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Review

Chaotic Time Series Forecasting Approaches Using Machine Learning Techniques: A Review

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Abstract: Traditional statistical, physical, and correlation models for chaotic time series prediction have problems, such as low forecasting accuracy, computational time, and difficulty determining the neural network's topologies. Over a decade, various researchers have been working with these issues; however, it remains a challenge. Therefore, this review paper presents a comprehensive review of significant research conducted on various approaches for chaotic time series forecasting, using machine learning techniques such as convolutional neural network (CNN), wavelet neural network (WNN), fuzzy neural network (FNN), and long short-term memory (LSTM) in the nonlinear systems aforementioned above. The paper also aims to provide issues of individual forecasting approaches for better understanding and up-to-date knowledge for chaotic time series forecasting. The comprehensive review table summarizes the works closely associated with the mentioned issues. It includes published year, research country, forecasting approach, application, forecasting parameters, performance measures, and collected data area in this sector. Future improvements and current studies in this field are broadly examined. In addition, possible future scopes and limitations are closely discussed.

Keywords: chaos; forecasting; hydrological systems; neural networks; oil and gas; power and energy; prediction; time series

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Citation: Ramadevi, B.; Bingi, K. Chaotic Time Series Forecasting Approaches Using Machine Learning Techniques: A Review. *Symmetry* **2022**, *14*, 955. https://doi.org/10.3390/sym14050955

Academic Editors: Marek Berezowski and Marcin Lawnik

Received: 4 April 2022
Accepted: 2 May 2022
Published: 7 May 2022

1. Introduction

The first section of this paper provides a brief description of the chaos and the properties of chaotic systems. In addition, the importance of chaotic time series forecasting in significant areas is addressed. Finally, this section covers the previous and current literature surveys on chaotic time series forecasting.

1.1. Chaotic Systems

The behavior of a nonlinear dynamical system that may be extremely sensitive to small changes in initial conditions is known as chaos. This sensitivity to initial conditions means that a slight change in the starting point can lead to different outcomes. For example, the butterfly effect shows how a small change in one state of a deterministic nonlinear system may result in enormous deviations in a subsequent state [1]. The other characteristic of a chaotic system is no periodic behavior. The symmetric property of these nonlinear dynamic systems can play a vital role in producing the systems' chaotic behavior. Due to this fact, various researchers have recently shown much interest in the symmetric properties of chaotic systems. In [2], the authors have proposed a chaotic oscillator with both odd and even symmetries. Similarly, some of the other applications of symmetric properties of chaotic systems lie in image processing, security, and communications [3]. The symmetric and asymmetric behavior has been observed in many natural phenomena. Due to these characteristics, the chaotic motion is difficult to forecast. For instance, predicting the butterfly effect for the long term is impossible [1]. This is because these systems are deterministic, i.e., the future behavior of these systems is entirely defined by their initial conditions. Hence, these systems are wholly deterministic and unpredictable.

On the other hand, a chaotic time series is generated when the variable changes with time in a chaotic system. This chaotic time series provides extensive information about the nonlinear system and helps evaluate and analyze the chaotic system's behavior. The phase space reconstruction technique reveals this dynamic information hidden in the chaotic time series and transforms the existing data into a more describable framework [4]. As a result, it is essential to have approaches that can forecast chaotic time series and differentiate chaotic data from stochastic data [5–7]. The traditional prediction methods for this purpose have failed to produce satisfactory performance. Thus, many advanced techniques using machine learning-based approaches have been proposed recently. Therefore, this paper presents a comprehensive review of the performance of traditional and machine learning-based methods for chaotic time series forecasting and their implementation on nonlinear dynamical systems, such as photovoltaic systems, wind farms, communication signals and systems, oil and gas, hydrological systems, weather, and other systems.

1.2. Importance of Chaotic Time Series Forecasting

Forecasting is an approach for creating predictions to determine the direction of future trends using historical data and current trend analysis as inputs [8]. Forecasting is the most significant optimization concept related to energy savings, material savings, increasing efficiency, making appropriate and suitable accurate decisions [8,9]. On the other hand, chaos theory is an essential part of nonlinear science, developed in the 1970s [10]. Chaos is a long-term non-periodic behavior in a predictable system with a high sensitivity to initial conditions. It shows the order and regularity hidden behind disorganized and complex occurrences. This tendency permeates and promotes many subjects. As a result, chaos research has access to a solution. In the meantime, chaos theory applications are becoming increasingly popular. They are significantly used in diverse scientific applications such as wind farms [11], PV systems, oil and gas [12,13], hydrological systems [14], etc. A brief description of the need for chaotic time series forecasting in each of these applications is explained below.

1.2.1. Chaotic Time Series Forecasting in Power and Energy

Electricity demand and market price predictions have played a significant role in the electric power industry for over a century [15]. Moreover, due to the worldwide energy crisis and alarmingly rising air, water, and soil pollution levels, renewable energy has become increasingly popular for power generation in recent years. This popularity is because renewable energy is a pure and limitless energy source [11]. As a result, a rising number of nations are becoming involved, and investors are committing to developing renewable energy plants. However, the lack of consistent energy sources due to intermittent nature represents renewable energies' main problem. Thus, forecasting renewable generation is the key to integrating these intermittent energies into the electricity grid for several reasons [9,16]. The main advantage of predicting the intermittent nature of renewable energy resources is that the number of backup systems can be reduced, thus, reducing the investments and need for electricity to meet the demand. Many forecasting approaches have been proposed using ANN, fuzzy, etc. These approaches are based entirely on time series analysis in which the chaotic time series data of renewable energy are one of the most challenging dynamics to be forecast.

1.2.2. Chaotic Time Series Forecasting in Oil and Gas

It is well known that the intake flow of a gasoline engine directly impacts the accuracy of the air–fuel ratio management under transient situations [12]. As a result, precise control becomes extremely difficult because the air ratio is far from stoichiometry for various reasons. Thus, forecasting the engine's intake flow with greater accuracy in less time can improve the convergence rate. Additionally, it will be able to overcome the shortcomings of the airflow sensor's lag. This is because it allows an accurate forecast of the future airflow. Similarly, it is also well known that there are abnormal fluctuations in the ventilation air in the nonlinear coal mines' ventilation systems [17]. These fluctuations in the air are due to the mining depth and intensity gradually increasing and equipment aging. The abnormalities, as mentioned earlier, can affect the entire system, resulting in various underground accidents and lost coal mines' ventilation system stability. Therefore, timely air quality prediction in coal mines' ventilation systems can help adequately manage systems, which directly influences the safety and output of the coal mine.

1.2.3. Chaotic Time Series Forecasting in Hydrological Systems

Hydrological forecasting plays a critical role in reducing future flood impacts, also helps produce more benefits for hydropower production, and enhances water resource management [18]. It is worth noting that predicting the destiny of a river inflow is an essential concern for water quality management [19].

1.2.4. Chaotic Time Series Forecasting in Other Systems

The distributed control system and information technology, which comprises supervisory information technology and management information systems, are commonly used technologies in thermal power plants [20]. The real-time data collected from power plant equipment and personnel controls using these technologies are a chaotic time series. Further, the instantaneous generator output power is critical to indicate the adjusting and controlling equipment's status. As a result, predicting the immediate generator power time series could provide decision-making, maintenance, and incident-handling information. Further, it positively impacts plant production, optimal operation, and problem detection and maintenance technology.

Natural hazards, such as earthquakes, severe floods, fires, and volcanic eruptions, and the destruction they create are worldwide issues that impose a high cost in terms of human lives and financial damages [21]. The wireless sensor networks monitor the urban river levels and other natural environmental conditions for predicting the floods before they occur so that the people at risk evacuate in time.

Similarly, the nonlinear spacecraft system contains various fields with advanced technology, and it has a significant impact on national economies, research, and technology. Faults in the spacecraft system are challenging to detect and rectify. As a result, studying the trend of spacecraft telemetry metrics and the variation law is essential for the early prediction of spacecraft problems.

1.3. Previous and Current Literature Survey

Few reviews have focused on applying chaos theory in multiple applications. For instance, in [14,22,23], a study on the application of the chaos concept in hydrology was reported. The study also reveals some critical issues raised while applying the chaos concept in hydrology. Similarly, a review of the application of chaos theory in traffic flow patterns was reported in [24]. In both works, some of the reviewed methods reported for the short-term forecasting are correlation dimension, Lyapunov exponent, Kolmogorov entropy, SVM, ANN, nonlinear prediction, and dynamic neural network. These reviews overlapped with elements of this field, though none have brought together all material related to chaotic time series forecasting approaches using machine learning techniques for various applications.

Considering the above research scope, the authors in this paper reviewed chaotic time series forecasting approaches using machine learning techniques in various applications. At first, the importance of chaotic time series forecasting is identified in multiple applications, including all the recently published methods, and addresses issues of individual techniques. The review of these chaotic time series forecasting approaches in the past three decades is summarized in Section 2. Section 3 gives a comprehensive review of machine-learning-based chaotic time series forecasting approaches developed using ANN, FNN, WNN, and optimization algorithms. The study on forecasting various chaotic parameters in multiple applications is detailed in Section 4. Section 5 discusses the various performance measures used for chaotic time series forecasting approaches. Finally, Section 6 concludes the current works, highlighting the shortcomings and suggesting possible future research perspectives.

2. Review on Chaotic Time Series Forecasting

In the past three decades, many researchers have rigorously researched forecasting of chaos in various areas, such as wind farms, photovoltaic systems, hydrological systems, communication systems, and oil and gas fields, using ANN. Thus, there is a scope for a critical review of chaotic time series forecasting in various areas using machine learning techniques. This manuscript critically reviews various works published from 1992 to 2021. The decade-wise research contributions to chaotic time series forecasting during this period are shown in Figure 1.

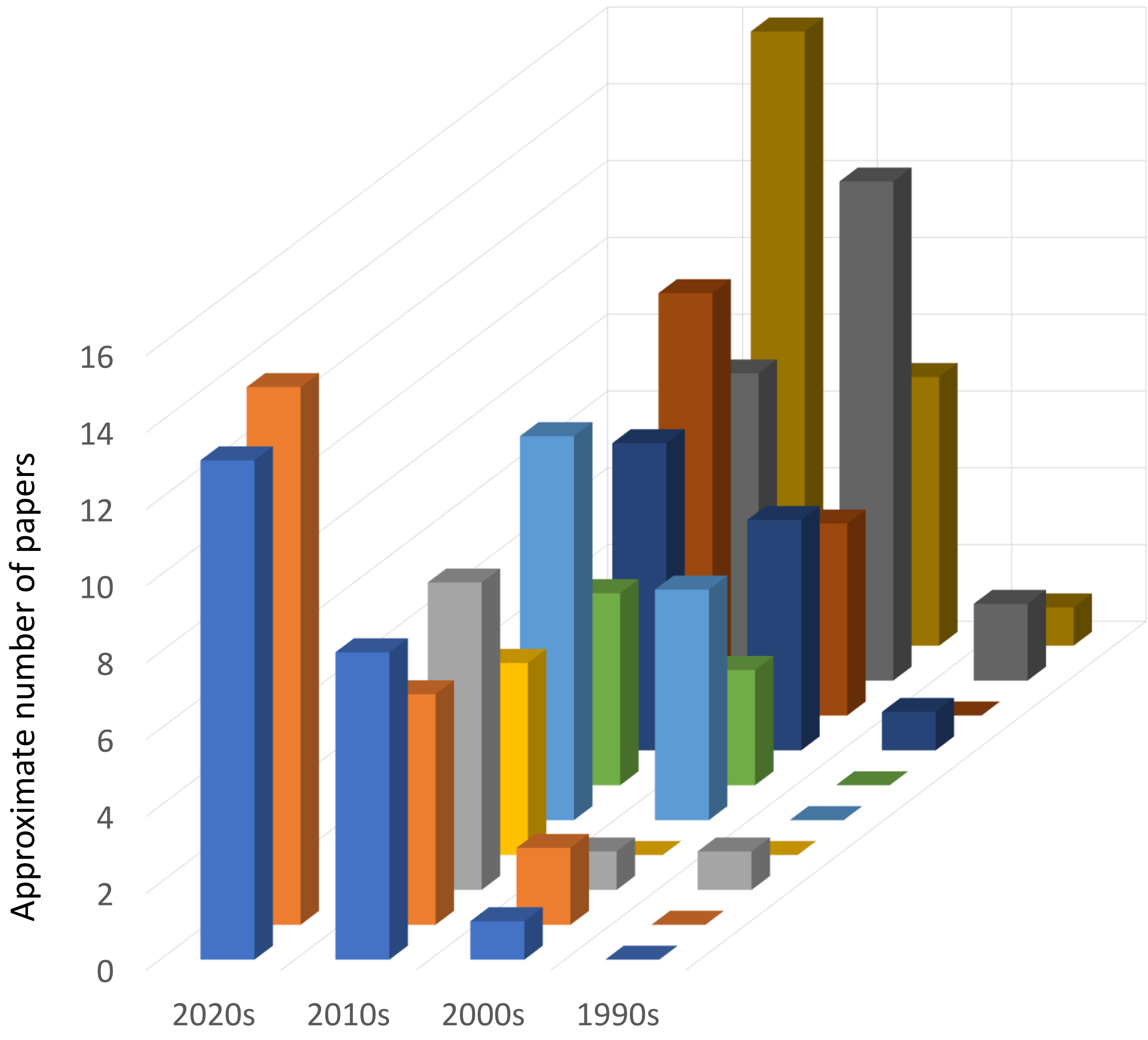

Figure 1. Decade-wise research contributions to chaotic time series forecasting from 1992 to 2021.

According to the literature review collected from Table 1, 43% of works have employed the ANN-based approaches in the literature for chaotic time series forecasting. The additional techniques are based on the following: FNN 24%, optimization algorithms 15%, WNN 6%, and other approaches 4%. In the 15% of optimization-algorithm-based techniques, the various algorithms used are GA, PSO, SSA, SA, SOM, CGO, GWO, CBAS, etc. The objective of these techniques is to improve accuracy, computational efficiency, and concerns due to the presence of uncertainties in various applications. Some novel techniques reported in Table 1 focused on efficiently tackling multiple objectives. Table 1 also shows that these articles have dealt with several forecasting parameters, such as load, power, speed, traffic flow, signals, etc. In some of these works, real-time data were also collected from various countries, including Australia, Belgium, Canada, China, Iran, Laos, Morocco, Thailand, and the USA, as shown in Figure 2. In the first decade, research on chaotic time series forecasting relied on statistical data to forecast the system's future behavior. The rest of the decades used artificial intelligence and other novel models for chaotic time series forecasting in various applications. The detailed analysis of various forecasting approaches in different applications is explained in the following sections.

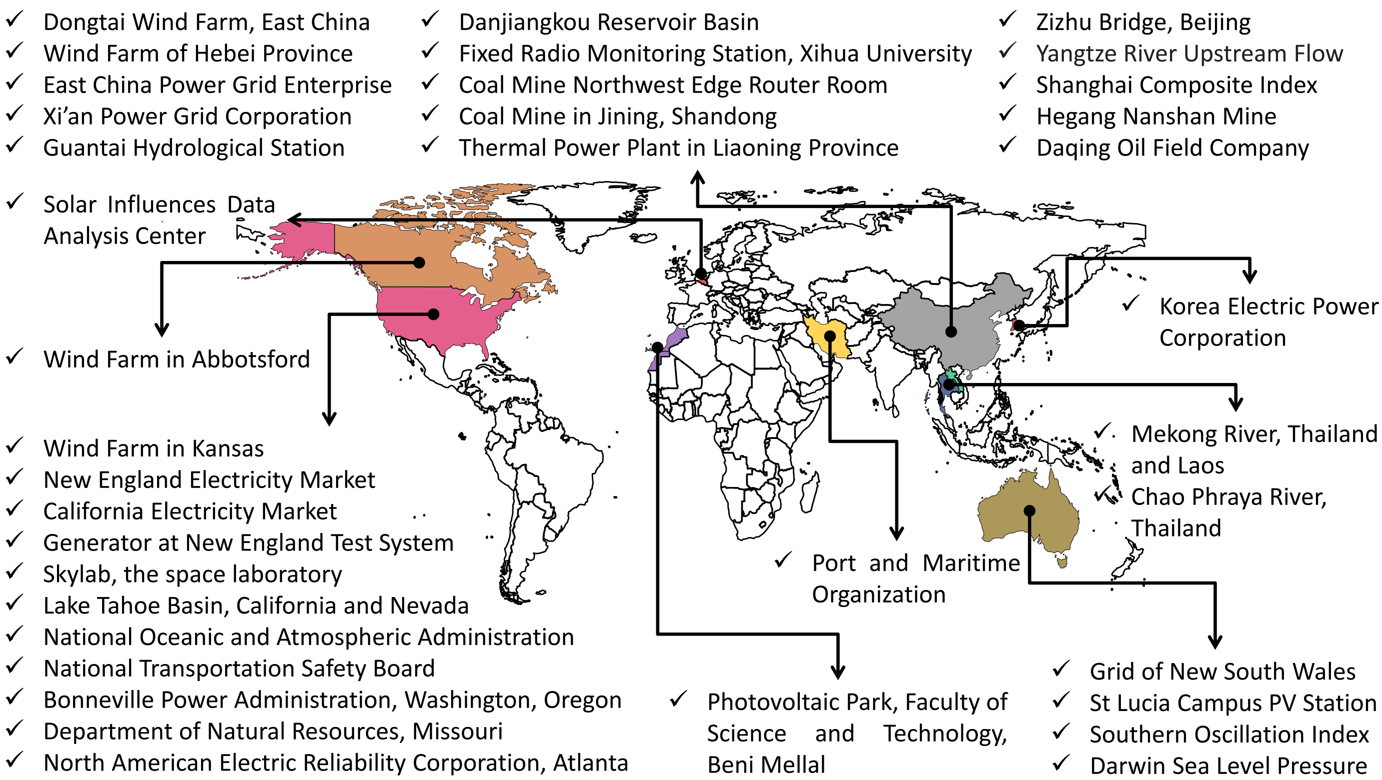

Figure 2. Locations of real-time data collected from various parts of the world.

Table 1. Summary of works focused on chaos forecasting using machine-learning-based approaches.

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[25], 1992	China	IEEE Conference	Complex weighted neural network	Music formula	Arrival direction	–	–	–
[26], 1996	South Korea	IEEE Conference	ANN	Power system	Daily peak load	–	MAPE	South Korea electric power corporation
[27], 1998	China	IEEE Conference	Embedding phase space using RNN	Mackey-Glass model	Time series	–	MSE	–
[28], 1998	Norway	Physica D: Nonlinear Phenomena	Ordinary least square method	Sunspot, R-R intervals of human ECG signals	Time series	PCR, PLS, TTLS, RR	NRMSE	–
[29], 1999	China	IEEE Transactions on Neural Networks	Temporal difference GA based reinforcement learning neural network	Henon map, Logistic map	External reinforcement signal	–	Prediction error	–
[30], 2000	China	IEEE Conference	Novel noise reduction	Chaotic interference	Frequency	–	Residual error	–
[31], 2001	Australia	IEEE Conference	Standard Gaussian approximation	Asynchronous DS-CDMA systems	Accuracy	Improved GA	–	–
[32], 2001	Spain	IEEE Conference	ANN	Hot wire anemometer	Turbulent flow temporal signals	–	MSE	–
[33], 2002	UK	IEEE Conference	Gaussian processes	Henon map	Time series	SVM	NMSE	Far infrared-laser
[34], 2004	Iran	Chaos, Solitons and Fractals	RBFNN	Logistic map, Henon map, Mackey-Glass model	Time series	-	MSE, NMSE	–
[35], 2004	Canada	IEEE Transactions on Biomedical Engineering	ANN	Silico model	Onset of state transitions	–	–	–
[36], 2004	China	IEEE Transactions on Signal Processing	Recurrent predictor neural network	Sunspot number	Time series	Kalman filter, ULN	RMSE, PE	–
[37], 2004	China	Chemical Engineering Science	Chaotic forecasting	Evaporator with two-phase flow	Heat-transfer coefficient	–	ARE	–
[38], 2004	China	IEEE Conference	WNN	Electricity	Spot market prices	–	MSE, APE	South china
[39], 2004	China	IEEE Conference	KIII-chaotic neural network	IJCNN CATS benchmark test data	Time series	N-based method	MSE	IJCNN'O4 CATS benchmark set
[40], 2005	China	IEEE Conference	RNN	Power system	Price	–	Mean and maximum percentage errors	New England electricity market, USA [1]

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[41], 2005	China	IEEE Conference	SVM	Market price	Exchange rate	ANN	MSE	–
[42], 2005	Japan	IEEE Transactions on Circuits and Systems	Master–slave synchronization scheme	FitzHugh–Nagumo model, Chua’s oscillator	Chaotic behavior	–	Prediction error	–
[43], 2006	Italy	Hydrological Sciences	RBFs	Henon map, Lorenz map, Sea-surface temperature	Time series	–	CMSE	Mekong river in Thailand and Laos, Chao phraya river in Thailand
[44], 2006	China	IEEE Conference	Sigmoid and wavelet hybrid transfer function	ESN	Memory capacity	ESN predictor	NRMSE	–
[45], 2006	Mexico	IEEE Conference	WNN	Lorenz system, Mackey–Glass model	Time series	BPNN	MSE	–
[46], 2006	Spain	Physica D: Nonlinear Phenomena	Discrete-time recursive update	Lorenz system	On-line parameter	Maybhate’s technique, d’Anjou’s technique	NMAE	–
[47], 2006	Iran	IEEE Conference	GA	Mackey-Glass model	Time series	ANN	NMSE	–
[48], 2006	Canada	IEEE Conference	Time delay neural network	Solar system	Number of dark spots	Weight elimination FFNN, Dynamical RNN, Hybrid clustering	NMSE	Skylab, Solar influences data analysis center, Belgium [2]
[49], 2007	South Korea	IEEE Conference	Terminal sliding mode controller	Duffing, Lorenz systems	Tracking error	Classical sliding mode control	MSE	–
[50], 2007	China	IEEE Conference	Self-organizing Takagi and Sugeno-type FNN	Traffic system	Traffic flow	RBFNN	RMSE	Zizhu Bridge in Beijing
[51], 2007	Greece	IEEE Conference	BPNN	Diode resonator circuits	Time series	–	RMSE	–
[52], 2007	Iran	IEEE Conference	Co-evolutionary	Solar system	Sunspot number time series	AR, Threshold AR model	NMSE	Solar influences data analysis center, Belgium [1]
[53], 2007	China	IEEE Conference	Evolving RNN	Lorenz, Logistic, Mackey–Glass, Real-world sun spots series	Time series	LLNF, Bidirectional RNN	NMSE, RMSE	Solar influences data analysis center, Belgium [1]

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[54], 2008	China	IEEE Conference	Distributed chaotic fuzzy RBFNN	Distribution network	Fault section	BPNN	–	–
[55], 2008	China	Expert Systems with Applications	Optimal BPNN	Signal deviation	Time series	Grey model, ARMA, RBFNN	MAD, MAPE, MSE	
[56], 2008	China	IEEE Conference	Generalized EKF	Lorenz system	Time series	MLP network	MSE	–
[57], 2008	Brazil	Neurocomputing	NARX neural network	Chaotic laser, Real-world video traffic	Time series	Time delay neural network, Elman RNN	NMSE	Chaotic laser, Variable bit rate video traffic time series
[58], 2008	China	IEEE Conference	ANN	Unimodal surjective map system	Generating sequences	–	PRE	–
[59], 2008	Greece	Engineering Applications of Artificial Intelligence	Nonlinear time series analysis, BP-MLP	Chaotic diode resonator circuits	Time series	–	NMSE	–
[60], 2008	China	IEEE Conference	LS-SVM	Power system	Marginal price	BPNN	APE, MAPE	California electricity market, USA
[61], 2008	China	IEEE Conference	Ensemble ANN	Mackey–Glass model	Turning points	Single ANN	–	–
[62], 2008	China	IEEE Conference	Chaotic adding-weight dynamic local predict model	Pseudo random number generator	ISN value	–	Scope error, Margin error	–
[63], 2008	China	IEEE Conference	Add-weighted one-rank multi-steps prediction	Electricity	Price	Mutual information, False neighbors methods	Maximum percentage error, Average error	–
[64], 2008	China	IEEE Conference	Hybrid accelerating GA	River flow model	Roughness parameter	Standard binary-encoded and real-valued accelerating GA	ARE	Yangtse river upstream flow, China
[65], 2008	Greece	Chaos, Solitons and Fractals	Nearest neighbor	Single transistor chaotic circuit	Time series cross	–	–	–
[66], 2008	China	IEEE Conference	Subtractive clustering based FNN modeling	Traffic system	Traffic flow	BPNN, FNN	MAE, MAPE, MSE, MSP_dE	–

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[67], 2009	China	IEEE Conference	Adaptive neural network fuzzy inference system	Hydrological stations	Average monthly flow	AR method	PRE	Guantai hydrological station of zhang river, China
[68], 2009	China	IEEE Conference	RBFNN	Shanghai composite index	Economic time series	BPNN	MAPE	Shanghai composite index, China
[69], 2009	Iran	Neural Computing and Applications	Fuzzy descriptor singular spectral analysis	Mackey–Glass, Lorenz, Darwin sea level pressure, Disturbance storm models	Time series	MLP, LLNF, RBFNN	NMSE	Darwin sea level pressure in Australia, Solar influences data analysis center, Belgium, US national oceanic and atmospheric administration [1]
[70], 2009	Iran	Chaos, Solitons and Fractals	Levenberg–Marquardt learning	Mackey–Glass model	Time series	–	MSE, NMSE	–
[71], 2009	China	IEEE Conference	Bee evolution modifying PSO chaotic network	Power system	Load	PSO	RMSE	Daqing oil field company, China
[72], 2009	China	IEEE Conference	Adding-weighted LLE	Grid	Load	Adding-weighted one-rank local	Maximum and minimal relative errors, ARE	Grid of New South Wales, Australia
[19], 2009	USA	Journal of Hydrology	Regression analysis, ANN, Chaotic nonlinear dynamic models	Hydrological systems	Temperature	–	R^2, RMSE, MSE	Lake Tahoe basin, California and Nevada, USA
[73], 2010	China	IEEE Conference	Gaussian particle filtering	Mackey–Glass model	Time series	EKF, UKF	Prediction error	–
[74], 2010	China	Renewable Energy	Wavelet decomposition method, ITSM	Wind farm	Power, Speed	BPNN	MAE, MSE, MAPE	–
[75], 2010	China	IEEE Conference	Chaos theory, FNN	Hydraulic pump	Vibration signal	–	APE, MSE	–

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[76], 2010	China	IEEE Conference	Dynamic recurrent FNN	Power system	Load	FNN	MSE	North china city
[77], 2010	China	IEEE Conference	Parallel RBFNN	Lorenz system, Hydraulic pump	Time series	RBFNN	APE	–
[78], 2010	China	Neurocomputing	Hybrid Elman–NARX neural network	Mackey–Glass, Lorenz, Real life sunspot models	Time series	AR model, GA, Fuzzy	MSE, RMSE, NMSE	Solar influences data analysis center, Belgium [1]
[79], 2010	China	IEEE Conference	Nonlinear AR	Chaotic system	Exchange rate	BPNN, SVM model	APE	FX data of USD
[16], 2010	China	IEEE Conference	SVM	Wind farm	Speed	ANN	RRMSE	–
[80], 2011	China	IEEE Conference	Rough set neural network	Wind farm	Power	Chaos neural network, Persistence models	NMAE	Wind farm in Beijing area, China
[81], 2011	China	Expert Systems with Applications	Chaotic wavelet decomposition–Grey model	Wind farm	Power	Direct prediction method	MAPE, NMAE, NRMSE	Dongtai wind farm, East China
[82], 2011	USA	IEEE Conference	Probabilistic collocation	Power system	Sparse grid points	Monte Carlo method	Measurement error	NASA
[83], 2011	China	Procedia Engineering	Global prediction method based on BPNN	Gas	Emission rate	First-order weighted local prediction method	MSE, RMSE	Hegang nanshan mine, China
[84], 2011	China	IEEE Conference	Chaotic RBFNN	Power system	Load	RBFNN	Absolute error	–
[85], 2011	China	IEEE Conference	Improved duffing oscillator-chaotic traffic prediction model	Coal gas	Traffic flow	–	Peak-to-peak error	Coal mine northwest edge router room, China
[86], 2012	France	IEEE Conference	Anchor selection based on polynomial chaos expansions	Anchor	Angle-of-arrival	–	RMSE, Median error	–
[87], 2012	China	Physics Procedia	Mutative scale chaos optimization	SVM parameters	Chaotic time series	Chaos optimization algorithm	RMSE	–

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[88], 2012	China	Systems Engineering Procedia	Chaotic local weighted linear forecast algorithm	Electricity	Daily load	Weighted first order local method	ARE	South china city
[89], 2012	China	IEEE Conference	Hierarchic ESN	Lorenz, Sunspot, Yellow river annual runoff models	Time series	ESN	RMSE	–
[90], 2012	South Korea	IEEE Conference	MLP	DC electric arc furnace	Voltage, Current signals, Arc resistance	RBFNN	Autocorrelation	DC electric arc furnace
[91], 2012	China	IEEE Transactions on Systems, Man, Cybernetics	H-infinity state estimation	Discrete time chaotic systems	H-infinity state	EKF	Estimation error	–
[92], 2012	China	IEEE Conference	Chaos algorithm	Radio wave	Amplitude	Traditional chaotic time series prediction method	RMSE	–
[93], 2012	Italy	IEEE Conference	Decentralized polynomial chaos theory	Power system	Voltage sensor validation	Decentralized polynomial chaos theory	Local covariance error	–
[94], 2013	Turkey	Electric Power Systems Research	Independent component analysis	Power system	Amplitude, Frequency signals	Zero-crossing, Discrete Fourier transform, Orthogonal filters, Kalman filter	MSE	–
[95], 2013	China	IEEE Conference	WNN with phase space reconstruction	Lorenz, Henon models	Time series	WNN without phase space reconstruction	SMAPE	–
[20], 2013	China	IEEE Conference	Global prediction of chaos	Generator	Output power	–	PRE	Thermal power plant in Liaoning province, China
[12], 2013	China	IEEE Conference	Chaotic RBFNN	Gasoline	Intake flow	RBFNN	MSD, MAE, ARE	–
[96], 2013	China	Fluid Phase Equilibria	Self-adaptive PSO based BPNN	Polymers	Gas solubility	BPNN, PSO-BPNN	MSE	–

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[97], 2014	Taiwan	IEEE Transactions on Cybernetic	Interval type-2 fuzzy cerebellar model articulation controller	Henon system	Time series	FNN, Interval type-2 FNN	MSE	–
[98], 2014	China	The Scientific World Journal	Phase space reconstruction-LS-SVM	FM radio	Band occupancy rate	GA-LS-SVM, Monte Carlo-LS-SVM	NMSE, RMSE, MAPE	Fixed radio monitoring station of Xihua university, China
[99], 2014	China	IEEE Conference	Chaos elitism estimation of distribution	Chaotic system	Elitism strategy	Estimation of distribution algorithm for large scale global optimization	Standard deviation	–
[100], 2014	Egypt	Journal of the Egyptian Mathematical Society	Adaptive chaos synchronization technique	Hyperchaotic system	System parameters	–	Error dynamics	–
[101], 2014	Greece	Simulation Modeling Practice and Theory	ANN	Chaotic dynamical system	Embedding dimension	–	RMSE	–
[102], 2014	Hong Kong	Building and Environment	ANN-chaotic PSO	Air quality	Particulate matter concentration	Mulleven Levenberg–Marquardt	R, MSE	–
[103], 2014	Mexico	IEEE Conference	SOM tuned neural network	Mackey–Glass, NN5	Time series	–	RMSE, MAE, SMAPE	–
[104], 2014	Japan	IEEE Conference	Jacobian matrix estimation	Wind farm	Speed,Power	ANN, GA	RMSE	Japan meteorological agency, Aomori area, North of Honshu, Japan
[105], 2014	China	Mathematical Problems in Engineering	Generalized Liu system	Chaotic secure communication, implementation of electronic circuits, numerical simulations	Global exponential stability	Weighted first order local method	RMSE	–

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[106], 2014	Canada	IEEE Transactions on Power Delivery	Minimum phase space volume-EKF equalization	Power line communications	Blind equalization	Inverse filter-based MPSV method	MSE	–
[107], 2015	China	Journal of Engineering Science and Technology Review	Improved GA	Lorenz model	Time series	GA	Percentage coordinate error	–
[108], 2015	China	Applied Energy	Hilbert–Huang transform and Hurst analysis	Wind farm	Power	EMD model, LS-SVM	NMAE, NRMSE	Wind farm of Hebei province, China
[109], 2015	Iran	Ocean Engineering	False nearest neighbor	Wind farm	Wave characteristics	–	–	Port and maritime organization, Iran
[110], 2015	Iran	Journal of Intelligent & Fuzzy Systems	Embedding theorem-repetitive fuzzy	Mackey–Glass, Lorenz, Sunspot number models	Time series	MLP gradient, Adaptive neuro fuzzy inference, AR, Fuzzy	MSE, RMSE, NMSE	Solar influences data analysis center, Belgium [1]
[21], 2015	Brazil	Neural Computing & Applications	MLP	Flood	River level	Elman-RNN	MAE, RMSE, R^2	Urban rivers by means of wireless sensor networks
[111], 2016	China	Journal of Parallel and Distributed Computing	Maximum velocity criterion, Sinusoidal wave frequency modulation, Chaotic control using fuzzy	Smart grid	Chaos	Raw smart grid	–	–
[112], 2016	China	Mathematical Problems in Engineering	Self-constructing recurrent FNN	Logistic, Henon maps	Time series	Self-constructing FNN	RMSE	–
[113], 2016	China	IEEE Conference	Chaos RBFNN prediction	Blast furnace	Carbon-monoxide utilization ratio	–	RMSE	–
[114], 2016	China	Mathematical Problems in Engineering	Chattering-free sliding mode control	Power system	Disturbances	Nonlinear disturbance observer based sliding mode control	Steady state error	–

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[115], 2016	Malaysia	Neural Computing & Applications	BPNN, Chaos search GA, Simulated annealing	Smart grid	Electrical energy demand	ANN	MAE, RMSE, MSE, MAPE	Grid of New South Wales, Australian
[116], 2016	Russia	IEEE Conference	Guaranteed	One-dimensional chaotic system	Guaranteed state, Parameter	LS method	Measurement errors	–
[117], 2016	Iran	Journal of Intelligent & Fuzzy Systems	Interactively recurrent fuzzy functions	Lorenz, Noisy Mackey–Glass, Real lung sound signals	Time series	FNN, WNN, ESN, LS	RMSE, PRE	Department of pneumology in Shariati hospital collected by Amirkabir University's researchers
[118], 2016	Italy	Chemical Engineering Transactions	Parallel chaos	Power system	Load	ANN	–	East China power grid enterprise
[119], 2017	China	Energy	Ensemble EMD, Full-parameters continued fraction	Wind farm	Power	HEA, MLE, RBF	NRMSE, NMAE	Farm in Xinjiang, China
[13], 2017	China	Chaos, Solitons and Fractals	Wavelet transform, Multiple model fusion	Lorenz, Mackey–Glass models	Time series	Improved free search-LS-SVM, Direct superposition without Gauss–Markov fusion	RMSE, MAE, SMAPE	–
[120], 2017	China	Renewable and Sustainable Energy Reviews	Wavelet decomposition, EMD	Electricity	Electricity demand	ANN, SVM	–	–
[121], 2017	China	IEEE Conference	RBFNN, Volterra filter	Spacecraft system	Spacecraft telemetry parameter	–	Absolute error, RE	–
[122], 2017	China	Chaos, Solitons and Fractals	Recursive Levenberg–Marquardt	Neural networks	Chaotic time series	On-line Levenberg–Marquardt algorithm	MSE	–

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[123], 2017	South Korea	Sustainability	Inverse model, Chaos time series inverse	Building energy management system	Electric energy consumption	SVM	MAE, CVRMSE	–
[124], 2017	China	Computer Methods in Applied Mechanics and Engineering	Fast initial solution prediction	Sheet metal stamping	Inverse isogeometric analysis	One-step inverse finite element method	–	–
[17], 2017	China	International Journal of Mining Science and Technology	Coal mine ventilation systems management technology	Coal mine	Gas concentration	–	MSE	Coal mine in Jining, Shandong, China
[125], 2017	Iran	IEEE Conference	Takens embedding theory	Chaotic Henon map	Time series	Pyragas method	Estimation error	–
[126], 2017	New Zealand	Wireless Communications and Mobile Computing	Adaptive multiuser transceiver scheme	DS-CDMA System	Bit error rate	Least mean square	MMSE	–
[127], 2017	India	IEEE Conference	LLE, HFD, SampEn	Electromyography signals	Chaos, Fractal dimension, Entropy	Grassberger–Procaccia algorithm, Approximate entropy	–	–
[128], 2018	China	Neural Computing & Applications	Chaotic BPNN	Power system	Load	BPNN, RBFNN, Elman, PSO-BPNN, RBFNN-Quantile regression	MRPE, MAPE	Electrical load data of a city in china network
[129], 2018	China	IEEE Conference	Equivalent circuit model, EKF	Li-ion batteries	State of charge	–	Estimation error	–
[130], 2018	Morocco	IEEE Conference	ANN–Discrete wavelet transform	PV system	Power	ANN, ANN–Phase space reconstruction	MSE, MAPE, RMSE	Photovoltaic park, faculty of science and technology, Beni Mellal, Morocco
[131], 2018	Russia	IEEE Conference	Deep CNN	Discrete dynamic systems	Lyapunov exponent	–	MAPE, MPE	Russian central bank [1]

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[132], 2018	China	Sensors	SA	Time series interferometric synthetic aperture radar	Deformation	–	–	Beijing area, china
[133], 2018	Indonesia	IEEE Conference	SOM extreme learning mechanism-RBFNN	Lorenz system	Multi-step ahead time series	AR, ARIMA models	Multiple correlation coefficient	–
[134], 2018	China	IEEE Conference	Generalized regression neural network of k-fold cross validation	Sunspot	Time series	RBFNN	Least generalization error, Normalized error	Solar influences data analysis center, Belgium [2]
[135], 2018	China	IEEE Conference	GA-LS-SVM	Fractional order systems	Nonlinear function	LS-SVM	MSE	–
[136], 2019	Indonesia	IEEE Conference	Roberts edge detection	Weather	Tornadoes	–	–	–
[18], 2019	China	Journal of Hydrology	Coupled quantity–pattern similarity	Hydrological application	Monthly precipitation	Local approximation prediction, Autoregressive models	R, RMSE, MARE, MSE	Danjiangkou reservoir basin, China
[137], 2019	Mexico	IEEE Conference	Superimposed chaos sequence	Quadratic base band, Orthogonal frequency division multiplexing-based cognitive radio Channel	Frequency	Pilot design method, Wavelet pilot design	–	–
[138], 2019	USA	IEEE Conference	Polynomial chaos expansion–Langevin MCMC	Power system	Inertia, Exciter gains, Damping ratio, Droop	Metropolis–Hastings algorithm	–	–
[139], 2019	China	IEEE Conference	Principal component analysis–chaotic immune PSO-GRNN	Cooling water	Corrosion	PSO-GRNN algorithm	ARE	Petrochemical enterprises
[140], 2019	UK	Electric Power Systems Research	Harmonic robust grid synchronization	Grid	Voltage signal	Second-order generalized integrator-frequency locked loop technique	Phase estimation error	–

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[141], 2019	China	Applied Soft Computing	Fuzzy information granules, LSTM-FNN	Zurich monthly sunspot numbers, Mackey–Glass model, Daily maximum temperatures in Melbourne	Time series, Granules	AR, Nonlinear AR neural network	RMSE, MAPE, MAE	–
[142], 2019	Switzerland	IEEE Conference	Chaos–Rivest shamir adleman, Chaos–Random number generator	Crypto system	Security vulnerabilities	–	–	–
[143], 2019	China	IEEE Conference	Correlation matrix augmentation	Bistatic co-prime MIMO array	Directions of departure and arrival	ESPRIT-Root MUSIC and RD-Root MUSIC	RMSE	–
[144], 2019	China	Renewable Energy	Markov chain switching regime	Wind farm	Speed, direction	Neural network, SVM	MAE, RMSE, MAPE	Bonneville power administration, Washington, USA
[145], 2019	USA	IEEE Conference	True random number generator	Chaotic jerk system	Sampling period	Pseudo random number generator	–	–
[146], 2019	USA	IEEE Signal Processing Letters	Kalman filter	Synchronous generator	Computing time	EKF	RMSE	–
[147], 2019	China	IEEE Access	Chaotic optimized-PSO	Mobile	Location	Chan, Taylor, PSO	RMSE, MSE	–
[148], 2019	China	Journal of Power Sources	Fractional-order	Li-ion battery and ultra-capacitor hybrid power source system	Load current, power	–	MAE, RMSE, MRE	–
[149], 2019	USA	IEEE Transactions on Smart Grid	Response surface-based Bayesian inference	Power system	Inertia, Exciter gains, damping ratio, droop	Traditional Bayesian inference	PE	North American electric reliability corporation, Atlanta, USA
[150], 2019	China	Physica A: Statistical Mechanics and its Applications	Electric field detector-Chaos SVM	Aircrafts	Accidents	SVM, Chaos SVM	NMAE, NRMSE, NMAPE	National transportation safety board, USA

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[151], 2020	USA	IEEE Transactions on Industrial Informatics	Multifidelity-surrogate-based Bayesian inference via adaptive importance sampling	Synchronous generator	Inertia, Exciter gains, Damping ratio, Droop	Importance sampling-based, polynomial chaos expansion-based-Bayesian inference models	NRMSE	Generator in New England test system, USA
[152], 2020	China	IEEE Access	Fractal dimension-Lorenz stenflo-Ensemble EMD, GA-BPNN	Wind farm	Speed	Ensemble EMD-GA-BPNN, LS-Ensemble EMD-GA-BPNN	RMSE, MAE, MAPE	Wind farm in Abbotsford, Canada
[153], 2020	China	IEEE Communications Letters	Amplitude phase shift keying based M-Ary-DCSK	Chaos shift Keying modulation system	SER, BER, PAPR	QAM based M-DCSK system	–	–
[154], 2020	Canada	IEEE Access	ML-PSV	Blind system	Frequency	MPSV technique	MSE	–
[155], 2020	China	IET Renewable Power Generation	Chaos theory, Ensemble EMD	PV System	Output power	Chaos-GA-BPNN, Ensemble EMD-GA-BPNN, NWP-GA-BPNN	MAPE, RMSE, MAE	St Lucia campus PV station, Australia [1]
[156], 2020	China	Complexity	Variational mode decomposition-Maximum relevance minimum redundancy-BPNN-LS-SVM	Power system	Load	EMD, Ensemble EMD	MAE, RMSE, MAPE	Xi'an power grid corporation, China
[157], 2020	Malaysia	Chaos, Solitons and Fractals	RNN-based LSTM	COVID-19	Mutation rate	–	RMSE	NCBI GenBank [1]
[158], 2020	Taiwan	Energies	CNN-SSA	PV system	Power	SVM-SSA, LSTM-Neural network-SSA	MAPE, MRE	–
[159], 2020	Belgium	IEEE Conference	General polynomial chaos	Distribution systems	Power	Monte Carlo	RMSE	European test feeder
[160], 2020	South Korea	IEEE Transactions on Instrumentation and Measurement	UKF	EEG dynamic model	Optimal parameters	Particle filter, EKF	RMSE	Intracranial EEG data set [2]

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[161], 2020	China	IEEE Access	Novel hybrid Jaya–Powell	Lorenz system	Relative error of the stopping criterion, fitness value	Jaya, Powell, TLBO, PSO, GA, CCO	RMSE	–
[162], 2020	China	Neural Processing Letters	Deep CNN	Flight	Training set loss value, Gradient value	CNN	Weight gradient, Hidden layer errors	–
[163], 2020	USA	IEEE Transactions on Power Systems	Hybrid MCMC	Power system	Inertia, Exciter gains, Damping ratio, Droop	Langevin MCMC algorithm	NRMSE	North American electric reliability corporation, Atlanta, USA
[164], 2021	Germany	Applied Energy	Non-intrusive load monitoring algorithm	Commercial buildings, Industries	Power	–	RMSE, MAE, MSLE, MAPE	–
[165], 2021	USA	Renewable Energy	Empirical dynamical modeling	Wind farm	Speed	Benchmark model	RMSE, MAE	Department of natural resources, Missouri
[166], 2021	China	IEEE Conference	BFA tuned double-reservoir ESN	Wind farm	Load	ESN	MAE, MSE, RMSE, MAPE	–
[167], 2021	China	Journal of Ambient Intelligence and Humanized Computing	Hybrid prediction	Wind farm	Power	–	Maximum value, Minimum value, Mean value, standard deviation	Wind farm of Hebei province, China [1]
[168], 2021	China	Optics Express	LSTM neural network	Optics	Amplitude	ACF, DMI, CNN	Signal-to-noise ratio	–
[169], 2021	Mexico	Neural Processing Letters	Gate recurrent unit-Deep RNN	Lorenz, Rabinovich–Fabrikant, Rossler systems	Time series	LSTM-Deep RNN	–	[2]
[170], 2021	China	Chaos, Solitons and Fractals	TCN-CBAM	Chen, Lorenz, sunspot systems	Time series	LSTM, Hybrid CNN-LSTM , TCN	RMSE, MAE, R^2	Solar influences data analysis center, Belgium [3]
[171], 2021	China	IEEE Sensors	CBAS-Elman neural network	Polyvinyl chloride polymerization	Temperature	CBAS-BPNN, CBAS-SVM	RMSE, MAE	–

Table 1. *Cont.*

Ref., Year	Country	Journal/ Conference	Forecasting Approach	Application	Forecasting Parameter(s)	Comparison Techniques	Performance Measures	Data
[172], 2021	Egypt	IEEE Access	CGO	Three diode PV model	Voltage, Current, Power	IGWO, MRFO, HBO, AOA	RMSE, IAE, APE	–
[173], 2021	China	Nonlinear Dynamics	ESN-GWO	Mackey–Glass, Lorenz systems	Time series	ESN, PSO-ESN, GWO-ESN	RMSE	–
[174], 2021	China	IEEE Access	YCO-PCS	Microwave filters	Yield	YCO	RMSE	–
[175], 2021	Australia	Energy	Adaptive variational mode decomposition-AOA-LSTM	Wind turbine	Power	Polynomial neural networks, FFNN, LSTM	MSE, RMSE, MAE, R^2	–
[176], 2021	China	IEEE Transactions on Vehicular Technology	Adaptive RBFNN	Online vehicle	Velocity	LSTM-Neural network, NARX-Neural network, Deep neural network	RMSE, ARMSE	Dongfeng Fengon Car
[177], 2021	India	International Journal of Applied Mathematics and Computer Science	FFNN	Fractional-order Chaotic Oscillators	System states	RNN	R^2, MSE	–

[1] https://zenodo.org/record/3874348#.YcGhC2BBxPZ (accessed on 1 March 2022), [2] https://github.com/Dajounin/DRNN-Chaos (accessed on 1 March 2022), [3] http://sidc.oma.be/. (accessed on 1 March 2022).

3. Neural Network-Based Forecasting Approaches

As mentioned in Section 2, various researchers have developed ANN, FNN, WNN, and optimization-based approaches for chaotic time series forecasting. The multiple techniques developed using these approaches are shown in Figure 3. A detailed explanation of these techniques, including the objectives and performance analysis, is presented underneath. The future scope of the method is also highlighted.

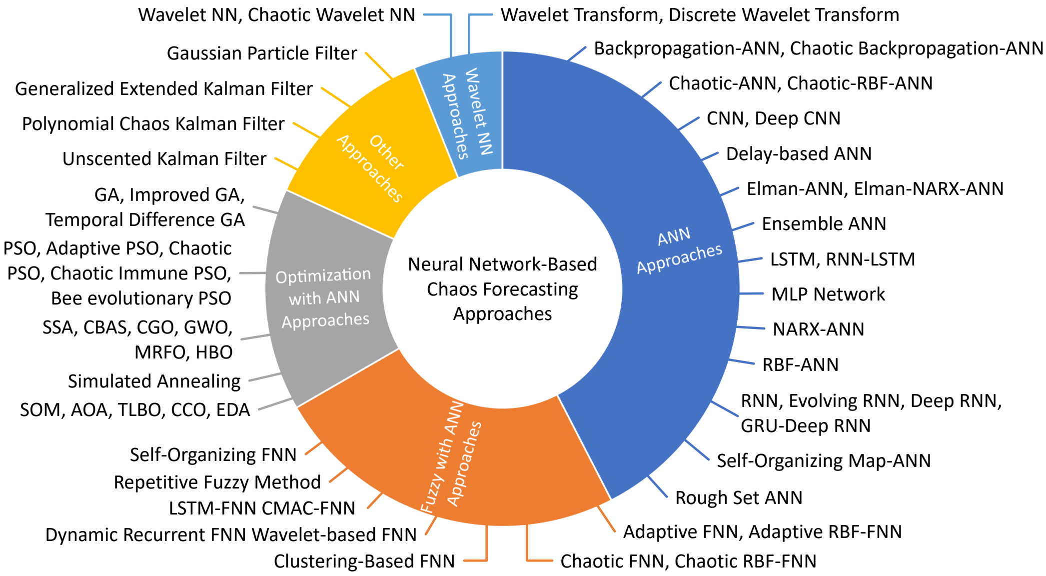

Figure 3. Summary of multiple techniques developed using ANN, FNN, WNN, and optimization-based approaches for chaotic time series forecasting.

3.1. ANN-Based Forecasting Approaches

ANN has multiple perceptrons' or nodes at each layer. For example, the network with two input nodes, two hidden layers with four nodes in each, and one output node is shown in Figure 4. This network can be called FFNN when its inputs are processed forward (refer to the red dotted line in Figure 4). The FFNN is one of the most straightforward neural networks, and it passes information in one direction through various input nodes until the output node [178]. This type of neural network may or may not have hidden layers, making its functioning more understandable. Some advantages of FFNN include storing information on the entire network, working with incomplete knowledge, offering tolerance, and having distributed memory. However, the disadvantages of FFNN include having hardware dependency and unexplained behavior that can leave us tormented with results. No particular rule for deciding the network's structure and the appropriate network structure is achieved through experience and trial and error.

BPNN is an essential mathematical tool for improving the accuracy of predictions in data mining and machine learning. In FFNN, the network propagates forward to obtain the output and compares it with real value to obtain the error. However, to minimize the error, the BPNN will propagate backward by finding the error derivative for each weight and then subtracting this value from the weight value. The architecture of a BPNN is also shown in Figure 4, and the direction of propagation is shown in the green dotted line. On the other hand, RNN is more complex than FFNN and BPNN. Here, the RNN's every node acts as a memory cell and continues the operations computation [4]. The RNN saves the output of processing nodes and feeds them back into the network, and hence, they do not pass the information in one direction only (refer to the blue dotted line in Figure 4). If the network's prediction is incorrect, the system self-learns and continually works toward correcting the forecast during backpropagation.

Researchers have utilized ANNs in numerous applications to predict or forecast various chaotic systems' behavior. For instance, in [25], the researchers developed the complex weighted neural network method for high-resolution adaptive bearing prediction. It is observed that this concept is especially effective in circumstances where the hermit matrix progressively changes over time due to adaptive tracking. Jae-Gyan Choi et al. proposed the application of ANN in power systems for predicting the one-day-ahead daily peak load based on chaotic time series data using absolute error as a performance measure [26]. It is to be noted that the proposed technique can also be used for other forecasting applications, such as predicting the special days, hourly load, temperature, etc. In [27], the researchers have presented the RNN model for Mackey–Glass chaotic time series. The proposed model's experimental results are more practicable and effective in making short-term predictions for chaotic time series than the multi-dimension embedding phase space method.

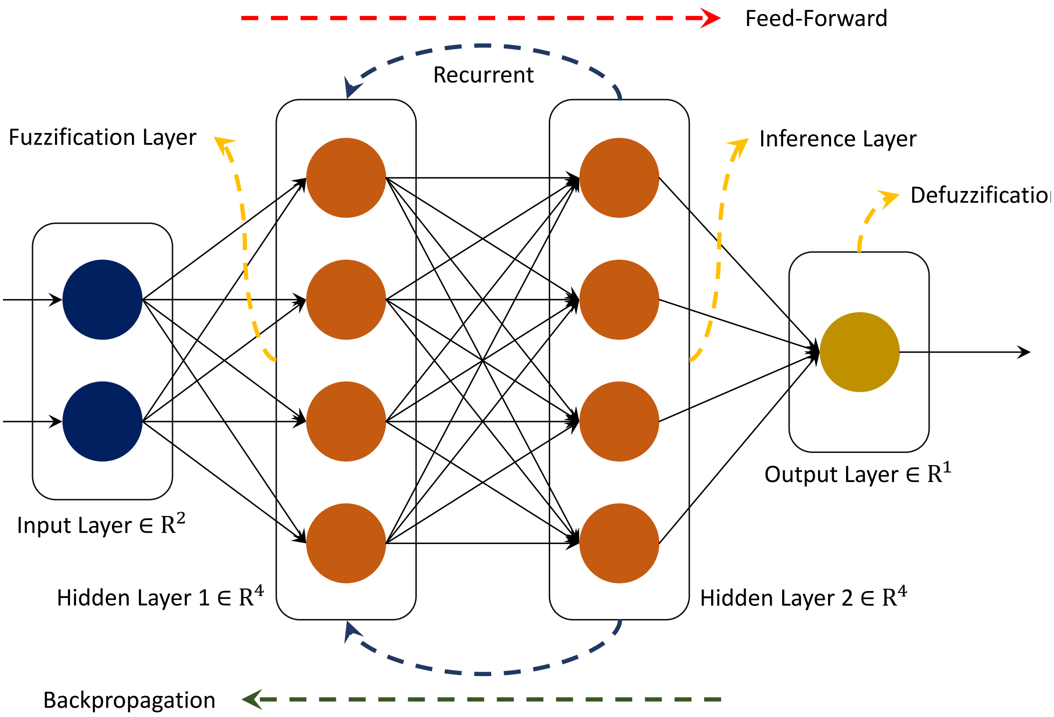

Figure 4. Architecture of various neural networks.

Guichao Yang et al. developed a multilayer neural network adaptive control algorithm for disturbance compensation in nonlinear systems. The work remarks that this developed algorithm can also be used simultaneously for nonlinear systems with mismatched uncertainties. Additionally, an extended state observer was employed to estimate the exogenous disturbance and predict the system's state [179]. In extension, the authors presented the integration of a full-state feedback control algorithm, adaptive neural network, and extended state observer to handle the unknown nonlinear dynamics and external disturbances. In addition, the output feedback control algorithm was combined with an adaptive neural network, extended state observer, and nonlinear disturbance observer to estimate the unknown nonlinear dynamics, unmeasured states, and external disturbances [180]. In both works, a double-rod hydraulic servo system was chosen to validate the two control schemes' high-performance control effect. The authors also introduced a neuroadaptive learning method for disturbance rejection in constrained nonlinear systems. Moreover, the neural network adaptive control and the extended state observer to estimate endogenous uncertainties and external disturbances in real time and correct them feedforwardly were presented in [181]. Further, the filtering problems and nonlinearity of the input were accounted for by adding an auxiliary system. Finally, the overall closed-loop stability was precisely ensured, and the accomplished control performance was validated by real-time nonlinear systems application results.

Another forecasting method known as delay-based ANN for predicting the turbulent flow temporal signals was proposed in [32]. These signals are obtained from a hot wire anemometer at a single point inside the cylinder to detect coherent structures. In [34], the authors presented the RBFNN model for forecasting the time series of the logistic map, Henon map, Mackey–Glass, and Duffing's systems. In [36], the researchers developed the recurrent predictor neural network model for predicting the annual and monthly sunspot time series. The experimental results of the proposed model are better than the Kalman filter and universal learning network in terms of accuracy and RMSE. The authors of [39] developed the KIII-chaotic neural network for forecasting the multistep time series data on a benchmark system. In [40], the researchers presented the RNN for predicting the electricity price of the power system. The work highlights that this approach is equally relevant to Chinese electrical market data. In [43], the authors presented the RBFNN model for forecasting the Henon map, Lorenz map, four real-time series discharge data, and sea-surface temperature anomaly data collected from various rivers. The work remarks that this presented model can also be used for geological time series. In [48], the authors raised the time delay neural network method for predicting the future behavior of the solar activity. In [51], the researchers demonstrated the BPNN to forecast the multistep nonlinear time series of the diode resonator circuit. From the presented work, it is to be noted that the approach can also be used in other chaotic time series.

Qian-Li Ma et al. presented the evolving RNN model for the Lorenz series, logistic, Mackey–Glass, and real-world sunspots series [53]. The experimental results of the proposed model showed to be better than the boosted RNN. Bao Rong Chang and Hsiu Fen Tsai proposed an optimal BPNN model for time series of signal deviation in the stock market [55]. The proposed method is based on SVM and AR models. The experimental results of the proposed model showed better performance than the ARMA, RBFNN, and other models in terms of MAD. In [57], the authors developed the NARX neural network model for empirically predicting chaotic laser, variable bit rate, and video traffic time series of real-world datasets. The simulation results of the developed model reliably performed better than the Elman architectures. Further, the work highlights that this model can also be used for electric load forecasting, financial time series, and signal processing tasks.

Yagang Zhang et al. developed an ANN model for predicting the stochastic generating sequences in a chaotic unimodal dynamical system [58]. It is observed that the presented strategy can also be further applicable for applications such as DNA-based groupings, protein structure arrangement, and financial market time series. The authors of [61] proposed an ensemble ANN model for forecasting the turning points in the Mackey–Glass system. An expectation–maximization parameter learning algorithm for the developed model was used for probability threshold prediction during the out-of-sample validation. The experimental result from the system proves the viability of the proposed technique and shows better results than the ANN model alone. In [68], the work presented the RBFNN model to predict the Shanghai Composite index that is chaotic according to the phase diagram analysis. The proposed technique's experimental results are better than the BPNN. In [78], the hybrid Elman–NARX neural network model is presented to chaotic systems, such as Mackey–Glass, Lorenz equations, and the real-life sunspot time series, for predicting the chaotic time series. The proposed method has performed more effectively and accurately than the AR model, GA, and fuzzy methods. Gao Shuang et al. presented the rough set neural network model for long-term wind power prediction [80]. The experimental results show that the rough set method has the least NMAE compared to the other three methods, the chaos neural network model, persistence model, and rough set neural network model. Another forecasting method for gas emission rate prediction, known as the global method based on the BPNN, was proposed in [83]. The proposed model showed good accuracy and stability predictions than the first-order weighted local prediction method. In [84], the researchers developed the chaotic RBFNN method for predicting the power systems' short-term load. The results of the proposed method showed promising results better than conventional RBFNN. In [12], a chaos RBFNN method was presented for forecasting the gasoline engine intake flow's transient condition. The simulation results showed more accuracy compared to conventional RBFNN.

In [101], the application of ANN in a chaotic dynamical system for forecasting embedded dimension and robust location was presented. In [103], the selecting and combining models with the SOM neural network model for long-term chaotic time series prediction from the Mackey–Glass equation, NN5 tournament, AR model, and sine function were presented. It is to be noted that this model can be used to assess the selected outcomes of the modeling techniques by considering the best-predicted SMAPE. In [21], the MLP model for enhancing the accuracy of a flood prediction through machine learning and chaos theory was presented. The experimental results of the proposed method performed better than the Elman-RNN method. It is to be noted that this concept is also applicable to sensors, allowing for more individual action in severe conditions. Further, the idea can also lower the system's total operational costs and ensure next-generation power grids' effective and reliable functioning. In [182], the authors developed a hybrid machine learning technique for forecasting the time series of NN5 using the nearest trajectory model, one-year-cycle model, and neural network. In [128], the self-adaptive chaotic BPNN algorithm was proposed based on Chebyshev's chaotic map for predicting the electrical power system's load. The presented algorithm results showed better global optimization performance than conventional BPNN, RBFNN, and Elman networks. The work highlights that the chaotic neural network regression using the probability density forecast method can predict the electricity demand. In [131], the deep CNN model was proposed for forecasting Lyapunov exponents from observed time series in discrete dynamical systems. In [157], the authors presented the RNN-based LSTM model to predict the mutation rate in a human body affected by COVID-19. The proposed approach can be extended further by inserting and deleting mutation rates in the model.

The authors of [162] presented the Deep CNN model using meteorological data to forecast flight delays. The results of Deep CNN showed to be better than the CNN, which is proven in terms of weight gradient error and hidden layer error. The authors of [168] presented the LSTM neural network model to forecast the delay time in a chaotic optical system and compared the model with the delayed mutual information method and autocorrelation function method. It is worth noting that the proposed model can also enhance the security and maturity of optical chaos secure communications. In [183], the authors presented a LSTM-based forecasting model by integrating ensemble and reinforcement learning techniques. Further, an adaptive gradient algorithm was used to train the network and validated on the Lorenz, Duffing, and Rössler systems. The authors of [184] developed a FFNN-based prediction model to estimate the change in future state values of a Rössler system. In [169], the authors presented a gate recurrent unit-based Deep RNN model to forecast time series of three chaotic systems, (i) Lorenz, (ii) Rabinovich–Fabrikant, and (iii) Rössler, which showed better performance than the LSTM-based Deep RNN model. This model can also be used for real-time applications to predict the hyper-turbulent frameworks to control the turbulence or synchronize the framework model.

3.2. Fuzzy with ANN-Based Forecasting Approaches

FNN is a hybrid network developed using ANN's learning ability and fuzzy logic's noise handling capability. The architecture of the FNN is also shown in Figure 4. The figure shows that the network has four layers: the input layer, fuzzification layer, inference layer, and defuzzification layer (refer to the yellow dotted lines in Figure 4). FNN uses two approaches, namely (i) Mamdani and (ii) Takagi and Sugeno. Fuzzy logic is represented using the neural network's structure and trained using either a BP or an optimization algorithm. The FNN is implemented in the following three ways:

- Real inputs with fuzzy weights;
- Fuzzy inputs with real weights;
- Fuzzy inputs and fuzzy weights.

In [50], the authors developed the self-organizing Takagi and Sugeno-type FNN model for predicting the short-term traffic flow. The experimental results of the developed model showed to be feasible and more effective than RBFNN. In [54], the researchers developed the distributed chaotic fuzzy RBFNN method applied to fault section estimation in the distribution network. The simulation results of the developed strategy achieved better efficiency, learning ability, fault-tolerance, and low convergence rates than the BPNN model. On the other hand, in [66], the work presented a subtractive clustering-based FNN for forecasting the traffic flow and used the GA for deciding the clustering radius. Ding Guan-bin and Ding Jia-Feng introduced an adaptive neural network-based fuzzy inference system for predicting the monthly average flow in a hydrological station, which showed better results than the AR model [67]. The authors of [69] developed the fuzzy descriptor model integrated with singular spectrum analysis for predicting the various time series, including Mackey–Glass, Lorenz, Darwin sea level pressure, and the disturbance storm time index. The presented model results showed to be better than the MLP and RBFNN models. Another forecasting method known as the FNN model based on chaos theory for predicting the hydraulic pumps' vibration signal was proposed in [75]. It is to be noted that this model can also be used to improve prediction accuracy by readjusting the minimal embedding dimension optimally. The dynamic recurrent FNN model used to predict the power systems' short-term load was developed in [76]. It was proved that the developed model's convergence rate and forecasting accuracy are enhanced compared to the conventional FNN model. In [97], the researchers presented the interval type-2 fuzzy cerebellar model articulation controller for forecasting the Henon system of chaotic time series and the chaos synchronization of the Duffing–Holmes system. The proposed model of simulation results showed to be better than the FNN and interval type-2 FNN.

In [104], the researchers proposed the saliency back-emf-based wavelet FNN model for a torque observer, using a new maximum torque per ampere control for forecasting the speed of a sensorless interior permanent magnet synchronous motor. In [110], the authors presented the embedding theorem-repetitive fuzzy method for predicting the time series data of Mackey–Glass, Lorenz, and sunspot numbers. The proposed model's experimental results provided better forecasting than the simple fuzzy, adaptive neuro-fuzzy inference and other models in terms of error indices. Qinghai Li and Rui-Chang Lin presented the self-constructing recurrent FNN model for forecasting the logistic and Henon time series [112]. The proposed model had a worthier performance in convergence rate and forecasting accuracy than the self-constructing FNN. The authors of [117] presented the interactively recurrent fuzzy functions model for predicting the time series data of Lorenz, Mackey–Glass, and real-time lung sound signal modeling. The benchmark and real-time models' results showed to be better than the recurrent networks, such as fuzzy WNN, self-evolving FNN, ESN, and LS. Luo Chao and Wang Haiyue presented the application of

- Generalized zonary time-variant fuzzy information granule;
- LSTM mechanism with FNN model.

For Zurich monthly sunspot numbers, Mackey–Glass time series, and daily maximum temperatures in Melbourne were used for predicting the granules [141]. The results of the proposed methods showed better performance than the AR and nonlinear AR neural network models. In [176], the researchers presented the adaptive RBFNN model for forecasting the online vehicle velocity, showing better prediction accuracy and computational efficiency than the LSTM, NARX, and deep neural network models.

3.3. Optimization Algorithms with ANN-Based Forecasting Approaches

The authors of [29] developed the temporal difference GA-based reinforcement learning neural network model to predict and control two chaotic systems, i.e., the Henon map and the logistic map. The advantage of the proposed concept is that it can apply directly to control chaotic physical systems in real-world models. Mohammad Farzad et al. proposed the GA for forecasting the Mackey–Glass chaotic time series, and the model showed better performance than the ANN and polynomials methods [47]. The proposed model may also be used to forecast any other chaotic systems. In [71], a modified bee evolution using a PSO-based chaotic neural network model was presented to predict the load in the power system. The proposed model's simulation results showed better outcomes than the PSO algorithm used to develop the power system's proper planning and has good prospects. In [96], a hybrid approach using the chaotic self-adaptive PSO algorithm and BPNN was presented to forecast the polymers' gas solubility. The proposed model is reliable, accurate, and practicable for analyzing and designing polymer processing technology, compared to PSO-tuned BPNN models. It is to be noted that the proposed approach can also be further extended to tackle actual difficulties. The chaotic PSO tuned ANN model was presented in [102] to forecast air quality by predicting the particulate concentration. It is to be noted that this model can also be used to prove the meteorological condition of wind speed, which has a significant effect at urban intersections for specific matter concentrations. In [107], the researchers developed the improved GA for forecasting the synchronous parameters of chaotic time series to achieve higher accuracy and efficiency than GA alone.

The authors of [115] proposed the modified BPNN based on chaotically optimized GA and simulated annealing algorithms to forecast electrical energy demand in a smart grid. It is to be noted that this concept can also be relevant to lowering the system's total operational costs and ensuring the effective and reliable functioning of next-generation power grids. Akhmad Faqih et al. developed the extreme learning mechanism using RBFNN and SOM models to predict the multistep ahead time series of Lorenz's chaotic system [133]. It is to be noted that this proposed model can also combine with several behaviors to provide the best behavior. In [135], the researcher presented the GA and LS-based SVM method to control fractional-order systems, which achieved better effectiveness and feasibility than the conventional LS-based SVM. The authors of [139] proposed the principal component analysis using the chaotic immune PSO tuned GRNN for forecasting the corrosion of circulating cooling water in a petrochemical enterprise. The approach achieved better forecasting accuracy and convergence speed than the traditional PSO-tuned GRNN model. The advantage of the proposed model is that it can also be employed to forecast other nonlinear systems. In [147], the authors proposed the chaotic PSO algorithm for predicting the mobile location and achieved better location accuracy and faster convergence rate than such algorithms as those of Chan, Taylor, and PSO. Ji Jin et al. developed the fractal dimension-based EMD method and GA tuned BPNN model for predicting the wind speed in wind farms by considering the atmospheric motions' fractal feature [152]. The proposed models showed better performance than LSTM, GA tuned BPNN, and ensemble EMD-GA-BPNN. It is to be observed that this model can also require further study to optimize the computational time. It is also necessary to analyze the model on various time scales to decide the proposed models' suitability to wind speed series on any timescale. Happy Aprillia et al. proposed the SSA tuned CNN for predicting the short-term power of PV systems [158]. The presented algorithm's results showed better accuracy than the SSA tuned SVM and LSTM methods. Further, the work highlights that this proposed model can also address uncertainty, particularly for wet weather, heavy overcast weather, peak time, and forecasting on typhoon days. Shuzhi Gao et al. developed the soft sensor model using the CBAS algorithm and Elman neural networks to forecast the conversion rate of vinyl chloride monomer [171]. The developed model's performance can be extended by utilizing the deep neural network approaches.

3.4. Wavelet NN-Based Forecasting Approaches

The merits of wavelet and neural networks are hybridized to form a new WNN to achieve better forecasting ability. WNNs have been used with great success in a wide range of applications. In some applications, it was proven that if the combination of a neural network and wavelet is used, the proposed model's efficiency is increased. The WNN architecture also follows the same fashion as the network shown in Figure 4. However, in the hidden layer, wavelet basis functions are used as activation functions instead of the conventional function of the FFNN.

Antonis K. Alexandridis et al. proposed machine learning algorithms, namely wavelet network and genetic programming, for forecasting the average temperature precisely when it comes to weather derivative pricing, compared to SVM and RBF [185]. Wei Wu et al. developed a WNN model for electricity-based chaotic time series data to predict the spot market prices [38]. In [45], the researchers proposed the WNN model and compared it with the BPNN model for single-step forecasting of Lorenz and Mackey–Glass chaotic time series. It is to be noted that this approach can be extended further to be used for real-world chaotic data. In [74,81], the authors proposed the forecasting models for wind farms. The wavelet decomposition method and ITSM in [74] showed an improved accuracy compared to ANN in predicting wind speed and power. Similarly, the developed hybrid algorithm using wavelet transform, chaotic theory, and grey model in [81] showed better prediction than the direct prediction method. The models in [74,81] can be further optimized and applied in various countries' wind farms, such as the Dongtai wind farm in China. Bo Zhou and Aiguo Shi presented the phase space reconstruction-based WNN method to predict Henon and Lorenz's chaotic time series [95]. The significant benefit of this proposed method over a WNN is the improvement in SMAPE. It is to be noted that this concept can also help optimize the process parameters and the execution time during the simulation. Tian Zhongda et al. presented the wavelet transform and multiple model fusion for forecasting the Lorenz and Mackey–Glass time series and achieved more effective performance in terms of SMAPE [120]. The models can be applied to real-world chaotic systems, such as geomagnetic series, network traffic series, etc. In [130], the ANN-discrete wavelet transform method was presented for forecasting the photovoltaic system's power based on chaos theory. The significant benefit of this method over the ANN and ANN-phase space reconstruction is the improvement in the Theil index.

3.5. Other Approaches

The authors of [56] developed the generalized EKF for forecasting the Lorenz time series with various Bernoulli distribution probabilities, which achieved an acceptable prediction precision and good robustness. Xue-dong Wu et al. proposed the GPF and compared it with UKF and EKF to forecast the Mackey–Glass time series [73]. In [106], the researchers proposed the EKF-based MPSV method to estimate the transmitted signal in power line communications and confirmed the better efficiency than the inverse filter-based MPSV method. However, the real-time validation of the proposed approach is the research gap. In [129], the authors developed the equivalent model using EKF to predict the state of charge in power Li-ion batteries. Yijun Xu et al. proposed the polynomial chaos-based Kalman filter to predict the nonlinear system dynamics [146]. In [160], the authors presented the UKF for forecasting the parameters of the gray-box model for dynamic EEG system modeling and achieved the lowest RMSE compared to the particle filter and EKF.

4. Forecasting of Chaotic Time Series in Various Applications

As mentioned in Table 1, various parameters have been forecast in multiple applications using the machine learning-based approaches detailed in Section 3. The list of these forecasting parameters categorized into the different applications is given in Figure 5. The detailed description of these forecasting parameters using various approaches in various fields is explained underneath.

4.1. Power and Energy

This section describes power and energy forecasting techniques, using various chaotic time series approaches applied in wind farms, solar, photovoltaic systems, etc.

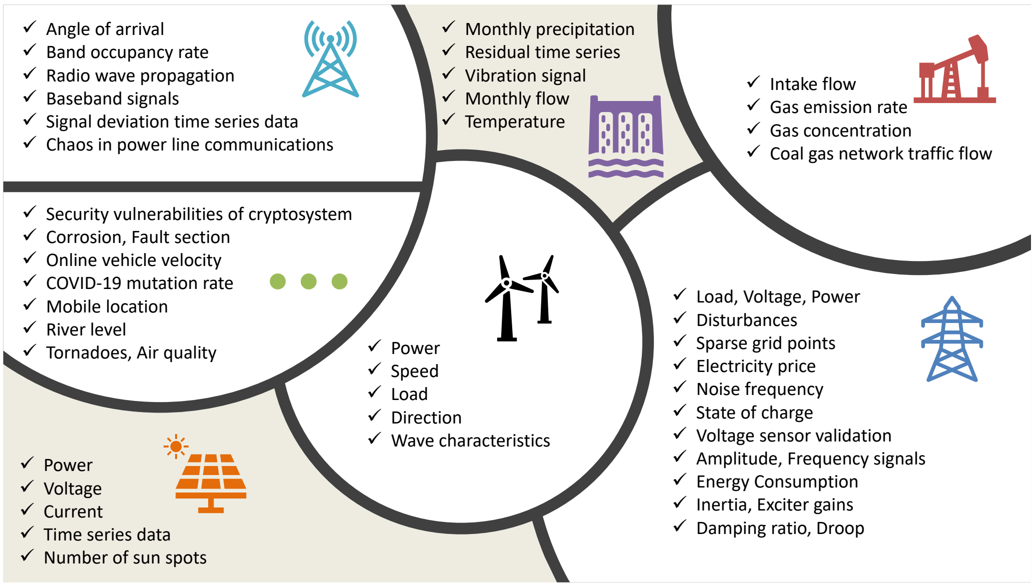

Figure 5. List of forecasting parameters categorized into the different applications.

4.1.1. Wind Farms

Many applications of wind power and speed forecasting approaches have been developed based on chaotic characteristics or chaotic time series and applied on various wind farms. For instance, the statistical type of forecasting approaches for predicting wind power, speed, and load for short-term and long-term wind power, speed, and load prediction in Beijing in China are as follows:

- ITSM with wavelet decomposition method [74];
- SVM [16];
- Rough set neural network [80];
- BFA tuned double-reservoir ESN [166].

The approaches, as mentioned earlier, showed good short-term and long-term performance, but the computational complexity is high to complete the task. Similarly, many other works have been attempted to predict weather conditions for wind farms whose operations are more complex.

Various researchers have proposed hybrid prediction methods to enhance accuracy. These approaches were made by integrating the following:

- Wavelet transforms with chaotic time series and grey model [81];
- Hilbert–Huang transforms with Hurst analysis [108];
- Hybrid neuro evolutionary [175].

The hybrid approaches mentioned above with multistep chaotic characteristics were validated for short-term forecasting of wind power at the Dongtai wind farm and Hebei province in the east of China. The work highlights that EMD-based combined forecasting methods can improve short-term forecasting accuracy based on their characteristics. The surrogate data technique and spectral analysis methods are applied to forecast wind wave height, period, and direction for three-hourly chaotic time series from three stations in the Caspian's southern, central, and northern parts of the sea [109]. The hybrid approach developed using ensemble EMD-sample entropy and the full parameters continued fraction model were developed for predicting the wind power of farm location at Xinjiang, China [119]. Moreover, the Markov chain switching regime model developed in [144] used hourly, short-term, and long-term chaotic time series data for predicting wind speed and direction of the farm located at Bonneville Power Administration control area in the Northwest USA. It is to be noted that these proposed approaches can also be used for the proper planning and scheduling of wind power. The self-adaptive and artificial intelligence type forecasting techniques for predicting the wind speed are as follows:

- Fractal dimension-Lorenz stenflo-Ensemble EMD;
- GA tuned BPNN model;
- Empirical dynamical model [152,165].

For short-term prediction of wind speed considers the atmospheric motion and fractal feature at Abbotsford in Canada, and Kansas and Missouri in the USA. It is to be noted that better results can be generated using exogenous variables in the ANN approach.

4.1.2. Solar and Photovoltaic Systems

The recurrent predictor neural network model presented in [36] is based on an extended algorithm of self-adaptive BP through a time learning algorithm for predicting the annual sunspot time series in Skylab. Similarly, the time-delay neural network model [48] and the multi-layered neural network-based co-evolutionary algorithm [52] are used for predicting the annual sunspot time series of the space laboratory launched by the USA in 1973 and the sunspot index data center in Belgium, respectively. The ANN-based discrete transform using chaos theory [130], ensemble EMD based on optimized chaotic phase space reconstruction [155], SSA tuned CNN [158], and CGO [172] are used for predicting the power, voltage, and current of PV system in Beni Mellal, Morocco, St Lucia campus PV station, Australia. The k-fold cross-validation with GRNN reported in [134] is used for predicting the accuracy of sunspot under different embedding dimensions for phase space reconstruction of chaotic time series according to the Takens theorem in the Solar Influences Data Analysis Center, Belgium.

4.1.3. Other Power Systems

Under certain circumstances, chaos in an electrical power system can show abnormal oscillations, threatening the electrical grid's reliability and stability. Because of the nonlinearities of electricity networks, chaos theory is a high priority. Hence, the application of chaos theory and several forecasting approaches to improve the accuracy and reliability of load forecasting. The proposed forecasting approaches for predicting the electrical daily peak load of the power systems, such as South Korea Electric Power Corporation, Daqing oilfield company in China, New South Wales in Australia, and North China city, are as follows:

- ANN [26];
- Bee evolution modifying PSO tuned chaotic neural network [71];
- Adding-weighted LLE [72];
- Dynamic recurrent FNN [76];
- Chaotic RBFNN [84];
- Chaotic local weighted linear forecast algorithm based on angle cosine [88].

The self-adaptive chaotic BPNN and parallel chaos algorithm reported in [128], and [118], respectively, are used for forecasting the short-term electrical power load in the China network. The limitations of the proposed approaches are eliminated with the application of hybridized chaotic RBFNN-quantile regression model for forecasting the weather, seasons, wind power, and electricity price. The hybrid forecasting approaches developed for predicting the dynamic characteristics of electricity are the wavelet decomposition methodology [120], variational mode decomposition-maximum relevance minimum redundancy based BPNN-LS-SVM [156], and short- and medium-term load in the Xi'an power grid corporation, China.

Short-term electricity price forecasting has become crucial in the power markets, as it allows for the foundation for market participants' profit maximization. The proposed methods for forecasting the short-term electricity spot market prices and the marginal price at the New England and California electricity markets in the USA are as follows:

- Nonlinear auto-correlated chaotic model-based WNN [38];
- RNN [40];
- LS-SVM algorithm [60];
- Add-weighted one-rank multi-steps prediction model [63].

The generation companies can decide on scheduling generators and provide high-quality power services to customers. Thus, the validation algorithm presented in [93] is based on the voltage sensor applied to a DC zonal shipboard electric power system, using decentralized polynomial chaos theory for the sensor validation decentralized state prediction. In addition, it is to be reported that the presented conventional algorithms were improved using artificial intelligence techniques. The independent component analysis method reported in [94] for predicting the amplitude and frequency of highly chaotic distorted power system signals is presented based on duffing oscillator solutions. The proposed approach can be used for the real-time control and measurement of the fundamental frequency of a power system while focusing mainly on chaotic disturbances. The maximum velocity criterion method, sinusoidal wave frequency modulation, and chaotic control algorithm are for forecasting the chaos and suppressing the predicted chaos to increase the security for cyber–physical power systems [112]. The modified BPNN, chaos-search GA, and SA algorithms are applied to predict a smart grid's short-term electrical energy demand in New South Wales, Australian grid [115]. The proposed approach can also lower the system's total operational costs and ensure the next-generation power grids' effective and reliable functioning. The polynomial chaos expansion-based Langevin Markov chain Monte Carlo and multi fidelity-surrogate-based Bayesian inference via adaptive importance sampling predict decentralized dynamic parameters, such as inertia, exciter gains, damping ratio, and the droop of the synchronous generator in New England, USA [138,151].

4.2. Hydrological Systems

The RBFNN model is developed to estimate the Mekong River's nonlinear hydrological time series in Thailand and Laos, the Chao Phraya River in Thailand, and sea-surface temperature anomaly data [43]. In addition, the presented approach can also be applied to other geological time series. In [67], an adaptive fuzzy inference-based neural network model is developed to predict the medium- and long-term hydrological residual time series. The data are collected from the Guantai hydrological station, Zhang River, China. An empirical, statistical, and chaotic nonlinear dynamic model in [19] was applied to forecast the stream water temperature from the available solar radiation and air temperature in the Lake Tahoe basin, California, Nevada, USA. The chaotic FNN for predicting the hydraulic pump's vibration signal was presented in [75]. It is to be reported that the proposed approach can be extended further to improve prediction accuracy by readjusting the minimal embedding dimension optimally. The coupled quantity–pattern similarity model reported in [18] predicts the monthly precipitation of hydrological systems in the Danjiangkou reservoir basin, China. The proposed approach can also be applied to time series with various lead time scales.

4.3. Communication Signals and Systems

The complex weighted neural network algorithm in [25] solves the principal component analysis problem and high-resolution adaptive bearing prediction. The proposed approach is especially effective in circumstances where the hermit matrix progressively changes over time due to adaptive tracking. The BPNN tuned SVM grey model in [55] is used for forecasting the signal deviation time series. The anchor selection method is based on polynomial chaos expansions [86] for angle-of-arrival prediction-based positioning systems. The chaos algorithm in [92] is proposed for forecasting the radio wave propagation in the ionosphere. The proposed algorithm can also forecast a set of radio transmission signals at a fading amplitude time series location. The phase space reconstruction-LS-SVM in [98] is developed to predict FM radio's band occupancy rate in German Rohde, Schwarz company, and fixed radio monitoring station of Xihua University, USA. The proposed approach can be extended further to improve multistep time series prediction. The minimum phase-space volume-EKF equalization method presented in [106] is for forecasting the chaos in power line communications. The LLE, Higuchi's fractal dimension, and sample entropy techniques are used for predicting the fractals, chaos, and parametric entropy features of surface electromyography signals during dynamic contraction of biceps muscles under a varying load [127]. The proposed process can also be helpful in physiotherapy and athletic biomechanics for testing muscular fitness. A deterministic chaotic sequences method is developed to forecast quadrature baseband signals and orthogonal frequency division multiplexing-based cognitive radio channel [137]. The proposed approach can also be applicable to bit error rate performance, which is projected to improve if an appropriate power management method is used.

4.4. Oil and Gas

The global prediction method uses a BPNN model for forecasting the gas emission rate in the Hegang Nanshan mine located in China [83]. The proposed model showed better step, accuracy, and stability predictions. The improved Duffing oscillator chaotic traffic prediction model in [85] was developed for coal gas' traffic flow prediction for a coal mine. The proposed approach can also increase signal detection accuracy. The chaos RBFNN method in [12] predicts the intake airflow of the gasoline engine. The coal mine ventilation systems' management technology reported in [17] can predict the gas concentration in Jining, Shandong, China. As a result, the system can provide reliable assurance for mine safety production.

4.5. Other Systems

The multistep time series prediction in diode resonator circuits is made by integrating the nonlinear signal prediction method with a BPNN [51]. The proposed approach can be extended further to be used in other chaotic time series. The integration of nonlinear time series analysis and backpropagation MLP for multistep nonlinear time series forecasting of chaotic diode resonator circuits was reported in [59]. The distributed chaotic fuzzy RBFNN is exploited for distributed network fault section prediction [54]. The global prediction of chaos method forecasts the chaotic instantaneous generator output power in Liaoning province in China [20]. The chaotic adding-weight dynamic local predict model predicts the pseudo-random number generator of the initial sequence number in the transmission control protocol stack [62]. The chaos-based Rivest Shamir Adleman algorithm and chaos-based random number generator forecast the security vulnerabilities of the cryptosystem [142].

5. Performance Measures

This section discusses the various performance measures used for chaotic time series forecasting approaches. According to the literature review summary in Table 1, it can be concluded that there are many approaches for chaotic time series forecasting. However, it is challenging to choose one proposed method that performs better based on the performance measures. Table 1 also shows that the researchers have evaluated the performance of the forecasting approach using various statistical errors. The different classifications of statistical performance measures used for chaotic time series forecasting are mean, relative, percentage, prediction, and coefficients. The classification and its subcategories are shown in Figure 6. The formula for computing these performance measures is demonstrated in Figure 7. In Figure 7, n denotes the number of samples, and $Y_{a,i}$ and $Y_{p,i}$ are the actual and predicted outputs by the chaotic time series forecasting model. Further, $\bar{Y}_a$, and $\bar{Y}_p$ are the averages of $Y_{a,i}$ and $Y_{p,i}$.

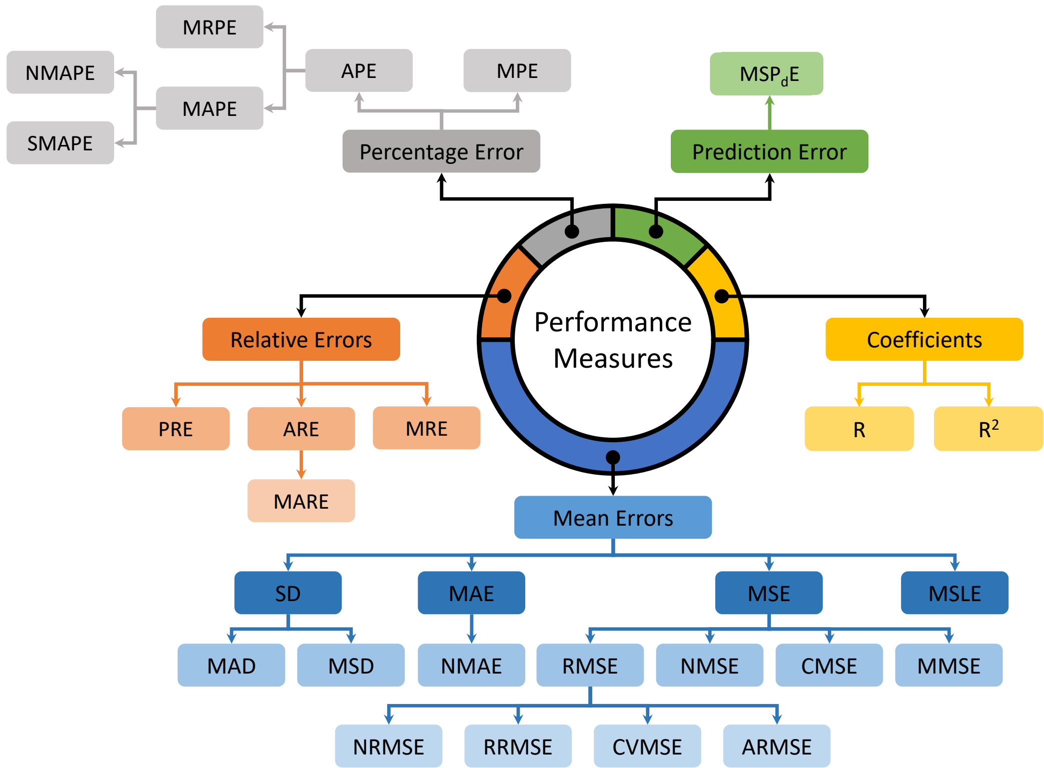

Figure 6. Classification of various performance measures used for chaotic time series forecasting.

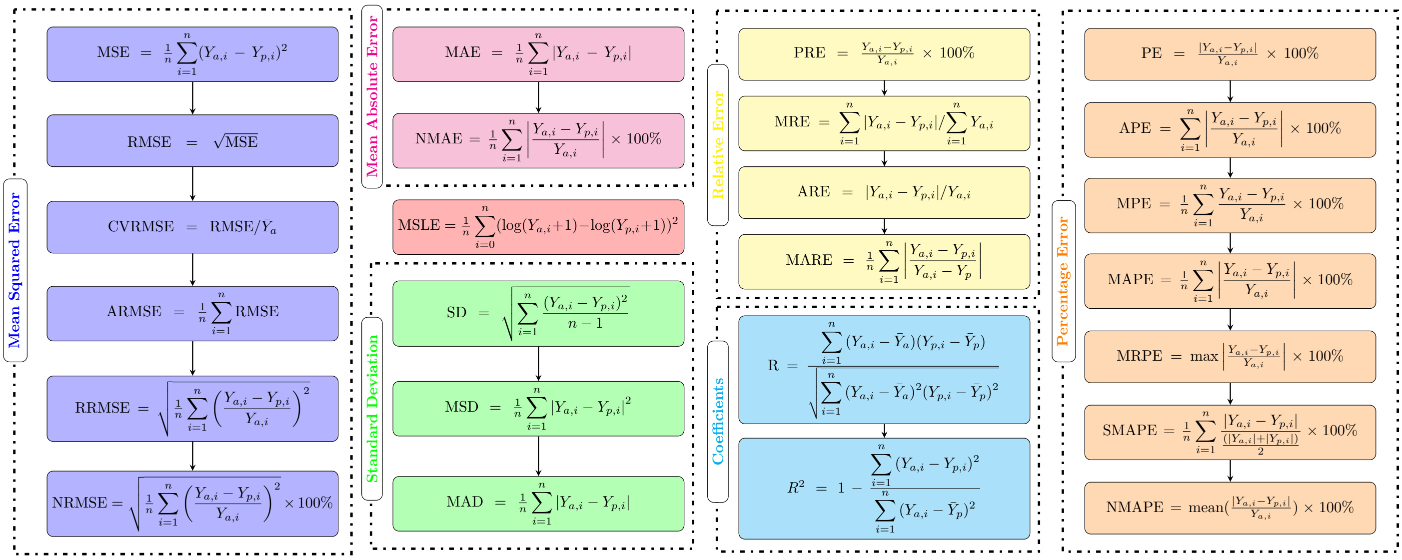

Figure 7. Formula for computing the various performance measures.

As shown in Figures 6 and 7, most of the performance measures used for chaotic time series forecasting are mean errors. Further, the review summary in Table 1 shows that MSE and its variants are the most widely used performance measures for chaotic time series forecasting. The MSE and its variants measure the error between Y_a and Y_p, and the closest value to zero indicates a better estimation of the forecasting approach [186,187]. After mean errors, the percentage errors are the second most used performance measure for chaotic time series forecasting. The percentage errors measure the percentage error between Y_a and Y_p. The closer values of percentage error to zero also indicate a better estimation of the forecasting approach. On the other hand, the coefficient of determination R^2 is most widely used to indicate the forecasting approach's predictive ability in fitting the actual data Y_a [188,189]. Thus, the values of R^2 range from zero to one, and the value equal to 1.0 indicates a perfect fit. The summary in Table 1 also shows that most of the researchers used a combination of different performance measures for evaluating the forecasting approach. The combinations are MAE, MAPE, and RMSE; MSE, MAPE, and RMSE; MAE and RMSE; MSE and RMSE; R^2 and MSE; R and MSE, etc.

6. Conclusions

This article reviewed various approaches for chaotic time series forecasting based on machine learning in multiple areas, such as wind farms, PV systems, hydrological systems, communication signals and systems, oil and gas, and other systems. At the beginning of this paper, the chaotic system/time series and the importance of chaos forecasting were introduced. Next, the various machine learning-based chaotic time series forecasting approaches were presented. These approaches use WNN, FNN, CNN, LSTM, and Markov chain models. Then, a review of the prediction of various parameters in multiple applications using machine learning-based techniques is presented. This review concludes that traditional prediction methods can hardly obtain satisfactory results. Hence, many chaotic time series prediction methods were developed using machine learning-based approaches, which enhanced their efficiency and accuracy.

6.1. Findings

This review summarizes the findings of various approaches developed for multiple applications as follows:

- The wavelet decomposition method predicted wind speed and power accurately and effectively using improved time series, chaotic time series, and grey models [74,81]. The false nearest neighbor analysis method forecast the chaotic behavior of the wind–wave characteristics, including wave period and height [109].
- Hilbert–Huang transform and Hurst analysis is a proper choice to forecast the multi-scale chaotic characteristics of wind power [108]. In contrast, ensemble EMD and full parameters continued fraction is appropriate for predicting wind power's nonlinear chaotic time series [119].
- The empirical dynamic model presented in [165] forecast the wind speed for various height levels. At the same time, the fractal dimensional-based self-adaptive model for wind speed predicted atmospheric motion and fractal features [152].
- The approaches such as the ordinary least square method [28], recurrent predictor neural network [36], hybrid Elman–NARX neural network [78], and embedding theorem-repetitive fuzzy [21] forecast the sunspot number (chaotic time series) effectively. In all these cases, the sunspot data were collected from the world data center for Belgium's sunspot index.
- The combination of chaos theory and techniques, such as ensemble EMD and CNN-SSA, effectively forecast the PV system's output power under certain conditions, such as rainy, heavy cloudy, lightly cloudy, and sunny conditions [155,158]. The data were collected from the St Lucia campus PV station, Australia, in all these cases.
- The integration of the BPNN with GA, SA algorithms [115], parallel chaos [118], wavelet decomposition-based methods [120,157] was successfully used to forecast the deregulated power system's short-term electrical energy demand. These methods help in proper economic power dispatching with an enhanced demand response that assists in efficient spot price-fixing in the deregulated power market.
- The regression analysis models using ANN and chaotic nonlinear dynamic [73] and coupled quantity-pattern similarity [18] were validated to predict the stream water temperature and monthly precipitation.
- The minimum phase space-based EKF method was used to forecast the blind equalization in power line communication systems to overcome channel noise [106].

- The response surface-based Bayesian inference [149] and PCE-based hybrid MCMC [163] approaches were used to predict the generator's dynamic parameters, such as inertia, exciter gains, damping ratio, and droop.
- The independent component analysis method in [94] adequately estimated the amplitude and frequency of power systems' highly distorted signals to avoid the ferroresonance effect.
- The Markov chain switching regime model enhanced the precision accuracy and is helpful for wind power forecasting during scheduling and planning [144].

6.2. Future Directions

This comprehensive review helped open up new scopes in the field of chaotic time series forecasting approaches in various applications and is highlighted underneath.

- Chaotic time series analysis and SVM can estimate short-term wind speeds while considering weather conditions and more complex scenarios of wind farm operations [16].
- To the dispersed power resource system, the wind power generation unit can be connected to the grid of this system through high-quality forecasting of the parameters using the Jacobian matrix estimate method and weather data optimal points using deterministic chaos [104].
- EMD-based forecasting approaches can increase short-term wind power prediction accuracy based on their behavior characteristics. Furthermore, the relationship between different scale subsequences and numerical weather forecasting can improve the accuracy of this short-term wind power forecasting [108].
- The hybrid neuro evolutionary approach, i.e., adaptive variational mode decomposition-AOA-LSTM proposed for wind farms, has employed multiple outlier identification methods with optimization and decomposition procedures to improve forecasting outcomes [175]. This method can also be adaptable to other geographies.
- The independent component analysis method can be extended for real-time monitoring and controlling the power system's fundamental frequency with an appropriate time delay between observed data frames [94].
- The precision accuracy of the response surface-based Bayesian inference method proposed for the power systems to predict the dynamic parameters has to be improved when there is a substantial outrageous deviation in the boundaries [149].
- The coupled quantity pattern similarity model proposed for the prediction of monthly precipitation can also be applied to the time series with different lead time scales [18].
- The hybrid algorithms proposed using CNN and wavelet transforms for predicting the chaotic time series of Chen, Lorenz, Mackey–Glass, and sunspot numbers can also be used for real-time series, such as geomagnetic, network traffic, and weather systems [13,170].
- The forecasting accuracy of an online vehicle velocity prediction approach proposed using adaptive RBFNN can be enhanced using additional data, such as driving time, climate, gas, and brake pedals [176].

Author Contributions: Conceptualization, B.R. and K.B.; formal analysis, B.R.; investigation, B.R.; resources, K.B.; data curation, K.B.; writing—original draft preparation, B.R.; writing—review and editing, K.B.; visualization, K.B.; supervision, K.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ACF	Auto correlation function
ANN	Artificial neural networks
AOA	Arithmetic optimization algorithm
APE	Absolute percentage error
APSK	Amplitude phase shift keying
AR	Autoregressive
ARE	Average relative error
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
ARMSE	Average root mean square error
BFA	Bacterial foraging algorithm
BP	Backpropagation
BPNN	Backpropagation neural network
CBAM	Convolutional block attention module
CBAS	Chaos beetle antennae search algorithm
CCO	Cluster chaotic optimization
CGO	Chaos game optimization
CMSE	Cumulative mean square error
CVRMSE	Coefficient of variance of the root mean square error
DCSK	Differential chaos shift keying
DMI	Delayed mutual information
EKF	Extended Kalman filter
EMD	Empirical mode decomposition
ESN	Echo state network
FFNN	Feed-forward neural network
GA	Genetic algorithm
GPF	Gaussian particle filtering
GRNN	Generalized regression neural network
GWO	Grey wolf optimization
HBO	Honey bee optimization
HEA	Hybrid evolutionary adaptive
HFD	Higuchi's fractal dimension
IGWO	Improved grey wolf optimizer
ITSM	Improved time series method
LLE	Largest Lyapunov exponent
LLNF	Locally linear neuro-fuzzy
LS	Least square
MAD	Mean absolute deviation
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MARE	Mean absolute relative error
MCMC	Monte Carlo Markov chain
MLE	Machine learning ensembles
MLP	Multilayer perceptron
MMSE	Minimum mean square error
MPSV	Minimum phase space volume
MRE	Mean relative error
MRFO	Manta ray foraging optimization
MRPE	Maximal relative percentage error
MSD	Mean squared deviation
MSE	Mean squared error
MSLE	Mean squared logarithmic error
$\mathrm{MSP_dE}$	Mean squared prediction error
NARX	Nonlinear autoregressive exogenous model
NMAE	Normalized mean absolute error
NMAPE	Normalized mean absolute percentage error

NMSE	Normalized mean square error
NRMSE	Normalized root mean square error
NWP	Numerical weather prediction
PCR	Principal component regression
PCS	Polynomial chaos surrogates
P_dE	Prediction error
PE	Percentage error
PID	Proportional–integral–derivative
PLS	Partial least square
PRE	Percentage relative error
PSO	Particle swarm optimization
PV	Photovoltaic
QAM	Quadrature amplitude modulation
R	Coefficient of correlation
R^2	Coefficient of determination
RBF	Radial basis function
RBFNN	Radial basis function neural network
RE	Relative error
RMSE	Root mean squared error
RNN	Recurrent neural network
RR	Ridge regression
RRMSE	Relative root mean squared error
SA	Simulated annealing
SMAPE	Symmetric mean absolute percentage error
SOM	Self-organizing map
SSA	Salp swarm algorithm
SVM	Support vector machine
TCN	Temporal convolutional network
TLBO	Teaching–learning-based optimization
TTLS	Truncated total least squares
UKF	Unscented Kalman filter
ULN	Universal learning network
YCO	Yield-constrained optimization

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