A Nonlinear Autoregressive Exogenous (NARX) Neural Network Model for Air Quality Prediction

R. Vijaya Prakash[1], Dr. Shrikaant Kulkarni[2] Prof Dr Midhunchakkaravarthy[3],

[1] Lincoln University College, Malaysia ; [2] Lincoln University College, Malaysia, Research Professor, Sanjivani University, India; [3]Lincoln University College, Malaysia;

Email ID [1]vijprak.r@gmail.com, [2]shrikaant.kulkarni@vit.edu.au [3]midhun@lincoln.edu.my,

---

Abstract: An advanced machine learning system for air pollution forecasting is detailed in this paper. Upon evaluating various machine learning models, the neuro-fuzzy model distinguished itself as the leading contender in the development of air pollution prediction systems. An ANFIS framework and learning algorithm are the foundations of the neuro-fuzzy architecture, which has been laid out. The proposed neuro-fuzzy model has been evaluated using various pollution parameters from different regions of Telangana state to assess the models' performance and reliability. The neural network, ANFIS, and nonlinear autoregressive exogenous (NARX) algorithms were used to acquire the learning data. To train and test the algorithms, we use the hourly pollution predictions for the Telangana regions. Using this data, we assess how well the neural network and neuro-fuzzy models operate. According to the simulation results, the anticipated output of the neuro-fuzzy model closely matches the real data with a high degree of accuracy. According to the simulation results, the anticipated output of the neuro-fuzzy model closely matches the real data with a high degree of accuracy. According to the findings, the ANFIS model is the best and most widely accepted way to forecast air pollution. The neuro-fuzzy model outperforms the other models tested when it comes to predicting hourly pollution data with specific parameters, according to the comparative analyses.

Keywords: Machine Learning; Artificial Neural Networks; air pollution; Autoregressive Exogenous (NARX); Adaptive Neuro-Fuzzy Inference System (ANFIS)

Introduction

Pollution significantly impacts humans, animals, the planet, and all forms of life. Pollution can precipitate erratic climate change, thereby destabilizing the ecosystem. Permitting exceeding the limit value only 35 times per year is the average daily concentration of particulate matter, which is 10. The EU and the World Health Organization assert that immediate action is required if the threshold value (50 µg/m3) is surpassed on more than 35 days annually in Turkey. This threshold is frequently surpassed, and typically no measures are implemented. Air pollution in Telangana has attained its peak level in recent years. Specifically in the regions of Hyderabad, Kothagudem, and Warangal. The rate of air pollution has escalated due to the utilization of coal in urban development and transportation. The high dust amount, which is the source of the pollutant particulate matter 10 (PM10) is increasing and the environmental consequences of the urban transformation processes are not considered and being ignored [1].

In 2015, 6.4 million deaths were directly caused by pollution. Pollution was found to be responsible for 19% of deaths from cardiovascular disease, 21% of deaths from stroke, and 23% of deaths from lung cancer on a global scale. Because of this, the authoritative predicting technique is needed to lead us to an important role in the danger of crisis response and emergency plans [2]

The purpose of this research is to find out how well a neuro-fuzzy and artificial neural network can forecast air pollution. Analyzing the patterns of changing types of pollutants will be supported by air pollution prediction. In the event of a pollution crisis or natural catastrophe, it will also be useful for planning and executing preventative measures.

To eliminate superfluous data, reduce the impact of multicollinearity, and improve the filtering model's generalizability, this research suggests using regularization-based feature selection as an input. As a comparison, two standard NN models are set up, one using NARX optimization and the other using BP model with feature selection. All the standard statistical measures are examined simultaneously, including the mean absolute error, the Pearson correlation coefficient (R), and the root mean square error (RMSE).

Related work

In our modern, industrialized world, the air and environment are constantly changing due to human activities and global warming. For the simple reason that when industries undergo a dramatic transformation, they unleash a deluge of gases, particles, and molecules into the air. As a result, these elements produce air pollution, which causes various diseases, allergies, and even the deaths of millions of people worldwide. According to the 2014 world health organization report, in 2012, it caused the deaths of 7 million people around the world [3].

Pollutants in the air pose a serious threat to human health, economic development, and the standard of living. Human health is severely impacted by air pollution, which exacerbates conditions like heart disease, lung cancer, and cardiovascular disorders [4][5]. There has been considerable interest in employing artificial intelligence (AI) for monitoring air quality. Policymakers and interventionists can leverage the accurate, real-time air quality data generated by artificial intelligence (AI) systems to mitigate pollution. Utilizing AI-driven recommendations facilitates the swift execution of actions to safeguard public health when air quality deteriorates.

To deliver real-time air quality reports, machine learning algorithms analyze data obtained from diverse sources, including sensors, satellite imagery, and meteorological records [6]. By employing machine learning to identify trends and patterns within the data, these algorithms can ascertain the origins of pollution, quantify its extent, and identify optimal strategies for its reduction.

Recent advancements in air quality analysis and forecasting have employed artificial intelligence algorithms, including artificial neural networks (ANNs), deep neural networks (DNNs), support vector machines (SVMs), and fuzzy logic. Comprehensive information requirements and local air pollution characteristics are the principal factors to consider when selecting an AI model. For example, a systematic review by J. Ma et al. [7] classified AI-based air pollution forecasting tools considering factors such as performance, input parameters, and the relative frequency of application of AI techniques. They concluded that the DNN is the most effective tool for environmental monitoring using AI. On the other hand, Feb et al. [8] compared other AI-oriented techniques/models for air pollutants and suggested Support Vector Regression (SVR) and Autoregressive Integrated Moving Average (ARIMA) as the best-performing techniques for time series analysis of Particulate Matter (PM) with a diameter <10 m and diameter <2.5 m. It is important to note that PM is considered in the study as it significantly affects health.

Another study by Y.H. Hoon et al. [9] suggested that hybrid models have better performance for environmental monitoring policy and decision-making. To make educated decisions regarding the long-term effects of air pollutants, hybrid models integrate the strengths of two artificial intelligence algorithms or methodologies. This has also been confirmed by Fu et al. [10], who found that hybrid AI models are more dependable for air quality forecasting.

Artificial intelligence has many benefits over more traditional methods for monitoring air quality. AI-based systems can analyze enormous volumes of data from numerous sources and present a comprehensive picture of air quality in real-time, enabling officials to make informed decisions and act quickly to reduce air pollution [11]. Air quality data is less likely to contain mistakes and inconsistencies when collected and analyzed by AI systems, which are more accurate and precise than conventional methods. In addition, AI algorithms can customize solutions based on the specific sources and regions of pollution. By analyzing data from specific places and sources, AI can offer customized air pollution solutions, such as regulating traffic flow, streamlining industrial processes, or altering urban planning [9][12].

Table 1 Summary of previous studies for the prediction of air quality monitoring using AI.

Research Aim	**Model**	**Data Source/ Study Area**	**Result Obtained**	**Recommendation**	**References**
The goal of developing algorithms based on artificial intelligence (AI) is to assess flue gas pollutants and waste-to-energy (WTE) capacity.	ANN	Continuous and Supervisory Emission Monitoring Systems	City-level W'TE capacity and FGP EIs were forecast using artificial neural network models with mean square errors from 0.003 to 0.19 in model validation parameters.	This provides insights and framework assistance for formulating effective waste-to-energy strategies and a pollutant emission management approach across different economic areas.	Ma et al., 2022

To forecast concentrations of O3, PM2.5, NO2, and CO in NCT Delhi	Long Short-term Memory (LSTM)	National Capital Territory (NCT), Delhi	Their Nash-Sutcliffe Efficiency (NSE) range (0.86—0.94) suggests the study's LSTM models can predict air pollution concentrations. Model validation settings.	The study only examined one station due to data availability, so the LSTM's spatial correlation ability was not assessed.	Krishan et al.,2019
Forecasts of air pollutants and particulate matter, along with an AQI	Support Vector Regression (SVR)	US, Environmental and Protection Agency	The accuracy rate was 94.1%. obtained when simulating concentrations of pollutants like O3, CO, and SO2.	It is imperative to enhance the forecasting capabilities of SVR, evaluate its application, and contrast it with other methods.	Castelli et al., 2020
To ascertain the concentration levels of present pollutants, which will facilitate Real Time Correction (RTC).	Artificial Neural Networks, Neuro-Fuzzy Regression, Deep Learning Long Short-Term Memory	Metrological website Seoul routes	The findings indicate that reduced error rates and enhanced correlation with test data contribute to the effectiveness of DL-LSTM in the analysis and forecasting of air pollutants over a 24-hour window.	Machine learning, For future research, data can be organized into hourly and weekly frameworks, allowing for the generation of diverse and novel findings.	Amuthadevi et al., 2021 Lim et al.,
Increase urban street air quality simulation and measurement with AirBeam, a smartphone-based particle counter.	Linear Regression (LR) Random Forest (RF) Stacked Ensemble (SE)	Seoul routes	Results showed R2 values of 0.80, 0.73, and 0.63. SE R2 values suggest that mobile sampling and many affordable air quality monitors can characterize urban street-level air quality with high spatial resolution.	The methodology employed in this research may be applied in locations lacking established air monitoring networks, including developing nations.	Lim et al., 2019

AI-based recommendations can play a critical role in air quality monitoring by providing actionable insights to mitigate pollution [13][14]. For example, AI algorithms can recommend changes in traffic patterns during peak pollution hours to reduce emissions, suggest optimal times for industrial operations to minimize environmental impact, and identify green zones where pollution levels are within safe limits [15][16]. The prompt implementation of these suggestions aids authorities in protecting public health by keeping air quality within acceptable limits.

Artificial intelligence (AI) air quality monitoring has multiple potential uses in many different sectors. Urban management and planning are key applications where AI algorithms analyze data on air quality, traffic patterns, and urban development to create specialized solutions for reducing air pollution in urban areas [17][18][19]. As an example, AI can suggest changes to traffic patterns or urban planning that can improve air circulation and decrease exposure to pollutants, thus reducing congestion and air pollution. In industrial operations, AI algorithms can analyze emissions data and suggest modifications to lower pollution levels, such as adopting more eco-friendly materials and energy sources or optimizing production processes to minimize waste and emissions [19]. Artificial intelligence-powered air quality monitoring has additional public health benefits. By evaluating data on air quality and health outcomes, AI algorithms can identify at-risk groups and create tailored interventions to promote public health [7][9]. To reduce the exposure of vulnerable populations to pollutants, AI systems can suggest alternative public transportation routes, for example. An overview of previous research that used AI for air quality monitoring can be found in Table 1.

Method, Experiments and Results

The program's flow chart for air pollution prediction is shown in Fig. 5.1. Choosing the parameters for the air pollution prediction is the second flow. Training and testing carry out the prediction system's design, while the second block executes testing pre-processing and sealing operations. This chart illustrates the implementation of an algorithm designed to optimize the weight and slope of ANFIS, thereby mitigating local minimum and enhancing forecasting accuracy. The root means square deviation. The AQI RMSE of the predicted daily mean is utilized to identify an improved fitness function. The schematic representation of the hybrid algorithm is presented above.

4.1 Artificial Neural Networks and NARX Model

Numerous problems can be solved with the help of Artificial Neural Networks (ANNs), including pattern classification, clustering, optimization, approximation of functions, and prediction [24][25][26]. Their ability to non-linearly transform an m-dimensional input space into an n-dimensional output space is due to their status as black-box modelling tools [27]. AIs are mathematically represented. The ANN model is determined by a priori knowledge of the system.

This study makes use of the NARX neural network, which is an effective time series predictor [21][22][23]. An industry standard for linear black-box system identification, the Autoregressive Exogenous (ARX) is a nonlinear generalization of the NARX concept [28]. A wide range of nonlinear dynamic systems can be modelled using NARX models. One of the many uses for them is in time-series modelling [29].

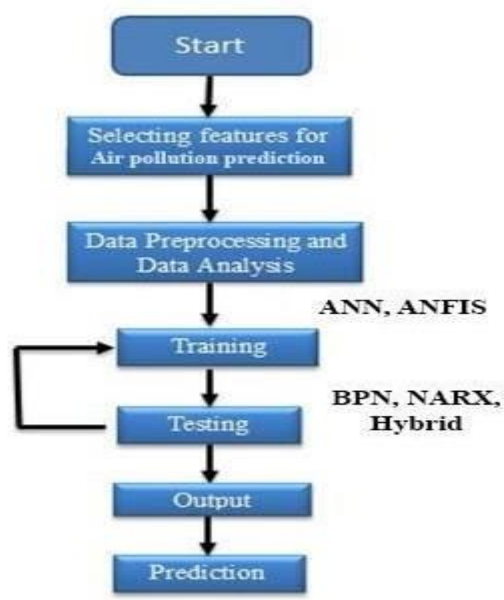

Figure 5. 1: Flowchart of predicting using ANFIS, NARX and BP

Another kind of dynamic neural network is the NARX. Several layers of the network are encircled by its feedback connections. Applying the NARX neural network's memory capability with previous values of predicted or real time series is an intriguing way to get the network's full performance for nonlinear time series prediction.

$$\hat{y}(t+1) = F\begin{pmatrix} y(t), y(t-1), \dots, y(t-n_y), x(t+1), \\ x(t), x(t-1), \dots, x(t-n_x) \end{pmatrix} \tag{1}$$

$$\hat{y}(t+1) = F\begin{pmatrix} \hat{y}(t), \hat{y}(t-1), \dots, \hat{y}(t-n_y), x(t+1), \\ x(t), x(t-1), \dots, x(t-n_x) \end{pmatrix} \tag{2}$$

In the neural network, F(·) is the mapping function, and $\hat{y}$ (t + 1) is the NARX output (also known as the predicted value of y). The past outputs of the N are $\hat{y}$ (t), $\hat{y}$ (t − 1),..., $\hat{y}$ (t − ny). ARX. y(t), y(t − 1), ..., y(t − ny) represent the desired output values of the time series during the past. Uses x(t + 1), x(t), ..., x(t − ny) as inputs for N. ARX. Input delays are nx and output delays are ny.

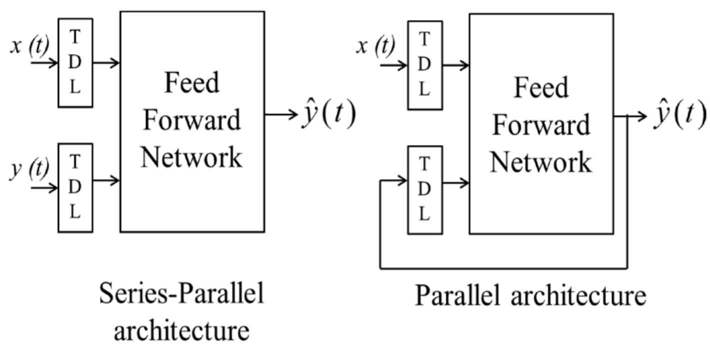

Figure 1. Architecture of the NARX neural network.

The series-parallel design predicts the future value of the time series y(t − 1) by considering the present and past values of x(t) and the actual past values of y(t). The predicted values of the time series $\hat{y}$(t), as well as the current and historical values of x(t), are used to execute the prediction in the parallel architecture.

The series-parallel architecture is employed in this research study's training phase due to the availability of the time series' actual historical values. There are two benefits to the series-parallel design. The primary advantage is that utilizing the actual values as input for the feedforward network enhances precision. The second advantage lies in the purely feedforward architecture of the resultant network, allowing for the application of conventional training algorithms for Multi-Layer Perceptron (MLP) networks. After the training phase, the NARX neural network is transformed into a parallel architecture, advantageous for multi-step-ahead prediction [30][31].

At first, the mapping function F(·) is not known and is estimated during the training of the prediction. This approximation is carried out by the Multi-Layer Perceptron (MLP), an internal structure of the NARX neural network model. The MLP provides a robust framework for learning any form of continuous nonlinear mapping.

The input, hidden, and output layers make up a traditional MLP, as seen in Figure 2. Additional components include neurons, activation functions, and weights. The information flow direction across the layers proceeds from the input layer to the output layer. In each layer, each neuron computes the scalar product of the input vector xj from the preceding layer and the weights vector wij, resulting in $xj \times wij$. An activation function f, as specified in Table 1, is subsequently applied to yield the following neuron output:

$$y_i = f(\sum_{j=1}^{n} x_j . w_{ij}) \tag{3}$$

where i denotes the index of the neuron within the layer. j denotes the input index in the artificial neural network (ANN).

Function	Definition	Codomain
Linear	x	The Real domain IR
Sigmoid (Logsig)	$\frac{1}{1+e^{-x}}$	]0, 1[
Hyperbolic tangent (Tansig)	$\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$	]-1, 1[

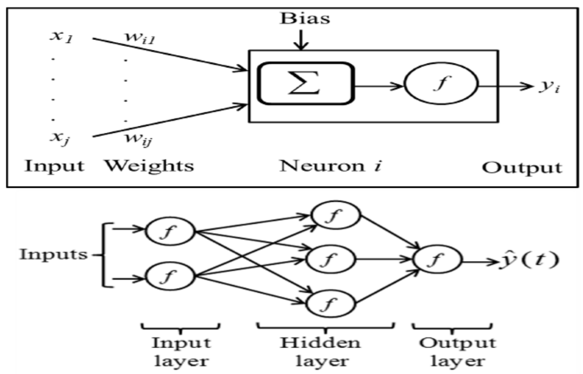

Figure 2. Details of a neuron (up) and MLP network (down).

Training involves adjusting the weights in a systematic manner with the help of a suitable algorithm. During the training process, a predetermined number of inputs and their corresponding desired outputs, also referred to as targets, are presented to the network. Subsequently, the weights are adjusted to ensure that the neural network generates outputs that closely align with the target values.

Providing an optimal solution on a global scale while avoiding local minima is another challenge during training. To do that, we initialize some weights at random and take into account the one that produces the best result.

Conclusions

Air pollution is an admirable phenomenon that is crucial to human survival. Due to shifting climatic conditions, the air quality cycle is altering, resulting in an increase in ground pollution from low to high levels. Accurate air quality forecasting can be beneficial for numerous concerns, particularly for timely air quality alerts. It encourages individuals to exercise caution and adopt preventive measures, such as avoiding direct exposure to polluted air. Combustion of fossil fuels in industry, transportation, and emissions from factories. Inadequate air quality significantly impairs human life, leading to a plethora of diseases. The ANFIS model is developed to forecast air quality to address this issue.

References

1. I. N. K.Wardana, J. W. Gardner, and S. A. Fahmy, “Collaborative Learning at the Edge for Air Pollution Prediction,” IEEE Transactions on Instrumentation and Measurement, vol. 73, pp. 1–12, 2024.
2. Wang, H., Naghavi, M., Allen, C., Barber, R. M., Bhutta, Z. A., Carter, A., ... & Coggeshall, M. (2016). Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980–2015: a systematic analysis for the Global Burden of Disease Study 2015. *The lancet*, *388*(10053), 1459-1544.
3. World Health Organization. (2014). 7 million premature deaths annually linked to air pollution. *World Health Organization, Geneva, Switzerland*.
4. A. Elessa Etuman and I. Coll, “Integrated Air Quality Modelling for Urban Policy: A Novel Approach with Olympus-chimere,” Atmospheric Environment, vol. 315, p. 120134, Dec. 2023. pp. 1–4, 2023.

5. S. Ameer, M. A. Shah, A. Khan, H. Song, C. Maple, S. U. Islam, and M. N.Asghar, “Comparative Analysis of Machine Learning Techniques for Predicting Air Quality in Smart Cities,” IEEE Access, vol. 7, pp. 128325–128338, 2019. Duke University, 2021.
6. Q. Chen, Q. Wang, B. Xu, Y. Xu, Z. Ding, and H. Sun, “Air Pollution and Cardiovascular Mortality in Nanjing, China: Evidence Highlighting the Roles of Cumulative Exposure and Mortality Displacement,” Chemosphere, vol. 265, p. 129035, 2021.
7. J. Ma, Z. Li, J. C. Cheng, Y. Ding, C. Lin, and Z. Xu, “Air Quality Prediction at New Stations Using Spatially Transferred Bi-directional Long Short-Term Memory Network,” Science of The Total Environment, vol. 705, p. 135771,
8. Z. Zhang, G. Zhang, and B. Su, “The Spatial Impacts of Air Pollution and Socio-Economic Status on Public Health: Empirical Evidence From China,”Socio-Economic Planning Sciences, p. 101167, 2021.
9. Y. H. Yoon, J. Y. Kim, and S. H. Choi, “Analysis of patients with acute toxic exposure between 2009 and 2013: data from the Korea health insurance review and assessment service and the national emergency department information system,”Journal of Korean Medical Science, vol. 33, Article ID e254, 2018.
10. Fu, M., Wang, W., Le, Z., & Khorram, M. S. (2015). Prediction of particular matter concentrations by developed feed-forward neural network with rolling mechanism and gray model. *Neural Computing and Applications*, *26*(8), 1789-1797.
11. Kumar, V., & Rao, S. (2024). *Advancing Air Quality Prediction Models in Urban India: A Deep Learning Approach Integrating DCNN and LSTM Architectures for AQI Time-Series Classification.* Environmental Science and Pollution Research. Retrieved from https://link.springer.com/article/10.1007/s40808-023-01934-9
12. Emeç, M., Yurtsever, M. A novel ensemble machine learning method for accurate air quality prediction. *Int. J. Environ. Sci. Technol.* 22, 459–476 (2025).
13. Zuhra Sadriddin, Remudin Reshid Mekuria, and Mekia Shigute Gaso. 2024. Machine Learning Models for Advanced Air Quality Prediction. In Proceedings of the International Conference on Computer Systems and Technologies 2024 (CompSysTech '24). Association for Computing Machinery, New York, NY, USA, 51–56.
14. Sharma, M., Jain, S., Mittal, S., & Sheikh, T. H. (2021). Forecasting and prediction of air pollutants concentrates using machine learning techniques: the case of India. In *IOP conference series: Materials science and engineering* (Vol. 1022, No. 1, p. 012123). IOP Publishing.
15. Gokulan Ravindiran, Gasim Hayder, Karthick Kanagarathinam, Avinash Alagumalai, Christian Sonne, Air quality prediction by machine learning models: A predictive study on the indian coastal city of Visakhapatnam, Volume 338,2023, 139518, ISSN 0045-6535,
16. U. Rusilowati, H. R. Ngemba, R. W. Anugrah, A. Fitriani, and E. D. Astuti, “Leveraging ai for superior efficiency in energy use and development of renewable resources such as solar energy, wind, and bioenergy,” International Transactions on Artificial Intelligence, vol. 2, no. 2, pp. 114–120, 2024.
17. Z. Ye, J. Yang, N. Zhong, X. Tu, J. Jia, and J. Wang, “Tackling environmental challenges in pollution controls using artificial intelligence: A review,” Science of the Total Environment, vol. 699, p. 134279, 2020.
18. Carbajal-Hernández, José Juan "Assessment and prediction of air quality using fuzzy logic and autoregressive models." Atmospheric Environment 60 (2012): 37-50. Jasim et al., 2020
19. Y. Zheng, X. Yi, M. Li, R. Li, Z. Shan, E. Chang, and T. Li, “Forecasting fine-grained air quality based on big data,” in *Proc. The 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 2267-2276, August 10, 2015.
20. Alpan and Sekeroglu, 2020, Pablo E. Saide, Gregory R. Carmichael, Scott N. Spak, Laura Gallardo, Axel E. Osses, Marcelo A. Mena-Carrasco, Mariusz Pagowski, Forecasting urban PM10 and PM2.5 pollution episodes in very stable nocturnal conditions and complex terrain using WRF–Chem CO tracer model, Atmospheric Environment, Volume 45, Issue 16, 2011, Pages 2769-2780, ISSN 1352-2310,
21. Mohanty, S.; Patra, P.K.; Sahoo, S.S. Prediction of global solar radiation using nonlinear autoregressive network win exogenous inputs (narx). In Proceedings of the 39th National System Conference (NSC), Noida, India, 14–16 December 2015.
22. Pisoni, E.; Farina, M.; Carnevale, C.; Piroddi, L. Forecasting peak air pollution levels using NARX models. Eng. Appl. Artif. Intell. 2009, 22, 593–602.
23. Ruiz, L.G.B.; Cuéllar, M.P.; Calvo-Flores, M.D.; Jiménez, M.D.C.P. An Application of Non-Linear Autoregressive Neural Networks to Predict Energy Consumption in Public Buildings. *Energies* 2016, *9*, 684.

24. Araújo, R.A.; Oliveira, A.L.I.; Meira, S. A morphological neural network for binary classification problems. *Eng. Appl. Artif. Intell.* 2017, *65*, 12–28.
25. Gong, T.; Fan, T.; Guo, J.; Cai, Z. GPU-based parallel optimization of immune convolutional neural network and embedded system. *Eng. Appl. Artif. Intell.* 2017, *62*, 384–395.
26. Sánchez, D.; Melin, P.; Castillo, O. Optimization of modular granular neural networks using a firefly algorithm for human recognition. *Eng. Appl. Artif. Intell.* 2017, *64*, 172–186.
27. Yu, S.; Zhu, K.; Zhang, X. Energy demand projection of China using a path-coefficient analysis and PSO–GA approach. *Energy Conver. Manag.* 2012, *53*, 142–153.
28. [28]Chen, S.; Billings, S.; Grant, P. Non-linear system identification using neural networks. *Int. J. Control* 1990, *51*, 1191–1214.
29. Cadenas, E.; Rivera, W.; Campos-Amezcua, R.; Heard, C. Wind Speed Prediction Using a Univariate ARIMA Model and a Multivariate NARX Model. *Energies* 2016, *9*, 109.
30. Ferreira, A.A.; Ludermir, T.B.; Aquino, R. Comparing recurrent networks for time-series forecasting. In Proceedings of the 2012 International Joint Conference on Neural Networks (IJCNN), Brisbane, Australia, 10–15 Junuary 2012.
31. Buitrago, J.; Asfour, S. Short-Term Forecasting of Electric Loads Using Nonlinear Autoregressive Artificial Neural Networks with Exogenous Vector Inputs. *Energies* 2017, *10*, 40.