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Review

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

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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 fulfil 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 Neurofuse 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

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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/Publishing House	Year	Analysis Scope	Country	Method, Model	Effectiveness			Model No.
		-	Years	-	-	Error, %			-
1.	Al-Fuhaid A.S. et al. *Neuro-Short-Term Load Forecast of the Power System in Kuwait* Elsevier (21:215-219) [18]	1997	1994	Kuwait	ANN(ea)—*Artificial neural network*	MAPE(ea)	1.84	4.84	1
2.	Almeshaiei E., Soltan H. *A Methodology for Electric Power Load Forecasting* Alexandria Engineering Journal (50) [19]	2011	2006–2008	Kuwait	MA(ea7,30)—*Moving Average (7, 30)*	MAPE(ea)	3.84		2
3.	Al-Shobaki S., Mohsen M. *Modeling and Forecasting of Electrical Power Demands for Capacity Planning* Elsevier Energy Conversion and Management (49) [20]	2008	2002–2007	Jordan	ARIMA(ea)	MAPE(ea)	5.25		3
4.	Badran S.M., Abouelatta O.B. *Forecasting Electrical Load using ANN Combined with Multiple Regression Method* The Research Bulletin of Jordan ACM II(II) [21]	2013	1988–2006	Saudi Arabia	MR—*Multiple Regression*	MAPE	11.58	14.35	4
					ANN—*Multiple Regression*	MAPE	2.44	8.04	5
5.	Brodowski S. et al. *A Hybrid System for Forecasting 24-h Power Load Profile for Polish Electric Grid* Elsevier B.V. Applied Soft Computing (58) [22]	2017	2013, 2015	Poland (NPS)	HA + MR—*Hierarchical Approximator + Multiple Regression*	MAPE	1.08	2.26	6
6.	Buitrago J., Asfour S. *Short-Term Forecasting of Electric Loads Using Nonlinear Autoregressive Artificial Neural Networks with Exogenous Vector Inputs* Energies 10(40) [23]	2017	2005–2015	USA (New England)	ANN—*Artificial Neural Network*	MAPE	0.85		7
7.	Ceperic E., Ceperic V. *A Strategy for Short-Term Load Forecasting by Support Vector Regression Machines* IEEE Transactions on Power Systems (1) [24]	2013	2006	USA	ANN—*Artificial Neural Network*	MAPE	1.50	3.72	8
					SDBWNN—*Similar Day—Based Wavelet Neural Network*	MAPE	1.26	2.70	9
					SASVR—*Seasonality—Adjusted, Support Vector Regression*	MAPE	0.93	1.86	10
8.	Chahkoutahi F., Khashei M. *A Seasonal Direct Optimal Hybrid Model of Computational Intelligence and Soft Computing Techniques for Electricity Load Forecasting* Energy (140) [25]	2017	2011.05.02–2011.07.03	Australia	ARIMA	MAPE	0.76	1.07	11
					ANN(MLP)—*Artificial Neural Network (Multilayer Perceptron)*	MAPE	0.72	1.23	12
					ANFIS—*Adaptive Neuro Fuzzy Inference System*	MAPE	0.83	0.95	13
					DOPH—*Direct Optimum Parallel Hybrid*	MAPE	0.58	0.71	14
9.	Chapagain K., Kittipiyakul S. *Short-Term Electricity Load Forecasting Model and Bayesian Estimation for Thailand Data* MATEC Web of Conferences (55) [26]	2016	2013–2015	Thailand	MR—*Multiple Regression*	MAPE	1.75	33.45	15
					MR(Gibbs)—*Multiple Regression (Gibbs Sampling)*	MAPE	0.85	23.06	16
10.	Chen H. et al. *ANN-Based Short-Term Load Forecasting in Electricity Markets* University of Waterloo, Department of Electrical & Computer Engineering [27]	2001	1999	Canada	ANN—*Artificial Neural Network*	MAPE	0.48	3.00	17
11.	Chheepa T.K., Manglani T. *A Critical Review on Employed Techniques for Short Term Load Forecasting* IRJET 04(06) [28]	2017	1996–1997, 2000	Iran	ARIMA	MAPE	1.48	1.99	18
12.	Clements A.A. et al. *Forecasting Day-Ahead Electricity Load Using a Multiple Equation Time Series Approach* NCER Working Paper Series 103(5) [29]	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.
		-	Years	-	-	Error, %			-
13.	Czapaj R. *Typowanie zmiennych objaśniających przy wykorzystaniu zautomatyzowanych metod statystycznych jako sposób optymalizacji wyboru metody estymacji szczytowego dobowego obciążenia KSE* Przegląd Elektrotechniczny 4(93) [30]	2016	2010–2014	Poland (NPS)	MARSplines	MAPE	1.86	6.99	20
					C&RT—*Classification and Regression Trees*	MAPE	2.57	7.18	21
					C&RT—*Classification and Regression Trees*	MAPE	2.56	6.77	22
					Chi^2—*Automatic interaction detector using Chi*^{2}	MAPE	4.06	7.33	23
					CHAID—*Chi*^{2} *Automatic Interaction Detector*	MAPE	3.69	9.40	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	6.99	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	MAPE	3.36	6.04	26
					MARSplines(ea)	MAPE(ea)	6.57		27
16.	Dąsal 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	9.79	28
17.	Dudek G. *Short-Term Load Forecasting Based on Kernel Conditional Density Estimation* Przegląd Elektrotechniczny 8(86) [34]	2010	2002–2006	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
			1997–2000		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)	NNWISA(*working days*) —*Nearest Neighbors with Weather Inputs for Similarity Analysis*	MAPE (*working days*)	1.55	1.67	39
				Belgium		MAPE (*working days*)	2.82	2.88	40
				New England		MAPE (*working days*)	2.41	3.26	41
				USA		MAPE (*working days*)	3.43	4.82	42

Table 1. *Cont.*

No.	Authors/Title/Publishing House	Year	Analysis Scope	Country	Method, Model	Effectiveness			Model No.
		-	Years	-	-	Error, %			-
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)	NNWISA(*weekends*) —*Nearest Neighbors with Weather Inputs for Similarity Analysis*	MAPE(*weekends*)	1.75	1.76	43
				Belgium		MAPE(*weekends*)	3.02	3.12	44
				New England		MAPE(*weekends*)	2.92	3.16	45
				USA		MAPE(*weekends*)	4.31	4.99	46
			2011–2014	Poland (NPS)	NNWISA(*Holidays*) —*Nearest Neighbors with Weather Inputs for Similarity Analysis*	MAPE(*Holidays*)	4.36	16.17	47
				Belgium		MAPE(*Holidays*)	4.05	12.61	48
				New England		MAPE(*Holidays*)	6.35	7.03	49
				USA		MAPE(*Holidays*)	6.05	7.62	50
19.	Dudek G. *Pattern-Based Local Linear Regression Models for Short-Term Load Forecasting* Elsevier, Electric Power System Research (130) [36]	2016	2002–2004	Poland (NPS)	MR(January)—*Multiple Regression*	MAPE(January)	2.37		51
					SR(January)—*Stepwise Regression*	MAPE(January)	1.52		52
					RR(January)—*Ridge Regression*	MAPE(January)	1.59		53
					Lasso(January)—*Least Absolute Selection Regression and the Constriction Operator*	MAPE(January)	1.51		54
					PCR(January)—*Principal Component Regression*	MAPE(January)	1.36		55
					PLSR(January)—*Partial Least Squares Regression*	MAPE(January)	1.18		56
					MR(July)—*Multiple Regression*	MAPE(July)	2.63		57
					SR(July)—*Stepwise Regression*	MAPE(July)	1.14		58
					RR(July)—*Ridge Regression*	MAPE(July)	1.23		59
					Lasso(July)—*Least Absolute Selection Regression and the Constriction Operator*	MAPE(July)	1.06		60
					PCR(July)—*Principal Component Regression*	MAP(July)	0.94		61
					PLSR(July)—*Partial Least Squares Regression*	MAPE(July)	1.00		62
			2002–2004	Poland (NPS)	PCR—*Principal Component Regression*	MAPE	1.35		63
					PLSR—*Partial Least Squares Regression*	MAPE	1.34		64
					ARIMA	MAPE	1.82		65
					ES—*Exponential Smoothing*	MAPE	1.66		66
					ANN(MLP)—*Artificial Neural Network (Multilayer Perceptron)*	MAPE	1.44		67
					NWE—*Nadaraya—Watson Estimator*	MAPE	1.30		38
					NM—*Naive Method*	MAPE	3.43		39

Table 1. *Cont.*

No.	Authors/Title/Publishing House	Year	Analysis Scope	Country	Method, Model	Effectiveness		Model No.
		-	Years	-	-	Error, %		-
19.	Dudek G. *Pattern-Based Local Linear Regression Models for Short-Term Load Forecasting* Elsevier, Electric Power System Research (130) [36]	2016	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
			2007–2009	Great Britain	PCR—*Principal Component Regression*	MAPE	1.60	77
					PLSR—*Partial Least Squares Regression*	MAPE	1.54	78
					ARIMA	MAPE	2.02	79
					ES—*Exponential Smoothing*	MAPE	1.85	80
					ANN(MLP)—*Artificial Neural Network (Multilayer Perceptron)*	MAPE	1.65	81
					NWE—*Nadaraya—Watson Estimator*	MAPE	1.55	82
					NM—*Naive Method*	MAPE	3.52	83
			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
20.	Dudek G. *Drzewa regresyjne i lasy losowe jako narzędzia predykcji szeregów czasowych z wahaniami sezonowymi* Politechnika Częstochowska [37]	2016	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

Table 1. *Cont.*

No.	Authors/Title/Publishing House	Year	Analysis Scope	Country	Method, Model	Effectiveness			Model No.
		-	Years	-	-	Error, %			-
20.	Dudek G. *Drzewa regresyjne i lasy losowe jako narzędzia predykcji szeregów czasowych z wahaniami 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	2009	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
					ED—*Empirical Decomposition*	MAPE	3.52		108
			2010		ANN—*Artificial Neural Network*	MAPE	3.81		109
					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	2.37	113
					ANN—*Artificial Neural Network*	MAPE	1.82	3.90	114
					SPAM+ANN—Hybrid Model (*Semi-Parametric Additive Model + Artificial Neural Network*)	MAPE	1.58	2.79	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

Table 1. *Cont.*

No.	Authors/Title/Publishing House	Year	Analysis Scope	Country	Method, Model	Effectiveness		Model No.
		-	Years	-	-	Error, %		-
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
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	FRI(ea)—*Fuzzy Regression without Interaction*	MAPE(ea)	14.21	126
					FRICV(ea)—*Fuzzy Regression without Interaction with Categorical Variables*	MAPE(ea)	5.16	127
					FRI(ea) + MR—FRI(ea)—*Fuzzy Regression without Interaction* + MR—*Multiple Regression*	MAPE(ea)	4.63	128
					FRI(ea)+TV—FRI(ea)—*Fuzzy Regression without Interaction* + TV—*Temperature Variables*	MAPE(ea)	3.68	129
28.	Janicki M. *Temperature Correction Method for Pattern Similarity-Based Short-term Electricity Demand Forecasting Models* Przegląd Elektrotechniczny 3(93) [45]	2017	2013–2014	USA	IS+TC(USA 2013)—IS—*Image Similarities* + TC—*Temperature Correction* (USA 2013)	MAPE	4.50	130
				USA	NM(USA 2013)—*Naive Method* (USA 2013)	MAPE	10.78	131
				USA	IS+TC(USA 2014)—IS—*Image Similarities* + TC—*Temperature Correction* (USA 2014)	MAPE	4.86	132
				USA	NM(USA 2014)—*Naive Method* (USA 2014)	MAPE	10.94	133
				Belgium	IS+TC(BEL 2013)—IS—*Image Similarities* + TC—*Temperature Correction* (Belgium 2013)	MAPE	3.80	134
				Belgium	NM (BEL 2013)—*Naive Method* (Belgium 2013)	MAPE	8.54	135
				Belgium	IS+TC(BEL 2014)—IS—*Image Similarities* + TC—*Temperature Correction* (Belgium 2014)	MAPE	3.66	136
				Belgium	NM(BEL 2014)—*Naive Method* (Belgium 2014)	MAPE	9.47	137

Table 1. *Cont.*

No.	Authors/Title/Publishing House	Year	Analysis Scope	Country	Method, Model	Effectiveness		Model No.
		-	Years	-	-	Error, %		-
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 Neuro 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 Częstochowska, 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
					WTWTMABC—Wavelet Transform—*Wavelet Transform—Modified Artificial Bee Colony—Extreme Machine Learning*	MAPE	0.59	147
					EMDDEEML—*Empirical Mode Decomposition—Differential Evolution – Extreme Machine Learning*	MAPE	0.39	148
					VMD—*Variational Mode Decomposition*	MAPE	0.30	149
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
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* Elsevier Ltd. Procedia Engineering (129) [51]	2015	2009–2012	Iraq	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
					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

Table 1. *Cont.*

No.	Authors/Title/Publishing House	Year	Analysis Scope	Country	Method, Model		Effectiveness			Model No.
		-	Years	-	-		Error, %			-
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* 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.)—*Artificial Neural Network*		MAPE (January)	6.30		168
					ARIMA(May)		MAPE (May)	8.20		169
					ANN—LSTM—RNN(September)—*Long—Short—Term Memories—Recurrent Neural Network*		MAPE (September)	5.90		170
					ANN(January)—Sztuczna sieć neuronowa		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 Wrocław 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
37.	Nowotarski J. et al. *Improving Short Term Load Forecast Accuracy* via *Combining Sister Forecasts* Hugo Steinhaus Center Wrocław University of Technology, University of North Carolina at Charlotte [54]	2015	2007.01.01–2011.12.31	USA	SA—Simple Averaging(ea)		MAPE(ea)	2.10	2.82	178
					AT(PU—ea) (*Average Trimming*)		MAPE(ea)	2.10	2.82	179
					WA(UW—ea) (*Winsor's Averaging*)		MAPE(ea)	2.10	2.83	180
					OLS(MNKea) (*Ordinary Least Squares*)		MAPE(ea)	2.14	2.82	181
					RMAD(ea) (*Regression of the Minimum Absolute Deviation*)		MAPE(ea)	2.14	2.83	182
					LSLPW(ea) (*Least Squares Limited —Positive Weights*)		MAPE(ea)	2.12	2.81	183

Table 1. *Cont.*

No.	Authors/Title/Publishing House	Year	Analysis Scope	Country	Method, Model		Effectiveness			Model No.
		-	Years	-	-		Error, %			-
37.	Nowotarski J. et al. *Improving Short Term Load Forecast Accuracy* via *Combining Sister Forecasts* Hugo Steinhaus Center Wrocław University of Technology, University of North Carolina at Charlotte [54]	2015	2007.01.01–2011.12.31	USA	LSL(ea) (*Least Squares Limited*)		MAPE(ea)	2.11	2.83	184
					IRMSEA(ea) (*IRMSE Averaging*)		MAPE(ea)	2.10	2.82	185
					BI—C(ea) (*The Best Individual Calibration Window*)		MAPE(ea)	2.25	2.93	186
					SM—Sister Model 1(ea)		MAPE(ea)	2.29	3.09	187
					SM—Sister Model 2(ea)		MAPE(ea)	2.24	3.15	188
					SM—Sister Model 3(ea)		MAPE(ea)	2.34	3.01	189
					SM—*Sister Model* 4(ea)		MAPE(ea)	2.32	3.17	190
					SM—Sister Model 5(ea)		MAPE(ea)	2.28	3.11	191
					SM—Sister Model 6(ea)		MAPE(ea)	2.30	3.18	192
					SM—Sister Model 7(ea)		MAPE(ea)	2.37	3.07	193
					SM—Sister Model 8(ea)		MAPE(ea)	2.31	3.21	194
38.	Hsiao-Ten P. *Forecast of Electricity Consumption and Economic Growth in Taiwan by State Space Modeling* Elsevier Ltd. Energy (34) [55]	2009	2002–2007	Taiwan	ECSTSP —*Error—Correction State Space Model*	2002–2007	MAPE	3.90		195
						2003–2007	MAPE	2.57		196
						2004–2007	MAPE	2.38		197
						2005–2007	MAPE	1.52		198
						2006–2007	MAPE	2.57		199
						2007	MAPE	2.04		200
					STSP —*State Space Model*	2002–2007	MAPE	4.04		201
						2003–2007	MAPE	2.62		202
						2004–2007	MAPE	2.43		203
						2005–2007	MAPE	1.75		204
						2006–2007	MAPE	2.34		205
						2007	MAPE	2.39		206
					SARIMA	2002–2007	MAPE	5.32		207
						2003–2007	MAPE	3.79		208
						2004–2007	MAPE	3.01		209
						2005–2007	MAPE	2.87		210
						2006–2007	MAPE	2.18		211
						2007	MAPE	1.20		212
39.	Rana M, Koprinska I. *Forecasting Electricity Load with Advanced Wavelet Neural Networks* Elsevier B.V. Neurocomputing (182) [56]	2016	2006–2007	Australia	WANN(F—Aus.)—*Wavelet Artificial Neural Network*		MAPE	0.27		213
				Australia	ANN(Aus.)—*Artificial Neural Network*		MAPE	0.28		214
				Australia	FL(Aus.)—*Fuzzy Logic*		MAPE	0.29		215
				Australia	MTR(Aus.)—*Model Tree Rules*		MAPE	0.35		216
				Australia	ESDS(n-1; Aus.)—*Exponential Smoothing—Daily Seasonality*		MAPE	0.30		217
				Australia	ESWS(n -7; Aus.)—*Exponential Smoothing—Weekly Seasonality*		MAPE	0.32		218
				Australia	ESDWS(n-1 i n -7; Aus.)—*Exponential Smoothing—Daily and Weekly Seasonality*		MAPE	0.30		219
				Australia	ARIMA(n-1; Aus.) *Daily*		MAPE	0.30		220
				Australia	ARIMA(n -7; Aus.) *Weekly*		MAPE	0.32		221

Table 1. *Cont.*

No.	Authors/Title/Publishing House	Year	Analysis Scope	Country	Method, Model	Effectiveness		Model No.
		-	Years	-	-	Error, %		-
			2006–2007	Australia	ARIMA(n-1 i n -7; Aus.) *Daily & Weekly*	MAPE	0.30	222
				Australia	IM(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
39.	Rana M, Koprinska I. *Forecasting Electricity Load with Advanced Wavelet Neural Networks* Elsevier B.V. Neurocomputing (182) [56]	2016	2010–2011	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
				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	IM(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)—*Naïve 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]	2009	2006–2008	Poland (NPS)	ANN(MLP)—*Artificial Neural Network* (*Multilayer Perceptron*)	MAPE	2.07	243
					ANN(SVM)—*Artificial Neural Network* (Support Vector Machines)	MAPE	2.24	244
					ANN(Elman)—*Artificial Neural Network* (Elman)	MAPE	2.26	245
					ANN(Koh)—Kohonen's *Artificial Neural Network*	MAPE	2.37	246
					ANN(MLPZ1)—*Artificial Neural Network* (*Committee—Multilayer Perceptron* 1)	MAPE	1.48	247

Table 1. *Cont.*

No.	Authors/Title/Publishing House	Year	Analysis Scope	Country	Method, Model	Effectiveness			Model No.
		-	Years	-	-	Error, %			-
40.	Siwek K., Osowski S. *Prognozowanie obciążeń 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
					ANN(BSSZ)—*Artificial Neural Network* (*Committee*—BSS)	MAPE	1.71		249
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
					SVR (*Support Vector Regression*)	MAPE	4.00		251
					SSN(FF)—*Artificial Neural Network* (*Fast Forward Training*)	MAPE	2.40		252
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	SSN(OK)—*Artificial Neural Network* (*Municipal Users*)	MAPE	6.13	22.39	253
					ANN(TSDSO)—*Artificial Neural Network* (*Transformer Station of a Distribution System Operator*)	MAPE	5.14	5.35	254
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	REM—*Recent Effect Method* (*Forecasts for each day with a year in advance*)	MAPE	4.27	4.38	255
44.	Wang Y., Bielecki J.M. *Acclimation and the Response of Hourly Electricity Loads to Meteorological Variables* Elsevier Ltd. Energy (142) [61]	2018	1999.07.28–2007.12.31. (*Calibration Set*)	USA	GRM(Temp.)—*General Regression Model* (Temperature)	MAPE (Temp.)	~0.10	~4.10	256
					FGRM(ea; *Temperature; Wind*)—*Full General Regression Model* (hourly delays of thermosensitivity, binary variables of historical temperatures in months, wind speed)	MAPE (ea; Temp.; Wind)	~0.20	~4.30	257
			2008.01.01–2014.12.31.		2SGRM(*Temperature; Wind; Humidity*)—2*-Step General Regression Model* (1.—*Fit to the full model*; 2.—*Adjustment to the model of the influence of humidity on demand*)	MAPE (Temp.; Wind; Humid.)	1.00	2.00	258
45.	Wyrozumski T. *Prognozowanie neuronowe w energetyce* Politechnika Lubelska, Konferencja REE [62]	2005	-	Poland	ANN(ea)—*Artificial Neural Network*	MAPE (ea)	1.31	4.87	259
46.	Yang J. *Power System Short-term Load Forecasting* TU Darmstadt, *Doctoral Thesis* [63]	2006	2002	China	C&RT—*Classification and Regression Trees*	MAPE	2.63	11.64	260
					ANN—*Artificial Neural Network*	MAPE	1.51	4.13	261
					SVM—*Support Vector Machines*	MAPE	1.51	3.87	262
47.	Yu X., Ji H. *A PSO-SVM-Based 24 h Power Load Forecasting Model* MATEC Web of Conferences (25) [64]	2015	2014	China	ANN(BP)—*Artificial Neural Network (Back Propagation Training)*	MAPE	3.28	4.13	263
					SVM+PSO—SVM—*Support Vector Machines* + PSO—*Particle Swarm Optimization*	MAPE	2.58	2.68	264

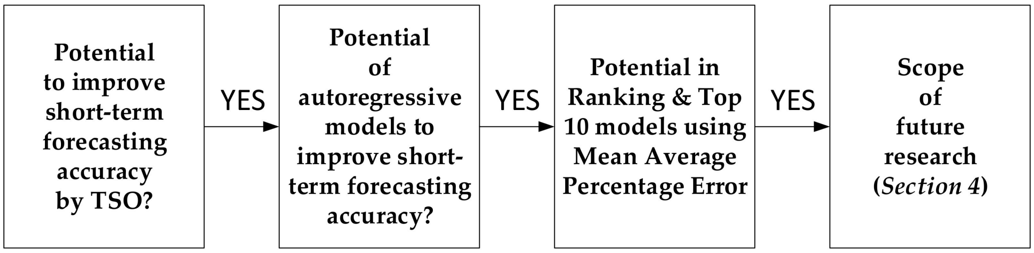

Figure 1. The design of the survey.

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

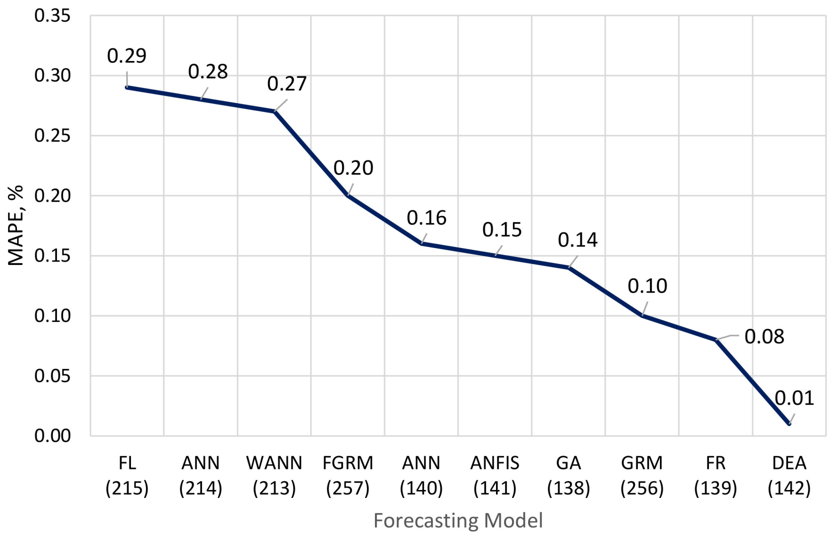

Figure 2. The effectiveness of forecasting models in the Top 10 set from a group of 264 models.

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 [13,23,40,42,43,46,49,57,62,65–78], 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 automatics [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), 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 Neurofuse 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%; 0.15%; 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:

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)

RBF	Radial Basis Function
FR	Fuzzy Regression
SARIMAX	Seasonal Auto-Regressive Integrated Moving Average with eXogenous Factors
SCADA	Supervisory Control and Data Acquisition
WANN	Wavelet Artificial Neural Network (AWNN)
SVM	Support Vector Machines
WAMS	Wide Area Management System

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