Journal of Trends in Computer Science and Smart technology (TCSST) (2021)
Vol.03/ No. 03
Pages: 222-237
https://www.irojournals.com/tcsst/
DOI: https://doi.org/10.36548/jtcsst.2021.3.005

Fault Diagnosis in Hybrid Renewable Energy Sources with Machine Learning Approach

Haoxiang Wang

Director and Lead Executive Faculty Member, GoPerception Laboratory, Cornell University, Ithaca, USA

E-mail: wanghaoxiang1102@hotmail.com

Abstract

In recent days the need for energy resources is dramatically increasing world-wide. Overall 80% of the energy resource is supplied in the form of fuel based energy source and nuclear based energy source. Where fuel based energy resources are very essential in day-to-day life. Fossil fuel is also one among the energy resource and due to the high demand we face shortage in these resources. Providing electricity in rural areas is still a difficult process because of the shortage of energy resources. This issue can be rectified by choosing an alternate to electricity. To achieve this we have integrated many renewable energy sources to form a hybrid-renewable energy source system and this is capable of providing power supply to these areas. We have adopted artificial neural networks (ANN) technique based on machine learning to accomplish this process. For short-term prediction other techniques such as MLP, CNN, RNN and LSTM are used. These values are used as reference value in final execution.

Keywords: Hybrid-Renewable Energy Source, Artificial Neural Network (ANN), Fuel-Based Energy, Nuclear-Based Energy, Machine Learning

1. Introduction

In recent days, utilization of energy resources is inevitable in our day-to-day life. Almost everyone is utilizing these resources in numerous forms such as oil, gas, coal, fuel and

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

Journal of Trends in Computer Science and Smart technology (TCSST) (2021)
Vol.03/ No. 03
Pages: 222-237
https://www.irojournals.com/tcsst/
DOI: https://doi.org/10.36548/jtcsst.2021.3.005

renewables [1]. Out of this petroleum faces shortage issues due to the huge demand on it. The environment gets polluted in straight line with increasing usage of energy resource [2]. To neutralize this we have to move towards renewable resources such as solar, wind, biomass, geothermal, etc. The pollution-free, abundant and sustainable characteristics of renewable energy attract the world. The major motive of renewable energy source is to provide electricity to rural and remote areas [3].

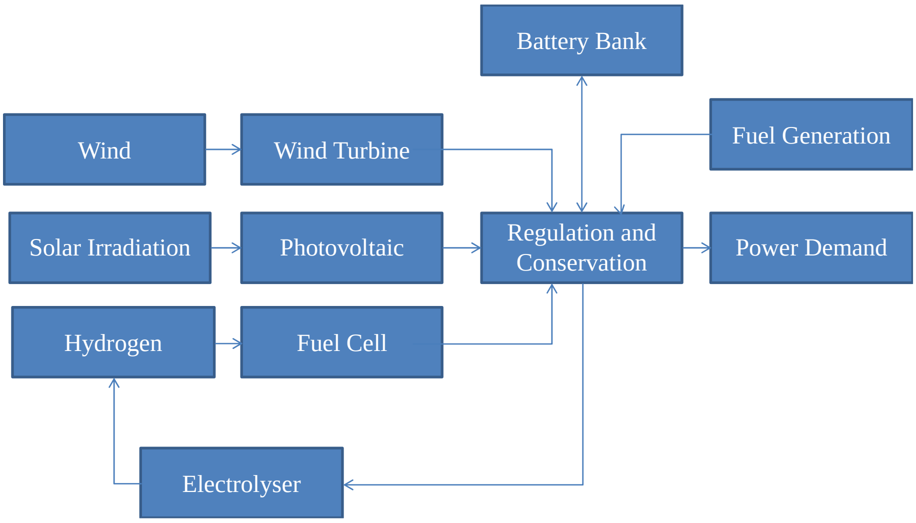

Figure 1. General Structure of HRES

Though renewable energy source produce hydrogen, we use hybrid-renewable energy model because the hybrid model comprises of different renewable sources which can perform better than the previous one. It has major advantages such as economic, reliable and highly efficient [4]. Many developing countries are focusing on a stable and green development of energy. The stand-alone power plan is constructed by involving various renewable energy sources in Hybrid Renewable Energy Source (HRES) model. Figure 1 represents the general structure of HRES [5]. There are many techniques such as artificial intelligence; multi-objective, probabilistic method and iterative method are used to optimize the HRES model. Our proposed work mainly concentrates on power consumption forecasting [6]. To achieve that we has used following methods

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

Journal of Trends in Computer Science and Smart technology (TCSST) (2021)
Vol.03/ No. 03
Pages: 222-237
https://www.irojournals.com/tcsst/
DOI: https://doi.org/10.36548/jtcsst.2021.3.005

a. Adaptive Fuzzy Network

b. Feed Forward Neural Network

c. Auto-Regressive Integrated Moving Average

Figure 2 provides the comparison between the subject areas of machine learning like energy, environmental science (EVS), engineering and others. From this comparison, it is evident that energy is the major application that makes use of the machine learning algorithms.

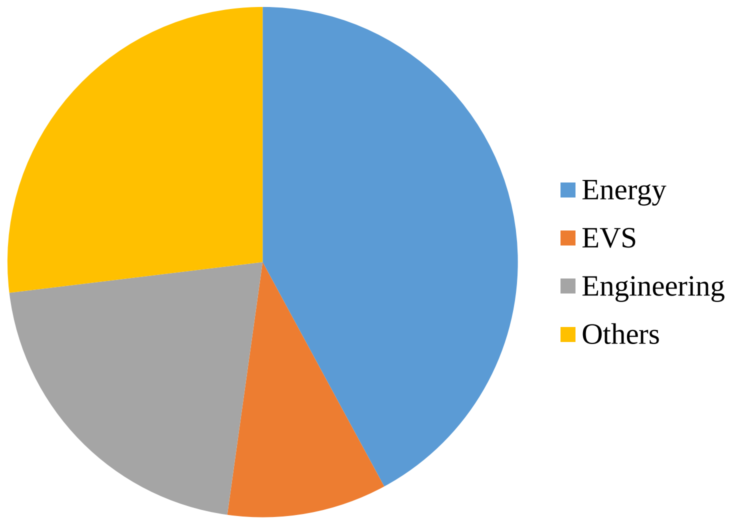

Figure 2. Subject Area of Machine Learning

2. Related Work

The Machine learning methods wide applications and it is also used in renewable energy system to predict the integration and generation of energy and it is also used to analyse the demand and consumption of energy [7]. To predict the mixed energy demand the South Koreans have used error back propagation and multi-layer algorithms based on ANN Model [8]. It is used to predict the energy demand based on the economic status of a country in terms of GDP, import, export and population using root mean square error on the scale value of FF

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

back-propagation [9]. The transport demand is predicted by using HASTEDE model. This method is capable of providing information such as ownership, GDP and population which can be used as a reference to determine the future power consumption estimation [10].

a. Artificial Neural Network (ANN)
b. Extreme Learning Machine (ELM)
c. Support Vector Machine (SVM)
d. Adaptive Neural Fuzzy Inference System (ANFIS)
e. Deep Learning
f. Decision Trees
g. Advanced Hybrid Machine Learning Models
h. Ensembles

The artificial neural network is capable of processing complex and irregular data and renewable energy resources follows irregularity, so ANN is highly used to predict renewable energy system. Solar energy, hydro power, wind power and solar irradiance are some of the prediction models of ANN [11]. Authors have implemented ANN model to predict RE applications such as solar radiation on daily average basis, solar irradiation on hour basis and so on. Other machine learning methods such as SVM, MLP, organizing feature maps, autoregressive neural network are tested to produce electricity for PV system [12]. Prediction of hour based solar radiation can be achieved with very minimal amount of data. They use humidity and temperature values for prediction [13]. Historical and weather forecasting data is used to predict wind energy. Non-linear auto-regressive exogenous input, back propagation network and radial basis function are the three ANN based model which are used to predict the speed of wind. For daily and monthly based prediction we adopt long short-term memory (LSTM) and recurrent neural network (RNN) [14]. For large scale data prediction of wind structure we use convolution neural network (CNN), recurrent neural network (RNN) and multi-layer perception (MLP) [15]. The deep learning methods perform better in prediction of wind speed and forecasting. The periodic analysis of hydroelectric energy is performed by

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

Journal of Trends in Computer Science and Smart technology (TCSST) (2021)
Vol.03/ No. 03
Pages: 222-237
https://www.irojournals.com/tcsst/
DOI: https://doi.org/10.36548/jtcsst.2021.3.005

machine learning. The hydro power is predicted by integrating feed forward and back propagation methods [16]. Power generation is achieved by surrogate and optimization methods by using genetic algorithm based on ANN. accurate prediction of hydroelectric power is obtained from single layer MLP [17]. The above mentioned machine learning methods are used to predict various applications of renewable energy source. The objective of our work is to provide electricity to rural and remote area using hybrid renewable energy resource system.

3. Proposed Work

In our proposed work we have used Machine learning technique to predict HRES. It is used for energy management and analyse demands on each sectors. It works on two forms namely, stand-alone and grid-connection [18]. The working procedure is based on the customer's requirement. The working procedure of Machine learning based HRES prediction is explained in detail as follows:

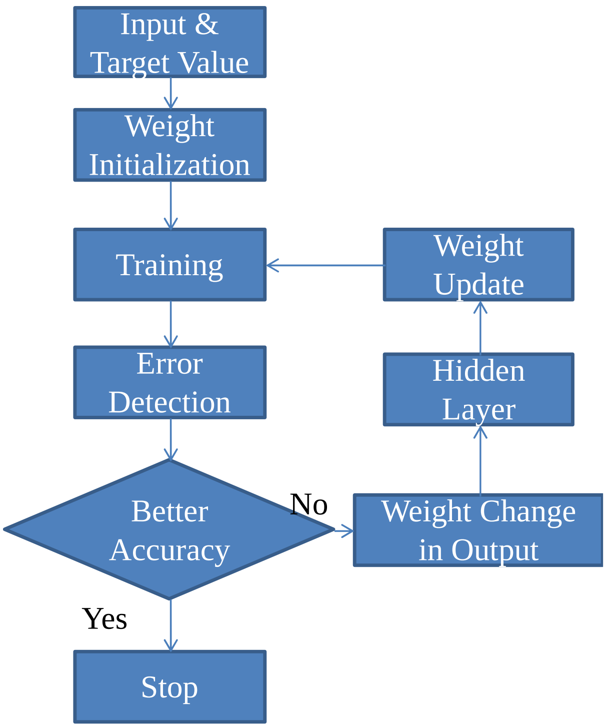

Figure 3. Flow chart of HRES prediction

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

Journal of Trends in Computer Science and Smart technology (TCSST) (2021)
Vol.03/ No. 03
Pages: 222-237
https://www.irojournals.com/tcsst/
DOI: https://doi.org/10.36548/jtcsst.2021.3.005

1. Predicting the generated renewable energy resource: This is a difficult task because it is completely depends on natural environment. Previous values are taken as reference value to predict wind and solar energy [19]. Various neural networks are adopted to predict the corresponding output in our proposed work.

2. Parameter specification of renewable energy: The parameter such as size, configuration and location of the renewable energy power plant are specified. This depends on climatic changes. Since it requires large area to construct the power plant we have to consider availability, cost, territory and weather [20]. For better performance we have to analyse the nature of the area selected for power plant construction in terms of weather, humidity, irradiation, speed and temperature. We require proper decision making algorithm to implement this.

3. Renewable energy integrated with Smart grid: The smart grid is upgraded version of power plant. It performs all the operations from cohort to supply along with storage capability [21, 22]. Since it is an advanced model it has high processing speed, efficient, effective and highly intelligent. It is customized as per stakeholder's need. It is a combination of Artificial intelligence, Internet of Things and information communication technology tool. It requires proper maintenance and effective management to improve its performance.

4. Demand estimation: Estimating the demand of energy is most essential thing in building a power plant. To establish a successful network system we have to maintain the demand and supply change [23]. HRES comprises of stakeholders with distinguee perceptions and it is our responsibility to satisfy them. So, we are in need of Machine learning algorithm which can handle this complex task. Proper maintenance of demand and supply gives good production results.

5. Emerging RE materials: The machine learning approach has further kept its foot print in development field of renewable energy. An inverse structure is designed

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

Journal of Trends in Computer Science and Smart technology (TCSST) (2021)
Vol.03/ No. 03
Pages: 222-237
https://www.irojournals.com/tcsst/
DOI: https://doi.org/10.36548/jtcsst.2021.3.005

to predict the RE material from the specified properties of HRES. Battery, solar cell, crystal and catalysis are some of the examples of RE materials.

3.1 Forecasting of Renewable Energy

In modern days, most of the industries are attracted towards renewable energy system and this creates a huge demand on renewable energy system [24]. To meet these requirements we have to obtain energy resources from various sources. There are two methods used in this forecasting model of renewable energy sources namely

a. Top-Down Approach
b. Bottom-Up / Build-Up Approach

In Top-Down approach the hierarchy of prediction is from highest value to the lowest value. In contrast to this method Bottom-Up / Build-Up approach uses lowest value to highest value prediction. Researchers have conducted many experiments on these approaches and finally mentioned that the Bottom-Up / Build-Up Approach is capable of performing well because the lowest to highest hierarchical data is used as reference for further development process. A brief description of renewable energy sources (solar, hydro, wind and biomass energy) are stated below.

3.2 Prediction of Solar Energy

Solar energy is an unaffectedly ecological energy obtained directly from sun and it has to forms namely

a. Photo-thermal (heat)
b. Photovoltaic (electricity)

The photovoltaic energy fails to produce green-house gas as like fuel-based as it has non-contaminating nature. Predicting a natural resource requires huge data and decision making tool for accurate prediction because of the uncertainty of the environment such as

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

changes in weather, air pressure, humidity, wind speed, direction of air flow, ambient temperature, sun's irradiation and duration of sun shine and so on. Machine learning techniques are used to solve these issues by collecting the historical data for hourly, daily and monthly basis for accurate prediction.

3.3 Prediction of Wind Energy

The next important energy source is wind energy. Electricity is obtained by converting the kinetic energy of wind into electrical energy and this is carried out in two forms namely,

a. On land / onshore
b. On ocean / offshore

As discussed earlier the natural resources are highly sensitive to environmental changes and it requires a history of periodical data for accurate prediction. The Machine Learning methods such as convolutional neural network (CNN) and recurrent neural network (RNN) based on artificial neural network (ANN) are implemented to accomplish this task.

3.4 Prediction of Hydro Power

Hydro power is the energy which produces electricity from the kinetic energy of water. Here turbines are used to produce electricity. The turbines are of two sizes

a. Bigger turbines
b. Smaller turbines

The bigger turbines are used during rainy season because the volume and speed of water flow will be high during rainy season. Smaller turbines are used during non-rainy season where the volume and speed of water flow will be lesser. The size of the turbine is depends on the volume and force of water. A continuous and periodic history of water level is required for better prediction. To predict this non-linear and complex behaviour we use support vector

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

machine (SVM), artificial neural network (ANN) and genetic algorithm (GA). It is easy to maintain and it is a cost effective model.

3.5 Prediction of Biomass Energy

Biomass energy is obtained from the biological wastes after decay. It depends on the carbon cycle which is originated from plants then transferred to soil and then transferred to the atmosphere. It can be used for small scale purpose such as biogas and as bio-diesel for transportation. There are two methods used to predict the biomass energy they are namely

a. Image-Driven-Based Prediction
b. Linear Regression Model

Out of these two methods, Image-Driven-Based Prediction method has high level of accuracy. As discussed earlier all renewable energy sources are highly depended on natural environment and they are very sensitive to change in the environmental condition. Proper estimation is required for better performance.

It is observed that out of these renewable energy sources wind and solar power has higher energy and they are visualized to be highly used in future.

3.6 Machine Learning Algorithm

In this section we have used Artificial Neural Network (ANN) based on machine learning. Back propagation algorithm is adopted to accomplish this task. The back propagation algorithm is one of the best algorithms used to predict the non-linear characteristics. This combines the input time series along with the estimated output. A target value is estimated in the beginning and the output is compared with the target value. If any difference between these two values exists that value is considered as the error value. Then it is reduced and the corrected values are updated. This process repeats until it reaches the acceptable value and the values are

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

Journal of Trends in Computer Science and Smart technology (TCSST) (2021)
Vol.03/ No. 03
Pages: 222-237
https://www.irojournals.com/tcsst/
DOI: https://doi.org/10.36548/jtcsst.2021.3.005

updated periodically. This is used to train the artificial neural network model. The working procedure of the back propagation algorithm is stated below

1. Propagation Phase: In this phase we have two corresponding propagation passes namely
   a. Forward Propagation
   b. Backward Propagation

   The forward propagation is used to evaluate the output of the output layer from the input layer. It is related to the top-down method. The backward propagation model is used to predict the error value by comparing the output with the targeted output. This is compared with all the values of neurons.

2. Weight Update Phase: The weight of each and every layer is updated in this phase. It has two methods for updating the data they are
   a. Multiplication
   b. Addition

   In the multiplication method the gradient of the weight factor is estimated by multiplying the input and the output delta value. The addition method new weight is obtained by adding the gradient ratio and the weight of the previous value.

3. The iteration is terminated after checking the epoch value using stopping criteria. It has two conditions namely
   a. Iteration gets terminated when there is minimum epoch
   b. Iteration is terminated when error occurs at the end of epoch.

   This is tested over more than thousand epochs to achieve proper neural network coverage and used for testing different networks and datasets.

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

Journal of Trends in Computer Science and Smart technology (TCSST) (2021)
Vol.03/ No. 03
Pages: 222-237
https://www.irojournals.com/tcsst/
DOI: https://doi.org/10.36548/jtcsst.2021.3.005

4. Result and Discussion

The non-linear transformation is obtained from the input time series by using the activation function and this enhances the expression ability of artificial neural network. It makes model to easily understand the complexity in the task and predicts accurately. Without activation function the proposed model becomes linear regressive model.

Sigmoid Function: $y = f(x) = \frac{1}{1+e^{-x}}$ (1)

Hyperbolic-Tangent Function: $y = f(x) = \tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$ (2)

Rectified Linear Unit Function: $y = f(x) = x^{+} = \max(0, x)$ (3)

Soft-Plus Function: $y = f(x) = \ln(1 + e^{x})$ (4)

The above mentioned functions are the activation functions and these are used to predict the non-linear characteristics. Figure 4 represents the above mentioned activation functions in a graphical manner.

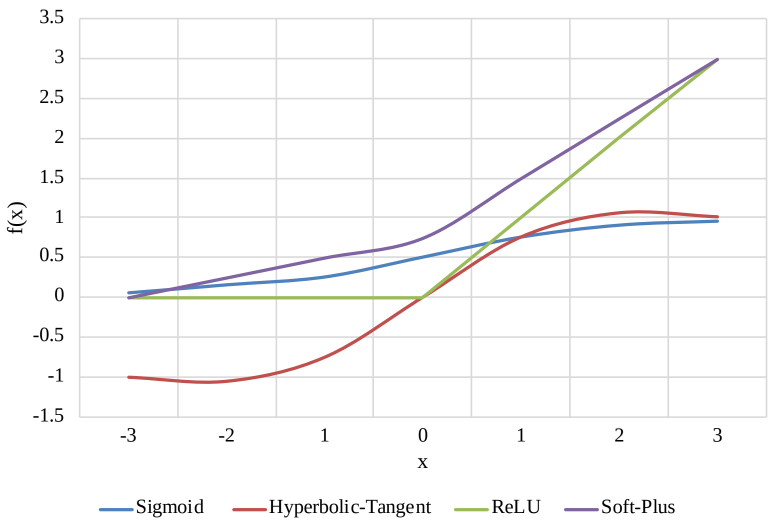

Figure 4. Comparison of the activation functions for prediction of non-linear characteristics

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

Journal of Trends in Computer Science and Smart technology (TCSST) (2021)
Vol.03/ No. 03
Pages: 222-237
https://www.irojournals.com/tcsst/
DOI: https://doi.org/10.36548/jtcsst.2021.3.005

4.1 Prediction Metrics

The error between the target value and the obtained output is derived from the below mentioned prediction metrics. The error variability between the measured and estimated value with N observations is given by RMSE and CV-RMSE.

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N}(y_k - x_k)^2}{N}} \quad (5)$$

$$CV - RMSE = \frac{RMSE}{\bar{x}} \times 100\% \quad (6)$$

With respect to the sample regression line, the predicted output's overall behaviour is represented by the average sample space error given by MBE. The MBE index normalization is represented by NMBE.

$$MBE = \frac{1}{N}\sum_{k=1}^{N}(y_i - x_k) \quad (7)$$

$$NMBE = \frac{MBE}{\bar{x}} \times 100\% \quad (8)$$

Other prediction performance measures representing the average error between the observations of each estimated value and the prediction accuracy percentage is given by MAE and MAPE.

$$MAE = \frac{1}{N}\sum_{k=1}^{N}|(y_k - x_k)| \quad (9)$$

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\frac{|(y_k - x_k)|}{x_k} \times 100\% \quad (10)$$

The coefficient of determination, represented by R^2 is bounded between 0 and 1.

$$R^2 = 1 - \frac{\sum_{k=1}^{N}(y_k - x_k)^2}{\sum_{k=1}^{N}(y_i - \bar{x})^2} \quad (11)$$

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

Journal of Trends in Computer Science and Smart technology (TCSST) (2021)
Vol.03/ No. 03
Pages: 222-237
https://www.irojournals.com/tcsst/
DOI: https://doi.org/10.36548/jtcsst.2021.3.005

The aforementioned parameters are estimated based on the heating and cooling energy demand requirements of a building over a duration of 12 months. The measured value, simulated value and the difference is estimated. For an overall utilization of 9426 kWh measure value, the simulated value obtained is 9438 kWh. A difference of 12 kWh is observed which is much lesser than the error percentage observed in other models discussed in the literature. MBE is estimated to be 12, and NMBE is 1.2%.

5. Conclusion

The proposed work adopts machine learning approaches to generate hybrid renewable energy system. Artificial intelligence is used for predicting irregularities and complex non-linear data. Solar, wind, hydro power and biomass are some of the major renewable energy resources and these are highly sensitive to climatic changes. The metrological data is unpredictable in nature, so proper historical data on periodic basis is required for accurate forecasting. Out of these energies solar and wind are promising energy sources that can be used in future. Artificial neural network based back propagation algorithm is utilized in our prosed work. It is observed that the back propagation algorithm performs well and has higher accuracy values with less error value.

Reference

[1] C. Zhang *et al.*, "An Improved ELM Model Based on CEEMD-LZC and Manifold Learning for Short-Term Wind Power Prediction," in *IEEE Access*, vol. 7, pp. 121472-121481, 2019.

[2] Madhura, S. "IoT Based Monitoring and Control System using Sensors." Journal of IoT in Social, Mobile, Analytics, and Cloud 3, no. 2: 111-120.

[3] Parvez, AHM Shahariar, Md Robiul Alam Robel, Mohammad Abdur Rouf, Prajoy Podder, and Subrato Bharati. "Effect of fault tolerance in the field of cloud computing."

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

Journal of Trends in Computer Science and Smart technology (TCSST) (2021)
Vol.03/ No. 03
Pages: 222-237
https://www.irojournals.com/tcsst/
DOI: https://doi.org/10.36548/jtcsst.2021.3.005

In International Conference on Inventive Computation Technologies, pp. 297-305. Springer, Cham, 2019.

[4] Amanuel, Thomas, Amanuel Ghirmay, Huruy Ghebremeskel, Robel Ghebrehiwet, and Weldekidan Bahlibi. "Comparative Analysis of Signal Processing Techniques for Fault Detection in Three Phase Induction Motor." Journal of Electronics 3, no. 01 (2021): 61-76.

[5] Q. Tong *et al*., "A Fault Diagnosis Approach for Rolling Element Bearings Based on RSGWPT-LCD Bilayer Screening and Extreme Learning Machine," in *IEEE Access*, vol. 5, pp. 5515-5530, 2017.

[6] Chen, Joy Iong-Zong, and Kong-Long Lai. "Deep Convolution Neural Network Model for Credit-Card Fraud Detection and Alert." Journal of Artificial Intelligence 3, no. 02 (2021): 101-112.

[7] Bipin, B. "Reducing Network Downtime by Intelligent Fault Analysis." In International Conference on Inventive Computation Technologies, pp. 692-701. Springer, Cham, 2019.

[8] Bindhu, V., and G. Ranganathan. "Effective Automatic Fault Detection in Transmission Lines by Hybrid Model of Authorization and Distance Calculation through Impedance Variation." Journal of Electronics 3, no. 01 (2021): 36-48.

[9] H. Yuan et al., "Energy-Optimized Partial Computation Offloading in Mobile-Edge Computing With Genetic Simulated-Annealing-Based Particle Swarm Optimization," in *IEEE Internet of Things Journal*, vol. 8, no. 5, pp. 3774-3785, 1 March1, 2021.

[10] Bhavana, Kotte, Vinuthna Nekkanti, and N. Jayapandian. "Internet of Things Enabled Device Fault Prediction System Using Machine Learning." In International Conference on Inventive Computation Technologies, pp. 920-927. Springer, Cham, 2019.

[11] Kamel, Khaled, and Eman Kamel. "Process Control Ladder Logic Trouble Shooting Techniques Fundamentals." IRO Journal on Sustainable Wireless Systems 1, no. 4 (2019): 206-241.-1

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

Journal of Trends in Computer Science and Smart technology (TCSST) (2021)
Vol.03/ No. 03
Pages: 222-237
https://www.irojournals.com/tcsst/
DOI: https://doi.org/10.36548/jtcsst.2021.3.005

[12] C. Huang and P. Kuo, "Multiple-Input Deep Convolutional Neural Network Model for Short-Term Photovoltaic Power Forecasting," in *IEEE Access*, vol. 7, pp. 74822-74834, 2019.

[13] B. Ray et al., "A New Data Driven Long-Term Solar Yield Analysis Model of Photovoltaic Power Plants," in *IEEE Access*, vol. 8, pp. 136223-136233, 2020.

[14] Sungheetha, Akey, and Rajesh Sharma. "3D Image Processing using Machine Learning based Input Processing for Man-Machine Interaction." Journal of Innovative Image Processing (JIIP) 3, no. 01 (2021): 1-6.

[15] T. K. Mahmoud et al., "A Developed Integrated Scheme Based Approach for Wind Turbine Intelligent Control," in *IEEE Transactions on Sustainable Energy*, vol. 8, no. 3, pp. 927-937, July 2017.

[16] Vishwakarma, Sunil Kumar, Akhtar Rasool, and Gaurav Hajela. "Machine Learning Algorithms for Prediction of Credit Card Defaulters—A Comparative Study." In Proceedings of International Conference on Sustainable Expert Systems: ICSES 2020, vol. 176, p. 141. Springer Nature, 2021.

[17] Sungheetha, Akey, and Rajesh Sharma. "A Comparative Machine Learning Study on IT Sector Edge Nearer to Working From Home (WFH) Contract Category for Improving Productivity." Journal of Artificial Intelligence 2, no. 04 (2020): 217-225.

[18] H. Zhang et al., "Short-Term Photovoltaic Power Forecasting Based on VMD and ISSA-GRU," in *IEEE Access*, vol. 9, pp. 105939-105950, 2021.

[19] M. F. Hashmi et al., "An Exploratory Analysis on Visual Counterfeits Using Conv-LSTM Hybrid Architecture," in *IEEE Access*, vol. 8, pp. 101293-101308, 2020.

[20] Adam, Edriss Eisa Babikir. "Evaluation of Fingerprint Liveness Detection by Machine Learning Approach-A Systematic View." Journal of ISMAC 3, no. 01 (2021): 16-30.

[21] Pradan, Md Anuvob, Mahia Binte Mizan, Moon Howlader, and Shamim Ripon. "An Efficient Approach to Software Fault Prediction." In International Conference on Communication, Computing and Electronics Systems: Proceedings of ICCCES 2020, vol. 733, p. 221. Springer Nature, 2021.

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021

[22] Haoxiang, Wang, and S. Smys. "Big Data Analysis and Perturbation using Data Mining Algorithm." Journal of Soft Computing Paradigm (JSCP) 3, no. 01 (2021): 19-28.

[23] H. Jahangir et al., "Deep Learning-Based Forecasting Approach in Smart Grids With Microclustering and Bidirectional LSTM Network," in *IEEE Transactions on Industrial Electronics*, vol. 68, no. 9, pp. 8298-8309, Sept. 2021.

[24] Ranganathan, G. "A Study to Find Facts Behind Preprocessing on Deep Learning Algorithms." Journal of Innovative Image Processing (JIIP) 3, no. 01 (2021): 66-74.

[25] Bhalaji, N., and C. Rimi. "Remaining Useful Life (RUL) estimation of lead acid battery using bayesian approach." J. Electr. Eng. Autom 2 (2020): 25-34.

[26] Z. Zhang et al., "Prediction of Dissolved Oxygen Content in Aquaculture Based on Clustering and Improved ELM," in *IEEE Access*, vol. 9, pp. 40372-40387, 2021.

Author's biography

Haoxiang Wang is currently a director and lead executive faculty member of GoPerception Laboratory, Ithaca, USA. His research interests are multimedia information processing, pattern recognition, machine learning, remote sensing image processing, and data-driven business intelligence. He has co-authored over 60 journal and conference papers in these fields on journals such as Springer MTAP, Cluster Computing, SIVP; IEEE TII, Communications Magazine; Elsevier Computers & Electrical Engineering, Computers, Environment and Urban Systems, Optik, Sustainable Computing: Informatics and Systems, Journal of Computational Science, Pattern Recognition Letters, Information Sciences, Computers in Industry, Future Generation Computer Systems; Taylor & Francis International Journal of Computers and Applications and conference such as IEEE SMC, ICPR, ICTAI, ICICI, CCIS, and ICACI.

ISSN: 2582-4104
Submitted: 15.07.2021
Revised: 03.09.2021
Accepted: 18.09.2021
Published: 02.10.2021