30 | United Arab Emirates | SARIMAX | MAPE 1.58 | 150 |
|     |                               |      |                |         | ANN—Artificial Neural Network | MAPE 2.29 | 151 |
| 33. | Magnano L., Boland J.W. Generation of Synthetic Sequences of Electricity Demand: Application in South Australia Elsevier Ltd. Energy (32) [50] | 2006 | 2000–2001 (Summer Time) | Australia | ARMA(Summer Time) | MAPE (Summer Time) 2.40 | 152 |
|     |                               |      |                |         | SVM+PSO—SVM—Support Vector Machines + PSO—Particle Swarm Optimization (including UV) | 2011.05.11. MAPE(UV; May 2011) 2.65 | 153 |
|     |                               |      |                |         |                       | 2011.08.31. MAPE(UV; August 2011) 1.23 | 154 |
|     |                               |      |                |         |                       | 2011.11.30. MAPE(UV; November 2011) 2.13 | 155 |
|     |                               |      |                |         |                       | 2012.01.26. MAPE(UV; January 2012) 1.73 | 156 |
| 34. | Nadhoka I.I., Al-Zihery B.M. Mathematical Modelling and Short-Term Forecasting of Electricity Consumption of the Power System, with Due Account of Air Temperature and Natural Illumination, Based on Support Vector machine and Particle Swarm Elsevier Ltd. Procedia Engineering (129) [51] | 2015 | 2009–2012 | Iraq | SVM+PSO—SVM—Support Vector Machines + PSO—Particle Swarm Optimization (including temperature) | 2011.05.11. MAPE(Temp.; May 2011) 2.60 | 157 |
|     |                               |      |                |         |                       | 2011.08.31. MAPE(Temp.; August 2011) 1.37 | 158 |
|     |                               |      |                |         |                       | 2011.11.30. MAPE(Temp.; November 2011) 1.94 | 159 |
|     |                               |      |                |         |                       | 2012.01.26. MAPE(Temp.; January 2012) 1.90 | 160 |
| No. | Authors/Title/Publishing House | Year | Analysis Scope | Country | Method, Model | Effectiveness | Model No. |
|-----|--------------------------------|------|----------------|---------|--------------|--------------|-----------|
| 34  | Nadtoka I.I., Al-Zihery B.M. Mathematical Modelling and Short-Term Forecasting of Electricity Consumption of the Power System, with Due Account of Air Temperature and Natural Illumination, Based on Support Vector machine and Particle Swarm Optimization Elsevier Ltd. Procedia Engineering (129) [51] | 2015 | 2009–2012 | Iraq | SVM+PSO--SVM -- Support Vector Machines + PSO -- Particle Swarm Optimization (including UV & Temperature) | 2011.05.11. MAPE(UV; Temp.; May 2011) 2.26 | 161 |
|     |                               |      |                |         |              |              |           |
|     |                               |      |                |         |              | 2011.08.31. MAPE(UV; Temp.; August 2011) 1.41 | 162 |
|     |                               |      |                |         |              | 2011.11.30. MAPE(UV; Temp.; November 2011) 1.61 | 163 |
|     |                               |      |                |         |              | 2012.01.26. MAPE(UV; Temp.; January 2012) 1.58 | 164 |
| 35  | Narayan A. Long Short Term Memory Networks for Short-Term Electric Load Forecasting IEEE International Conference on Systems, Man, and Cybernetics [52] | 2017 | 2006–2016 | Canada | ANN(January)--Artificial Neural Network MAPE(January) 4.60 | 165 |
|     |                               |      |                |         | ARIMA(May) MAPE(May) 5.70 | 166 |
|     |                               |      |                |         | ANN-LSTM-RNN(September)—Long—Short—Term Memories—Recurrent Neural Network MAPE(September) 4.40 | 167 |
|     |                               |      |                |         | ANN(sty.)—Sztuczna sie neutronowa MAPE(January) 3.80 | 171 |
|     |                               |      |                |         | ARIMA(May) MAPE(May) 3.90 | 172 |
|     |                               |      |                |         | ANN-LSTM-RNN(September)—Long—Short—Term Memories—Recurrent Neural Network MAPE(September) 3.80 | 173 |
| 36  | Nowicka-Zagrajek J., Weron R. Modeling Electricity Loads in California: ARMA Models with Hyperbolic Noise Hugo Steinhaus Center Wroclaw University of Technology, KBN [53] | 2002 | 1999.01.01–2000.12.31 | USA | ARMA(1,6) (January 1.—February 28.) MAPE 1.66 | 174 |
|     |                               |      |                |         | ARMA Adaptive (January 3.—February 28.) MAPE 1.66 | 175 |
|     |                               |      |                |         | ARMA(1,6) (January 1.—February 28.) MAPE 1.24 | 176 |
|     |                               |      |                |         | ARMA Adaptive (January 3.—February 28.) MAPE 1.23 | 177 |
|     |                               |      |                |         | SA—Simple Averaging(ea) MAPE(ea) 2.10 | 178 |
|     |                               |      |                |         | AT(FA) Average Trimming MAPE(ea) 2.10 | 179 |
|     |                               |      |                |         | WA(UW) Winsor's Averaging MAPE(ea) 2.10 | 180 |
|     |                               |      |                |         | OLS(MNKea) (Ordinary Least Squares) MAPE(ea) 2.14 | 181 |
|     |                               |      |                |         | RMAD(ea) (Regression of the Minimum Absolute Deviation) MAPE(ea) 2.14 | 182 |
|     |                               |      |                |         | LSLP(ea) (Limit Squares Limited—Positive Weights) MAPE(ea) 2.12 | 183 |
| No. | Authors/Title/Publishing House                                                                 | Year Scope                  | Country | Method, Model                                           | Effectiveness | Model No. |
|-----|-----------------------------------------------------------------------------------------------|-----------------------------|---------|----------------------------------------------------------|---------------|-----------|
| 37. | Nowotarski J. et al. Improving Short Term Load Forecast Accuracy via Combining Sister Forecasts | 2015 2007.01.01–2011.12.31  | USA     | LSL(ea) (Least Squares Limited)                           | MAPE 2.11     | 184       |
|     |                                               |                             |         | IRMSE(ea) (IRMSE Averaging)                                | MAPE 2.10     | 185       |
|     |                                               |                             |         | BI—C(ea) (The Best Individual Calibration Window)          | MAPE 2.25     | 186       |
|     |                                               |                             |         | SM—Sister Model 1(ea)                                      | MAPE 2.29     | 187       |
|     |                                               |                             |         | SM—Sister Model 2(ea)                                      | MAPE 2.24     | 188       |
|     |                                               |                             |         | SM—Sister Model 3(ea)                                      | MAPE 2.34     | 189       |
|     |                                               |                             |         | SM—Sister Model 4(ea)                                      | MAPE 2.32     | 190       |
|     |                                               |                             |         | SM—Sister Model 5(ea)                                      | MAPE 2.28     | 191       |
|     |                                               |                             |         | SM—Sister Model 6(ea)                                      | MAPE 2.30     | 192       |
|     |                                               |                             |         | SM—Sister Model 7(ea)                                      | MAPE 2.37     | 193       |
|     |                                               |                             |         | SM—Sister Model 8(ea)                                      | MAPE 2.31     | 194       |
| 38. | Hsiao-Ten P. Forecast of Electricity Consumption and Economic Growth in Taiwan by State Space Modeling Elsevier Ltd. Energy (34) | 2009 2002–2007  | Taiwan   | ECSTSP —Error—Correction State Space Model                | MAPE 3.90     | 195       |
|     |                                               |                             |         | STSP —State Space Model                                    | MAPE 4.04     | 201       |
|     |                                               |                             |         | SARIMA                                                    | MAPE 3.97     | 206       |
| 39. | Rana M, Koprinska I. Forecasting Electricity Load with Advanced Wavelet Neural Networks Elsevier B.V. Neurocomputing (182) | 2016 2006–2007  |         | WANN(F—Aus.)—Wavelet Artificial Neural Network            | MAPE 0.27     | 213       |
|     |                                               |                             |         | ANN(Aus.)—Artificial Neural Network                         | MAPE 0.28     | 214       |
|     |                                               |                             |         | FL(Aus.)—Fuzzy Logic                                      | MAPE 0.29     | 215       |
|     |                                               |                             |         | MTR(Aus.)—Model Tree Rules                                 | MAPE 0.35     | 216       |
|     |                                               |                             |         | ESDS(n-1; Aus.)—Exponential Smoothing—Daily Seasonality    | MAPE 0.30     | 217       |
|     |                                               |                             |         | ESW(n-1; Aus.)—Exponential Smoothing—Weekly Seasonality    | MAPE 0.32     | 218       |
|     |                                               |                             |         | ESDSW(n-1; Aus.)—Exponential Smoothing—Daily and Weekly Seasonality | MAPE 0.30     | 219       |
|     |                                               |                             |         | ARIMA(n-1; Aus.) Daily                                     | MAPE 0.30     | 220       |
|     |                                               |                             |         | ARIMA(n-7; Aus.) Weekly                                    | MAPE 0.32     | 221       |
| No. | Authors/Title/Publishing House | Year Scope | Country | Method, Model | Effectiveness | Model No. |
|-----|--------------------------------|------------|---------|---------------|--------------|----------|
|     |                                | - Years    | -       | -             | -            | -        |
| 39. | Rana M, Koprinska I.  
Forecasting Electricity Load with Advanced Wavelet Neural Networks Elsevier B.V. Neurocomputing (182) [56] | 2006–2007 | Australia | ARIMA(n=1 i n-7; Aus.) Daily & Weekly | MAPE 0.30 | 222 |
|     |                                |            | Australia | RM(Aus.)—Industrial Model | MAPE 0.31 | 223 |
|     |                                |            | Australia | NAM(Aus.)—Naive Averaged Method | MAPE 13.48 | 224 |
|     |                                |            | Australia | NDM(Aus.)—Naive Delayed Method | MAPE 0.47 | 225 |
|     |                                |            | Australia | NM(n=1; Aus.)—Naive Method (Previous Day) | MAPE 5.05 | 226 |
|     |                                |            | Australia | NM(n=7; Aus.)—Naive Method (Previous Week) | MAPE 4.94 | 227 |
|     |                                |            | Spain | ANN(F—Esp)—Wavelet Artificial Neural Network | MAPE 1.72 | 228 |
|     |                                |            | Spain | ANN(Esp)—Artificial Neural Network | MAPE 2.12 | 229 |
|     |                                |            | Spain | FL(Esp)—Fuzzy Logic | MAPE 2.25 | 230 |
|     |                                |            | Spain | MTR(Esp)—Model Tree Rules | MAPE 2.24 | 231 |
|     |                                |            | Spain | ESDS(n=1; Esp)—Exponential Smoothing—Daily Seasonality | MAPE 2.54 | 232 |
|     |                                |            | Spain | ESWS(n=7; Esp)—Exponential Smoothing—Weekly Seasonality | MAPE 2.01 | 233 |
|     |                                | 2010–2011 | Spain | ESDWS(n=1 i n-7; Esp)—Exponential Smoothing—Daily and Weekly Seasonality | MAPE 1.95 | 234 |
|     |                                |            | Spain | ARIMA(n=1; Esp) Daily Seasonality | MAPE 2.45 | 235 |
|     |                                |            | Spain | ARIMA(n=7; Esp) Weekly Seasonality | MAPE 2.00 | 236 |
|     |                                |            | Spain | ARIMA(n=1 i n-7; Esp) Daily & Weekly Seasonality | MAPE 1.89 | 237 |
|     |                                |            | Spain | RM(Esp)—Industrial Model | MAPE 0.31 | 238 |
|     |                                |            | Spain | NAM(Esp)—Naive Averaged Method | MAPE 21.18 | 239 |
|     |                                |            | Spain | NDM(Esp)—Naive Delayed Method | MAPE 5.05 | 240 |
|     |                                |            | Spain | NMPD(n=1; Esp)—Naive Method (Previous Day) | MAPE 9.45 | 241 |
|     |                                |            | Spain | NMPW(D-7; Esp)—Naive Method (Previous Week) | MAPE 7.42 | 242 |
| 40. | Siwek K., Osowski S.  
Prognozowanie obciążeń 24-godzinnych w systemie elektroenergetycznym z użyciem zespołu sieci neuronowych Przegląd Elektrotechniczny 8(85) [57] | 2006–2008 | Poland (NPS) | ANN(MLP)—Artificial Neural Network (Multilayer Perceptron) | MAPE 2.07 | 243 |
|     |                                |            | Poland (NPS) | ANN(SVM)—Artificial Neural Network (Support Vector Machines) | MAPE 2.24 | 244 |
|     |                                |            | Poland (NPS) | ANN(Elman)—Artificial Neural Network (Elman) | MAPE 2.26 | 245 |
|     |                                |            | Poland (NPS) | ANN(Koh)—Kohonen’s Artificial Neural Network | MAPE 2.37 | 246 |
|     |                                |            | Poland (NPS) | ANN(MLPZ1)—Artificial Neural Network (Committee—Multilayer Perceptron 1) | MAPE 1.48 | 247 |
| No. | Authors/Title/Publishing House | Year | Analysis Scope | Country | Method, Model | Effectiveness | Model No. |
|-----|--------------------------------|------|----------------|---------|--------------|--------------|-----------|
| 40. | Siwek K., Osowski S. Prognozowanie obciążeni 24-godzinnych w systemie elektroenergetycznym z użyciem zespołu sieci neuronowych Przegląd Elektrotechniczny 8(85) [57] | 2009 | 2006–2008 | Poland (NPS) | ANN(SVMZ)—Artificial Neural Network (Committee—Support Vector Machines) | MAPE 1.35 | 248 |
| 41. | Selivan R.A., Rajagopal R. A Model For The Effect of Aggregation on Short Term Load Forecasting IEEE, Stanford University [58] | 2014 | - | USA | ARMA | MAPE 2.00 | 250 |
| 42. | Sousa J.C., Neves LP., Jorge H.M. Assessing the Relevance of Load Profiling Information in Electrical Load Forecasting Based on Neural Network Models Elsevier Ltd. Electrical Power and Energy Systems (40) [59] | 2012 | 2006.12.15–2009.11.30 | Portugal | ARMA | MAPE 6.13 | 253 |
| 43. | Wang P., Liu B., Hong T. Electric Load Forecasting with Recency Effect: A Big Data Approach Hugo Steinhaus Center Wrocław University of Technology [60] | 2015 | 2007 | USA | ARMA | MAPE 2.40 | 252 |
| 44. | Wang Y., Bielecki J.M. Electricity Loads Acclimation and the Response of Hourly einen to Meteorological Variables Elsevier Ltd. Energy (142) [61] | 1999.07.28–2007.12.31. (Calibration Set) | USA | ARMA | MAPE 2.63 | 260 |
| 45. | Wyrozumski T. Prognozowanie neuronowe w energetyce Politechnika Lubelska, Konferencja REE [62] | 2005 | - | Poland | ANN(ea)—Artificial Neural Network | MAPE 1.31 | 259 |
| 46. | Yang J. Power System Short-term Load Forecasting TU Darmstadt, Doctoral Thesis [63] | 2006 | 2002 | China | ANN—Artificial Neural Network | MAPE 1.51 | 261 |
| 47. | Yu X., Ji H. A PSO-SVM-Based 24 h Power Load Forecasting Model MATEC Web of Conferences (25) [64] | 2015 | 2014 | China | SVR | MAPE 3.28 | 263 |
Figure 1. The design of the survey.

Table 2. Forecasting model ranking for the position from 1 to 132.

| Ranking (1–33) | Model No. | Ranking (34–66) | Model No. | Ranking (67–99) | Model No. | Ranking (100–132) | Model No. |
|---------------|-----------|-----------------|-----------|-----------------|-----------|-----------------|-----------|
| 1             | 142       | 34              | 16        | 67              | 91        | 100             | 43        |
| 2             | 139       | 35              | 98        | 68              | 67        | 101             | 204       |
| 3             | 256       | 36              | 10        | 69              | 18        | 102             | 33        |
| 4             | 138       | 37              | 61        | 70              | 247       | 103             | 30        |
| 5             | 141       | 38              | 103       | 71              | 8         | 104             | 65        |
| 6             | 140       | 39              | 62        | 72              | 54        | 105             | 114       |
| 7             | 257       | 40              | 258       | 73              | 261       | 106             | 1         |
| 8             | 213       | 41              | 60        | 74              | 262       | 107             | 29        |
| 9             | 214       | 42              | 6         | 75              | 52        | 108             | 80        |
| 10            | 215       | 43              | 100       | 76              | 198       | 109             | 20        |
| 11            | 149       | 44              | 58        | 77              | 78        | 110             | 25        |
| 12            | 217       | 45              | 99        | 78              | 39        | 111             | 237       |
| 13            | 219       | 46              | 56        | 79              | 82        | 112             | 117       |
| 14            | 220       | 47              | 102       | 80              | 71        | 113             | 125       |
| 15            | 222       | 48              | 212       | 81              | 115       | 114             | 160       |
| 16            | 223       | 49              | 101       | 82              | 150       | 115             | 31        |
| 17            | 238       | 50              | 59        | 83              | 164       | 116             | 159       |
| 18            | 218       | 51              | 154       | 84              | 53        | 117             | 234       |
| 19            | 221       | 52              | 177       | 85              | 77        | 118             | 236       |
| 20            | 216       | 53              | 176       | 86              | 163       | 119             | 250       |
| 21            | 148       | 54              | 9         | 87              | 93        | 120             | 233       |
| 22            | 225       | 55              | 104       | 88              | 74        | 121             | 32        |
| 23            | 17        | 56              | 68        | 89              | 81        | 122             | 79        |
| 24            | 14        | 57              | 259       | 90              | 66        | 123             | 200       |
| 25            | 147       | 58              | 96        | 91              | 75        | 124             | 35        |
| 26            | 28        | 59              | 64        | 92              | 174       | 125             | 243       |
| 27            | 12        | 60              | 63        | 93              | 175       | 126             | 73        |
| 28            | 146       | 61              | 248       | 94              | 92        | 127             | 178       |
| 29            | 11        | 62              | 19        | 95              | 70        | 128             | 179       |
| 30            | 145       | 63              | 55        | 96              | 249       | 129             | 180       |
Table 2. Cont.

| Ranking (1–33) | Model No. | Ranking (34–66) | Model No. | Ranking (67–99) | Model No. | Ranking (100–132) | Model No. |
|----------------|-----------|-----------------|-----------|-----------------|-----------|-------------------|-----------|
| 31             | 13        | 64              | 158       | 97              | 228       | 130               | 185       |
| 32             | 144       | 65              | 113       | 98              | 156       | 131               | 184       |
| 33             | 7         | 66              | 162       | 99              | 15        | 132               | 183       |

Table 3. Forecasting model ranking for the position from 133 to 264.

| Ranking (133–165) | Model No. | Ranking (166–198) | Model No. | Ranking (199–231) | Model No. | Ranking (232–264) | Model No. |
|-------------------|-----------|-------------------|-----------|-------------------|-----------|-------------------|-----------|
| 133               | 229       | 166               | 203       | 199               | 87        | 232               | 227       |
| 134               | 155       | 167               | 5         | 200               | 108       | 233               | 76        |
| 135               | 38        | 168               | 235       | 201               | 112       | 234               | 226       |
| 136               | 181       | 169               | 232       | 202               | 136       | 235               | 240       |
| 137               | 182       | 170               | 36        | 203               | 86        | 236               | 254       |
| 138               | 211       | 171               | 22        | 204               | 105       | 237               | 127       |
| 139               | 34        | 172               | 21        | 205               | 129       | 238               | 3         |
| 140               | 37        | 173               | 196       | 206               | 24        | 239               | 207       |
| 141               | 188       | 174               | 199       | 207               | 106       | 240               | 166       |
| 142               | 231       | 175               | 264       | 208               | 208       | 241               | 170       |
| 143               | 244       | 176               | 157       | 209               | 134       | 242               | 50        |
| 144               | 186       | 177               | 202       | 210               | 171       | 243               | 253       |
| 145               | 230       | 178               | 57        | 211               | 173       | 244               | 120       |
| 146               | 161       | 179               | 260       | 212               | 109       | 245               | 168       |
| 147               | 245       | 180               | 94        | 213               | 2         | 246               | 49        |
| 148               | 191       | 181               | 153       | 214               | 172       | 247               | 97        |
| 149               | 151       | 182               | 40        | 215               | 195       | 248               | 124       |
| 150               | 187       | 183               | 89        | 216               | 251       | 249               | 27        |
| 151               | 192       | 184               | 85        | 217               | 201       | 250               | 121       |
| 152               | 194       | 185               | 210       | 218               | 48        | 251               | 242       |
| 153               | 72        | 186               | 107       | 219               | 23        | 252               | 169       |
| 154               | 190       | 187               | 45        | 220               | 110       | 253               | 135       |
| 155               | 189       | 188               | 88        | 221               | 255       | 254               | 241       |
| 156               | 205       | 189               | 111       | 222               | 46        | 255               | 137       |
| 157               | 95        | 190               | 84        | 223               | 123       | 256               | 122       |
| 158               | 51        | 191               | 209       | 224               | 47        | 257               | 131       |
| 159               | 193       | 192               | 44        | 225               | 167       | 258               | 133       |
| 160               | 246       | 193               | 263       | 226               | 130       | 259               | 4         |
| 161               | 197       | 194               | 26        | 227               | 116       | 260               | 119       |
| 162               | 206       | 195               | 42        | 228               | 165       | 261               | 118       |
| 163               | 152       | 196               | 69        | 229               | 128       | 262               | 224       |
| 164               | 252       | 197               | 143       | 230               | 132       | 263               | 126       |
| 165               | 41        | 198               | 83        | 231               | 90        | 264               | 239       |
2. Short-Term Forecasting Methods and Models Used for Power Systems

2.1. Classical Methods of Artificial Intelligence

There main methods are successfully used in forecasting, optimization, diagnostics, detection, and design in the power industry: artificial neural networks, evolutionary algorithms, and expert systems. Neural networks are used, among others, in optimization of tap changer settings in transformers, optimization of capacitor bank settings, and forecasting of the peak load of the power system and its daily loads using Artificial Neural Networks [13,23,40,43,46,49,57,62,65–78], in addition to using Deep Neural Networks [43], and autoregressive models [79], Big Data [1,80], short-circuit analyses, and transformer damage detection. Artificial Neural Networks are the most commonly used artificial intelligence methods [81] in forecasting the operating parameters of power systems and networks. Artificial Neural Networks [82,83] are an effective tool for forecasting in the power industry (not only the loads mentioned above in the power grid [84–87], but also electricity prices [88], especially in short-term forecasting [72]. In practical applications, Artificial Neural Networks are also supported by the techniques of Fuzzy Logic functions [89] and the Neuro-Fuzzy Approach [90–93].

The indication of the greater effectiveness of Artificial Neural Networks over the improvement of traditional methods in short-term forecasting of power system loads, presented in [72], does not always translate into short-term forecasting of energy prices on Polish and foreign electricity trading floors [94]. In this context, it is possible to obtain an inverse relationship. For example, the multiple regression method gives significantly greater forecasting efficiency when compared to the models of Artificial Neural Networks [95]. Artificial Neural Networks are highly effective not only in the short term, but also in long-term forecasting [96,97].

Evolutionary algorithms are used, among others in [84]: forecasting daily loads of electric power systems [46,67], optimizing the configuration of power grids, optimizing voltage levels in power grids, designing power grids, planning power plant operation, creating an economical distribution of loads, planning power grid development, supporting regulatory activities in power systems, and protection automations [83,98]. Expert systems are used, among other things, in [99]: designing power grids and stations and reconstruction of power systems in post-emergency states [100,101].

Additional information on the application of artificial intelligence methods, taking into account the studied subject of the variability in power system loads and their forecasting, can be found in [81,84,85,102,103].
2.2. Data Mining Methods

In the literature focusing on the analysis of large data sets and forecasting using Data Mining methods, there are many definitions of these methods and ideas [104].

The main definitions of Data Mining are:

1. An interdisciplinary approach using techniques from machine learning, image recognition, statistics, databases and visualization to extract information from large databases [42,105,106];
2. An analysis of large, previously collected data sets to discover new regularities and describe the data in a new way that is understandable and useful for the data owner [107].

The first definition comes from 1998, while the second comes from 2001; thus, their evolution is noticeable.

Further definitions of Data Mining methods are:

3. The process of searching for valuable information (knowledge) when the researcher is dealing with a large amount of data [108–111];
4. The process of examining and analyzing large amounts of data by automated or semi-automatic methods to discover meaningful patterns and rules [112,113];
5. Methods of broadly understood data analysis aimed at identifying previously unknown regularities occurring in large data sets, from which the results are in a form that is easy to interpret by the researcher [109].

At the beginning of their development, Data Mining methods were accused of being unscientific, assuming no theory, having no elegance or formal evidence, and being primitive and for application only [114].

The classical approach to data analysis uses the scheme [115,116] from defining the problem through creating a mathematical model, preparing the input data, and analyzing the problem, to interpreting the obtained results. The Data Mining approach uses a scheme from problem definition through preparing input data, problem analysis, and creating a mathematical model, to interpreting the obtained results. The algorithms used in the field of Data Mining are divided into supervised learning and non-supervised learning [104]. In the supervised learning methods, the main goal is to recreate the value of the examined parameter. In the non-supervised learning methods, the aim is to detect structures or hidden patterns in the analyzed data due to the lack of distinguishing a single feature. Teaching forecasting models using a supervised learning approach can be conducted as an implementation of a classification or regression problem. In classification problems, the analyzed parameter is qualitative, and in regression problems, this parameter is quantitative.

The knowledge derived from empirical research is proven, and due to the collection of larger and larger sets of data, it is beneficial for further research, both empirical and forecasting (in a certain sense speculative); it is useful to analyze these sets and draw additional conclusions. Additional research, including experimental studies, may result in obtaining a greater number of answers than the questions posed by the researcher [117–119]. The classification indicated in [118] of problem types and their respective Data Mining methods concerning time series analysis notes the inclusion of MultiLayer Perceptron (MLP) and Radial Basis Function (RBF) Artificial Neural Networks in this method. It must be concluded that the classifications of methods overlap and do not function as hermetic.

The group of Data Mining methods and models also includes forecasting problems, which are divided into two groups. The first group includes regression and classification trees, and the second group includes advanced machine learning methods. Classification and regression trees include Classification and Regression Trees (C&RT) and Chi-Square Automatic Interaction Detection (CHAID) trees [96,120]. The advanced machine learning group consists of the methods Multivariate Adaptive Regression Splines (MARSplines), Support Vector Machines (SVMs), k Nearest Neighbors [121,122], k—Means [123,124], Naive Bayes Classifier (only applicable to classification problems), Random Forest [125], and Boosted Trees [96]. The use of Data Mining methods in forecasting regression problems consists of evaluating many models, comparing their effectiveness results, and creating
hybrid systems, due to which it is possible to maintain the smallest deviations in the forecasted values from the realized values of the analyzed parameters. The distinguishing feature of Data Mining methods is the speed of their creation. The MARSplines and Boosted Tree methods are among the most effective predictive models from the group of Data Mining methods for forecasting power demand in power systems.

The MARSplines method is in the niche of practical applications in forecasting problems in large-scale power engineering. In the MARSplines method, a non-parametric type belonging to the group of supervised learning methods, the co-variability in features is used to predict the value of a selected feature, and in classification problems [126,127]. The indicated convenience excludes from research activities the necessity to analyze the correlation between the independent variables, which in many cases may correlate with the predicted variable, but do not affect it.

The Multivariate Adaptive Regression Splines (MARSplines) method [128–130] uses the method of recursive division of the feature space to build a regression model in the form of spline curves [131–133] and is an extension of the methods of regression trees and multiple regression [105]. Due to the above properties, the MARSplines [131–133] is an effective tool for Big Data applications [134,135].

The MARSplines method also enables the automatic selection of explanatory variables for forecasting models. The efficiency of this selection is in many cases greater than that for classical methods of selecting variables [30,31,136–138]. Thus, the method can be successfully used, in addition to the multiple regression method, in selecting input variables for forecasting models and short-term forecasting of time series, including power demand in power systems. [31,32,139].

The principal components method is an alternative to those analyzing the correlations between the explanatory variables in the forecasting process. It not only allows the removal of variables that are overly correlated with each other, but also the acquisition of uncorrelated variables that are responsible for part of the variability in groups of variables or even for the variability in entire groups of variables [140]. The application of the method creates new variables, which are linear combinations of the original variables, and the following components capture as much information contained in the original data as possible. The disadvantage of the method is the difficulty in interpreting the meaning of principal components [140].

2.3. Big Data

Big Data is a term that describes, on a very general level, exceptionally large data sets. These collections are characterized by a diversified structure of high complexity. The main difficulties are data storage, real-time analysis, and data visualization and analysis results [141,142]. The process of examining massive amounts of data to reveal hidden patterns and secret correlations is called Big Data analysis. In the 1990s and the first decade of the 21st century, Big Data analysis was understood as Data Mining. Big Data sets are characterized by: high volume (Volume) [98,141,143,144], high growth rate (Velocity) [98,141,143,144], reliability and accuracy (Veracity) [141,142], great variety (Variety) [98,144], and value for decision making processes (Value) [98,141,144,145].

The use of Big Data analysis for the needs of data sets containing electrical measurements, including the load size of power systems, includes practical applications, e.g., techniques, i.e., correlation analysis and machine learning techniques (including deep learning: Multilevel Deep Learning [146], Pooling Deep Recurrent Neural Network [147], Convolutional Neural Network Based Bagging Learning Approach [148], TensorFlow Deep Learning Framework and Clustering-regression [149], Long Short—Term Memory Neural Network [150], using Scikit-Learn and TensorFlow [151], with the Keras library [152], Deep Neural Networks [43,153], and introducing Multilevel Deep Learning Methods for Big Data Analysis [146] and databases [114]). Processing of electrical measurement data includes distributed processing (data storage and processing—Distributed Computing), memory
processing (data reading and processing—Memory Computing) and stream processing (real-time data processing—Stream Processing) [141,154].

The use of Big Data techniques in the energy system in the energy sector [155–157] and in the field of Smart Grids [1,80,154,158] includes the use of RBF Artificial Neural Networks [159] using a Convolutional Neural Network Based Bagging Learning Approach [148]. This also encompasses compatibility of aid for technical measures concerning the integration of the generating sources [160], with special regard to renewable sources [161,162] and in creating backup data sets that can be used in situations of information and communication disruptions [163].

The use of sets, techniques, and processes concerning Big Data for the power industry is inextricably linked with the security of the stored data. The security of this type of data can be increased through its location dispersion (e.g., SCOOP system) [144].

Data streams supplying Big Data sets in transmission and distribution power systems come from [164–166]: Supervisory Control And Data Acquisition (SCADA) systems [167], phasor measurement systems in Wide Area Management System (WAMS) technology [168], Intelligent Electronic Devices (IEDs), network asset management systems, conventional and smart meters [147,169–171], and information exchange systems with electricity market participants, from seismic and meteorological institutes, Global Positioning System (GPS) systems, and Geographic Information System (GIS) systems. The practical method of the similarity of days [172–176] allows the quality of forecasting power demand to be below 3.00% per day and the efficiency achieved by the Polish Transmission System Operator (PSE S.A.) to be approx. 1.00%. Similar days are selected based on the most recent demand factor forecasts in the first step. In the second step, the weighted average is calculated for each hour of the day, considering the historical values. In the classical approach, there is a slight variation in the values of individual weights. Due to weighting of the most similar days, it is possible to obtain minimum, maximum, and average errors for the entire day below 2% [176]. The method of self-adaptive weighing is successfully used in forecasting the demand for electric power in microgrids. Compared to the standard methods of dynamic demand profiles, multiple regression, and Artificial Neural Networks, it almost doubles forecasting effectiveness (approx. 3.5%) [177]. A similar level of effectiveness (3.99%) using the multiple regression method for the power system shows that despite the longer computation time (for a seven-day horizon), its classical version [178], using as input data (explanatory variables) forecasts of weather parameters, gives a similar quality. The use of Artificial Neural Networks in short-term forecasting of electrical power demand in power systems does not always give exceptionally effective forecasting results compared to other methods. Artificial Neural Networks require significant research experience, and the results, even using efficient network learning methods [147], rarely give effectiveness below 1.00% per day. Often, advanced Artificial Neural Networks provide forecasting efficiency expressed by the values of Mean Average Percentage Error (MAPE) from approx. 3.00% to even approx. 13.00% (in the 20-day horizon) [5]. The knowledge of electrical power quality parameters is one of the key elements of entities operating in the electricity market [179]. Cyclical measurements of these parameters (including the assessment of the condition of electrical apparatus and devices [180]), and their transmission and collection, in addition to the conducted analyses, may affect the medium-term planning of outages of individual elements of the transmission network and, thus, indirectly, short-term forecasting of power demand.

3. The State of Research in Short-Term Power Demand Forecasting for Power Systems Using Autoregressive and Non-Autoregressive Methods and Models

The study (Figure 1) was planned in such a way as to answer the question of whether the use of autoregressive methods in short-term forecasting of electricity demand in power systems can be even more effective and, at the same time, inexpensive and quick to implement. In order to answer this question, scientific articles presenting the effectiveness of autoregressive forecasting models determined by the MAPE were analyzed. The result
of the review is Table 1 and a ranking of forecasting models (Tables 2 and 3), and the Top 10 collection of the ten most effective forecasting models. As a result of the review and development of the ranking of forecasting models, it was confirmed that the use of autoregressive models may support the transmission system operator to achieve better forecasting efficiency.

The literature review (Table 1) included 47 unique items and titles, several dozen forecasting methods, and 264 forecasting models (Table 1). Scientific papers were published in the period from 1997 and concerned short-term forecasting of power demand. The source data used by the authors of the analyzed publications, constituting the input for the forecasting models, covered the period from 1998 to 2014. Diverse and international teams of authors conducted their research based on data on the functioning of power systems in 25 countries located on four continents—in the countries of the Near and the Far East, Western Europe (including the British Isles), Central Europe (including Poland), North America (USA), and Australia. The publications indicated were compiled by 44 different authors' teams and published in 23 publishing houses. The analysis concerning the nomenclature of forecasting models covers a set of 185 unique items. Diversifying the observed relationships in individual forecasting models results in identifying 197 unique abbreviations assigned to forecasting models. The MAPE(ea) in Table 1 means that the accuracy results are measured in ex ante mode.

All the reviewed references describe the effectiveness of the presented forecasting models, in terms of the MAPE measure, to assess the accuracy of the forecasts. To analyze the collected forecasting results, 27 unique names of MAPE errors were distinguished for this analysis, reflecting the forecasting models used in the analysis. Some of the forecast results described by the MAPE index, contained in selected publications, are presented from the lowest value (MAPE min) to the highest value (MAPE max). In contrast, the remaining part of the results is described by one value.

The analysis of monovalent results was decomposed into minimum and maximum values to standardize the dominant approach used in selected publications. The lowest values of MAPE min are recorded in the range from 0.01% to 21.18%, while in the MAPE max category, the corresponding range of variability in the MAPE ranges from 0.01% to 33.45%. The MAPE min category includes 196 unique items from a set of 264 models, while the MAPE max category includes 212 unique items from the same set.

Further analysis of the results of the effectiveness of the forecasts obtained, described by the forecasting quality measure using the MAPE, concerns the MAPE category, min. A set of the ten smallest results expressed as percentages was selected in this category (Figure 2). This collection was called Top 10. The smallest values of MAPE errors min, in ascending order, in the Top 10 set (Figure 2) are obtained for the following models: Data Envelopment Analysis (DEA), Fuzzy Regression (FR), General Regression Model (GRM), Genetic Algorithm (GA), Adaptive Neuro Fuzzy Inference System (ANFIS [181,182]), Artificial Neural Network (ANN), Artificial Neural Network (WANN), Full General Regression Model (FGRM), Wavelet Artificial Neural Network (WANN), Artificial Neural Network (ANN), and Fuzzy Logic (FL). The values of MAPE min were: 0.01%; 0.08%; 0.10%; 0.14%; 0.15%; 0.16%; 0.20%; 0.27%; 0.28%; and 0.29%. The summary of the abbreviations used for the forecasting methods and models in the Top 10 set is as follows: DEA; FR; GRM; GA; ANFIS; ANN; FGRM; WANN; ANN; and FL.

Only analytical studies on the GRM forecasting model in the Top 10 set are performed ex ante (ea). In the case of this model, the efficiency obtained in the third position should be considered very high. The GRM model uses information about the shaping of the ambient temperature as an input variable. The second model that uses the input variables is the FGRM model, which considers both the variability in the ambient temperature and the wind speed. The FGRM model ranks seventh in the Top 10 ranking in the MAPE category, min.

The forecasting effectiveness described by the lowest value of the MAPE min has an ambiguous effect on high forecasting efficiency. The power systems subject to forecast
analysis in the Top 10 list are (in ascending order) the systems of Iran (two items), USA (one item), Iran (three items), USA (one item), and Australia (three items).

The length of the analyzed period significantly affects the quality of forecasting obtained. Along with the extension of the analysis period, including the natural impact of non-working days and holidays, both cyclical and non-cyclical, there is a decline in the effectiveness of the obtained forecasts of the load on power systems. The full forecasting model ranking is presented in Tables 2 and 3, where the column Model No. represents the model number from Table 1 (the last column on the right), and the column Ranking shows the position in the model ranking (1 equals the first position and 264 equals the last position). Table 2 consists of the models from Table 1 from 1 to 132 (in four pairs of Ranking and Model Number), and Table 3 shows the same scheme for the models from 133 to 264. Tables 2 and 3 present four sets of Ranking and Model Number. Articles [183–185] from 2019 to 2021 indicate that analysis and research are being continued, including with the use of some of the analyzed methods.

4. Conclusions

The 47 publications describing 264 models published from 1997 to 2018 were analyzed in detail by applying methods that use explanatory variables to broaden the background of analyses. Some relevant publications from 2019 to 2021 were also included to determine if autoregressive methods are still of interest. The results of the review confirm the significant potential of the autoregressive approach to power demand forecasting. The analyzed methods enable very high accuracy to be achieved in short-term forecasting with the resolution of one hour (accuracy measured in terms of MAPE is below 1%). The methods whose effectiveness were classified in the top ten sets are Fuzzy Logic (LR), Artificial Neural Network (ANN), Wavelet Artificial Neural Network (WANN), Full General Regression Model (FGRM), Artificial Neural Network (ANN), Adaptive Neurofuzzy Inference System (ANFIS), Genetic Algorithm (GA), General Regression Model (GRM), Fuzzy Regression (FR), and Data Envelope Analysis (DEA). These methods allowed them to achieve MAPE-determined values of: 0.29%; 0.28%; 0.27%; 0.20%; 0.16%; 0.14%; 0.10%; 0.08%; and 0.01%. All of the Top 10 models achieved high accuracy; however, the DEA model reached the accuracy of 0.01% MAPE. Models No. 257 (FGRM) and No. 256 (GRM) of the Top 10 set use the explanatory variables, and the other eight models were autoregressive (models No.: 215—FL, 214—ANN, 213—WANN, 140—ANN, 141—ANFIS, 138—GA, 139—FR, and 142—DEA). This shows the potential of the autoregressive prediction approach used in the models for short-term power demand forecasting in power systems.

5. Critical Discussion, Major Findings and Future Scope of Research

The results of the review show that the use of short-term forecasting of electric power demand with hourly resolution enables efficiency of below 1% to be achieved. It should be borne in mind that such effectiveness should apply to the entire calendar year. In the analyzed collection of 47 articles from all over the world, the analysis period ranges from several months to several years, which indicates that the research covers significant periods of time, and the analyzed models are stable and resistant to changes in external conditions (economic and climatic conditions). The group of the most effective prognostic models includes models using artificial intelligence techniques (e.g., Artificial Neural Networks, Fuzzy Logic, and Genetic Algorithms). The effective methods also include classic forecasting methods (e.g., ARIMA, Multiple Regression, Exponential Smoothing) and methods from the Data Mining group (e.g., Support Vector Machines, Nearest Neighbors, Random Forest).

The article confirms the authors’ thesis about the enormous potential inherent in the use of the autoregressive approach for short-term forecasting of electricity demand. The results of the review (the prepared ranking of prognostic models and the knowledge from the analyzed articles) constitute an excellent starting point for further tests and pave the way for future research in this area.
The future research of the authors will focus on the first step of testing the prognostic models from the Top 10 set. The tests will take into account both the achieved effectiveness and the necessary financial costs and time consumption of the process. In the next step, the most effective prognostic methods selected in the first step will be tested, including individual testing in off-line mode. In the third step of further research, prognostic model committees will be established. The developed committees will assign weights to the participation of individual models (step 1) and test the suitability of individual models for forecasting individual hours of the day or periods of the day (step 2). The MAPE selected by the authors for the review analysis, despite the undoubted advantage of being able to be used to easily compare the effectiveness between forecasting models, has a tendency to average forecasts. Therefore, in future studies, the authors will also use other measures to assess the quality of forecasts, such as Mean Absolute Error, Mean Absolute Scaled Error, and Root Mean Square Error, and others as needed. The usefulness of the tested forecasting models will be assessed, taking into account the seasonality, periodicity, and ranges of hours during the day. The developed review encompasses an excellent range of forecasting methods and models that can be used at any time, and the usefulness of each of them may prove invaluable from the point of view of the needs of the Polish Transmission System Operator.

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Abbreviations
The following abbreviations are used in this manuscript:

| Abbreviation | Description |
|--------------|-------------|
| AG | Genetic Algorithm (GA) |
| ANFIS | Adaptive Neuro Fuzzy Inference System (ANFIS) |
| ANN | Artificial Neural Network (ANN) |
| ARIMA | Autoregressive Integrated Moving Average |
| C&RT | Classification And Regression Trees |
| CHAID | Chi-Square Automatic Interaction Detection |
| DEA | Data Envelopment Analysis |
| ea | ex ante |
| GIS | Geographic Information System |
| GPS | Global Positioning System |
| IED | Intelligent Electronic Device |
| FL | Fuzzy Logic |
| MAPE | Mean Average Percentage Error |
| MARSplines | Multivariate Adaptive Regression Splines |
| MLP | Multilayer Perceptron |
| GRM | General Regression Model |
| FGRM | Full General Regression Model |
| NPS | National Power System |
| PSE S.A. | Polskie Sieci Elektroenergetyczne S.A. (The Transmission System Operator in Poland) |
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