International Journal of Advance and Applied Research
www.ijaar.co.in
ISSN – 2347-7075 Impact Factor – 8.141
Peer Reviewed Bi-Monthly
Vol. 11 No. 6 July-Aug 2024

# A Time Series Wavelet Analysis And Its Applications: A Review

**Stavelin Abhinandithe K[1], Prerana M[2], Sridhar Ramachandran[3], Balasubramanian Somanathan[4]**

[1]Research Scholar, Division of Medical Statistics, School of Life Sciences, JSS AHER, Mysuru, Karnataka, India.

[2]Assisstant Professor, Division of Medical Statistics, School of Life Sciences, JSS AHER, Mysuru, Karnataka, India.

[3]HOD, MCA, Ramakrishna Mission Vidyalaya, Coimbatore, Tamil Nadu, India.

[4]Former, Director Research, JSSAHER, Mysore, Karnataka, India.

**Corresponding Author: Stavelin Abhinandithe K**

**Email:** Stavelin.ak@jssuni.edu.in

**DOI- 10.5281/zenodo.13382681**

**Abstract:**

Time series, being a universal and firm mathematical tool, has various applications in numerous fields. The concept regarding wavelets was discussed in the present work. Information from both frequency and time domain of a signal is used. Focus has been mainly on the design and on wavelet transforms. The key point of this review is on the basis of neural network combinations and wavelet theory. Evolution of wavelets, system architecture and algorithm implementation are being covered in this review. The applications and a clear trend of rapid development, combining Wavelet Neural Network (WNN) along with the existing neural network algorithms will also be examined. We have reviewed various types of applications that are wavelet-based and summarized the benefits of wavelets in terms of various applications and then comparing the results. This review verifies some research challenges and gaps that can act as a guide for possible applications that are wavelet-based and new system designs.

**Key words:** Wavelet, time series analysis, wavelet transform, ANFIS, CWT, DWT,

**Introduction:**

Information on joint distribution with respect to time and frequency domains, serves as a dominant mathematical apparatus to analyse non-stationary signals that vary in time is provided by time frequency analysis. Enriched Wegener distribution, Short-Time Fourier transform (STFT, along with Gabor transformation), Gabor-Wigner distribution function and S transform, Cohen distribution function (along with Wegener distribution) [1] are some of the standard time-frequency distribution functions. Greater consideration has been paid to the data feature extraction and multi-resolution analysis in signal processing. The clear physical meaning, showing representation of energy that is contained in every component of the signal's frequency over a particular time interval is an advantage of STFT. A structure of time-frequency, which is based on actual test signals is constant with intuitive perception of the people. However, the window's width function in STFT of the time or frequency resolution and hence cannot be optimized together [2]. These drawbacks have been overcome by wavelets. Wavelet transform (WT) can be defined as projecting a particular signal into a group of basic functions, providing frequency domain localization that will provide constant and equally spaced time-frequency localization, that are like Fourier transform; whereas, wavelet transform will provide higher frequency resolution at lower frequencies and at higher frequencies, higher time resolution can be obtained.

Wavelet transform is different from the Fourier transform and uses a sequence of orthogonal bases along with various resolutions that can either denote or estimate a signal through translation and expansion of the wavelet based function. The focus is mainly on the extraction of features from time series and signals using Fourier and Wavelet transforms. Time series analysis is considered to be a significant breakthrough in various fields like health data analysis, meteorological data analysis and predication, mathematical analysis. For example, rainfall and draught prediction, signal processing, ECG analysis, image processing, speech analysis, pattern recognition, EEG analysis, and various applications can be considered as wavelet analysis. During 1980s, wavelet research developed rapidly; existence of wavelet functions was proved by in 1981. Meyer et. al. designed various functions based on wavelet having fast decay characteristics between 1984 and 1988 [3]. Based on multi-resolution analysis [4], Mallat algorithm showed quick wavelet transform algorithm for reconstruction and signal analysis, is a two-channel filter which is. It is greatly applied in reconstruction and signal decomposition. Wavelet packet theory was proposed by Soman and Vaidyanathan in 1992 [5]. Wavelet packet will more stupendously divide the time-frequency plane when compared to wavelet transform, and its high-frequency signal resolution outperforms the WA's. Wavelet theory, which was first put forth by Zou and Tewfik [6] in 1992, changed the focus of wavelet transform research from "two-band" to "multi-band." Goodman et al. [7] in 1994, developed a multi-wavelet theoretical framework on the basis of multi-resolution analysis and R-order multi-scaling functions. Higher degrees of freedom are obtained by using numerous scale functions in one particular wavelet to create a multi-resolution space. A multi-scale wavelet transform was designed by Geronimo and his team in 1994 [8]. Multiple scaling functions were used to construct the wavelet function. Various characteristics of orthogonality can be present, along with tight support, interpolation and symmetry at the same time. A novel wavelet construction algorithm- Lifting Scheme was proposed by Swedens et. al. in 1995. Odd and even sample points in the initial discrete sample signal can be separated, and these sample points are subsequently filtered. Lifting schemes can be used to construct all first generation wavelets. Fast computation speeds, little memory usage, and the capability to implement conversion of integer-to-integral are some of the traits [9]. Wavelet design has advanced in recent years to adapt to new categories of image analysis and signals, through contemporary communication technologies. Wavelet transformation has been continuously evolving. Numerous innovative wavelet systems have been developed and used to improvise the limitations of traditional wavelets. Traditional discrete wavelets are translation-sensitive, meaning, even a small change in the signals will result in fluctuations in a wide range of wavelet coefficients. Complex wavelet transform (complex WT) can solve the aforementioned difficulty, although another issue has been identified [10]. The building of the sophisticated WT's complete reconstruction filter is difficult when the input form has more than one level of decomposition. In 1990, Kingsbury created the Dual-Tree Complex Wavelet Transform (DT-CWT) [11]. While comparing to the classical wavelet transform, the DT-CWT could potentially be used to obtain phase information. It maintains the various benefits of complex wavelets while also meeting the need of thorough reconstruction. It has been used in a number of image processing applications. The combined benefits of neural networks and wavelet transform are a growing area of research. Pre-processing the signal using wavelet analysis is one approach. The signal's features are extracted using a wavelet transform; the extended feature vector is given to a neural network for further processing. After researching the connection between neural networks and wavelet transforms, Pati et al. [12] developed the concept of a discrete affine wavelet network model. Zhang et al. [13] first formally introduced the idea and algorithm of wavelet networks in 1992. Basic concept behind using wavelet functions as opposed to Sigmod functions for the activation functions is to replace neurons with wavelet elements. In the wavelet neural network (WNN), the hidden layer of the neural network is replaced by the wavelet function. Additionally, the threshold of the hidden layer, the corresponding weights from the input layer to the hidden layer. The two adaptive WNN models were then proposed by Szu et al. based on continuous wavelet transform [15]. Since there are no reconstruction issues, wavelets' orthogonality requirements are not very strict. However, despite the significant signal change, the orthogonal wavelet basis still performs reasonably well in terms of time-frequency resolution; the network can enhance the resolution scale to verify the approximation's precision. Additionally, because the function bases are orthogonal, adding or removing network nodes during the training process has no effect on the trained network weights that can significantly reduce the learning time for the network. An orthogonal multi-resolution WNN employing the orthogonal wavelet function as the activation neuron function was presented by Bhavik et al. [16]. The network consists of the wavelet functions and scale function together, the step by step learning method uses the network based on the theory of multi-resolution analysis for training.

Key intention of this paper is to review and summarize the recent research works with regard to the applications of wavelet analysis.

**Time series analysis (TSA)**

TSA is a statistical methodology that is more apt for a vital class of longitudinal research designs. At regular intervals, this type of designs usually include single subjects or research units that are measured recurrently over a greater number of observations. An example of longitudinal design is the time series analysis. Time series helps understand the change pattern over time, the underlying naturalistic process, or evaluating the consequence of a planned intervention or an unplanned intervention.

Likewise, we can use time series analysis to forecast the weather changes, which can help the meteorologists to predict everything from the next day's weather report to climate change in the future years.

TSA can be used to analyse various types of data including weather data, rainfall measurements, quarterly sales, temperature readings, draught forecasting, industry forecasts, heart rate monitoring

(ECG), stock prices, brain monitoring (EEG), interest rates, automated stock trading, etc.

The most effective technique for time series analysis is wavelet analysis (WA). The main goal of WA is to fully portray the localised and transient events that take place over a range of temporal scales. Discrete and continuous wavelet studies are two of the different types of wavelet analysis. Continuous wavelet analysis will reveal a signal's scale contents as well as their temporal variations. Discrete wavelet analysis provides the right wavelet and decomposition level to break down a series into sub-signals, which aids in guiding various time series, such as wavelet decomposition, wavelet de-noising, wavelet assisted hydrologic forecasting, and wavelet assisted complexity description.

There are two types of time series. They are:

**2.1. Discrete time series -** Data points in a discrete time series are separated by intervals of time longer than one second. It could report data infrequently or erratically (for example, once per minute). For instance, at login time and throughout any gaps where values are omitted as a result of reporting disruptions, a network that occasionally goes down or a sporadic server.

**2.2. Continuous time series -** One data point per second makes up a continuous time series. A continuous time series has a data value that corresponds to every point in time and can be shown on the X-axis of a chart because we accept and store data with a precision of up to 1 second.

**Objectives of time series analysis:**

**2.3.a. Description**

In the initial stage of the study, data are graphed and straightforward descriptive measurements are taken, such as checking for trends, seasonal changes, displaying data, etc. Outliers—those that don't seem to be consistent with the rest of the data—is made possible by a graph. It is possible to locate the points when an ascending trend sharply changed into a downward trend by plotting time series. Different models may require to be fitted to the two halves of the series when a turning point occurs.

**2.3.b. Explanation**

Remarks were noted on two or more than two variables, which made it feasible to utilise in one time series variation, explaining the dissimilarity in other series. This may cause an in-depth understanding. Multiple regression models prove beneficial in this case.

**2.3.c. Prediction**

When a time series is observed, one may wish to forecast the upcoming values of series. It is a vital task in sales of predicting and it is the investigation of industrial and economic time series. Forecasting and prediction can be used conversely.

**2.3.d. Control**

Time series are produced to track and control a manufacturing process's quality. There are different kinds of control processes. Observations are plotted on a control chart during quality control, the controller responds after reviewing the charts. A stochastic model is used to fit the series. The input process variables are then modified to maintain the process's progress once future values of the series are forecasted.

**Fourier transform (FT)**

FT is a mathematical technique; it converts a function of time, x(t), into a function of frequency, X(ω).

STFT refers to the FT of a windowed signal. Contrary to the usual FT, which provides frequency information that is averaged over the entire signal time period, a signal's frequency components fluctuate with time to provide time-localized frequency information.

**Wavelet transforms (WT)**

WT is a mathematical function that is applied in digital image processing & compression. Improving the image quality is its main purpose. Wavelets can also divide signals into time and frequency components.

WT as a decomposition of a signal to the frequency components. In signal processing, wavelet transform is one of the most widely used transforms. It is also used in pattern recognition, data compression, and more. It is also a solution to the shortcomings of the Fourier transform. Many machine learning applications use the wavelet transform as a pre-processing step.

The wavelet toolbox in Matlab includes various types of wavelets like Daubechies, Haar, Biorthogonal, Morlet, Coiflets, Symlets, Meyer wavelets and Mexican Hat.

There are two basic wavelet transforms:

4.1. Continuous Wavelet Transform (CWT) is a tool that gives complete signals. It does this through translating and scaling the wavelet parameter to vary continuously.

4.2. Discrete Wavelet Transform (DWT) is a tool which decomposes signals into sets.

Wavelets provide a wide variety of applications in several research areas, such as; for feature extraction, de-noising, compression, image watermarking, blood pressure, heart rate, ECG/EEG analysis, fingerprint verification, DNA and protein analysis, speech recognition, geophysical study like predicting drought and rainfall, etc.

**Fuzzy Inference Systems (FIS)**

FIS is one of the most noticeable applications of fuzzy logic and fuzzy sets theory. It utilises fuzzy set theory to map inputs to outputs, to visualize the outcome by prediction and the Mamdani and the Sugeno model are the types of FIS. Main factor is the rule generation and the conditions are investigated and given for rule base. FIS proposes a higher performance and a decent generalization capability to obtain optimum solutions. The rule base precision is a vital aspect and is the main benefit of using FIS. Basically, a FIS comprises of 5 functional blocks:

(i) Rule base, which consists of various fuzzy if-then rules;
(ii) Database that defines the membership functions of the fuzzy sets are used in the fuzzy rules
(iii) Decision-making unit which will perform the inference operations on the rules
(iv) Fuzzification interface that will transform the crisp inputs into degrees of match, along with linguistic values
(v) De-fuzzification interface that will transform fuzzy results of the inference into a crisp output.

**Artificial Neuro-Fuzzy Inference Systems (ANFIS):**

ANFIS is an integration system to optimize the fuzzy inference system, neural networks are applied. ANFIS will construct a series of fuzzy if–then rules along with appropriate membership functions for the production of stipulated input–output pairs. They are a class of adaptive networks and they use hybrid learning algorithm.

Except the piece-wise differentiability, there are no major functional restrictions on the node functions of the adaptive network, with the exception of piece-wise differentiability. The sole restriction for network setup when the structure is taken into account is that it must be of the feed-forward type. Because of the aforementioned limited limits, the adaptive network has numerous immediate and extensive applications.

According to a research, a fusion method of DWT along with ANN and ANFIS denoted as DWT-ANN and DWT-ANFIS was assumed to accurately forecast LAM coke price. DWT-ANFIS and DWT-ANN model was determined to be suitable model for estimating the price of LAM coke, with MAPE less than 5%.

**Discussions:**

SPI, DWT, ANFIS, SVM, ANN were used effective to forecast drought and performance enhanced when improvised with fusion models in the north-western part of Turkey [17].

Results of a study indicated that the wavelet models have projected lower extremes of time series at extended time steps ahead. It can be understood by this that droughts can be modelled using the algorithms along with the presence of stationarity concerns which is a substantial factor for India, which is a tropical country [18].

Multistage wavelet transform (WT) to forecast financial time series was presented along with discussing the effect of control parameters of particle swarm optimization (PSO) to highlight the significance in search mechanism, particularly in regression problems [19].

The aptness of ANFIS and DWT in analysing time-series data modelling of weather related parameters was examined. Plotting ANFIS data against linear regression with the help of 1-input data was the ideal values combination of output predictions [20]. When the eyes are opened and closed, a robotic hand opens and shuts using an online Brain-Machine Interface (BMI) based on Electroencephalography (EEG). In comparison to existing BMI algorithms, the provided on-line DWT's average processing time (APT), as well as the ANFIS classification, were comparatively quick, at 37.9 ms [21].

A precise algorithm to locate defects in a power cable of medium voltage, laid underground was presented using a combination of DWT and ANFIS. 5 ANFIS networks and consisting of 2 stages, along with error type classification and precise fault location was used by the proposed method [22]. To accurately estimate water quality parameters (WQPs), machine learning (ML) algorithm's performance should be improved. It is essential to precisely estimate water quality parameters (WQPs). TDS and EC are estimated with the help of a hybrid framework called the adaptive neural fuzzy inference system-discrete wavelet transform-gradient-based optimisation (ANFIS-DWT-GBO) [23].

Components of high frequency from the original signal/details of the inflow in to the Três Marias reservoir in Sao Francisco River, Brazil, were removed using the DWT. A method was tested using the reservoir's inflow records. An ANN model could anticipate inflows seven days in advance using this modified signal as input, and the error RMSE fell by more than 50% (from 454.2828 to 200.0483) [24].

Planning & management of water resource systems require appropriate drought forecasting. A hybrid wavelet and adaptive neuro-fuzzy inference system (WANFIS) was presented for forecasting drought. When the results were compared, WANFIS model showed better results than the traditional ANFIS and ARIMA models [25].

To predict chaotic time series, wherein the goal was to reduce prediction error, ANFIS was used, considering stock data as time series. Results showed that the stock price prediction performance can be greatly enhanced by using ANFIS. The prediction performance of this method showed benefits of ANFIS. It was swift, easily operable, and inexpensive. Findings validated the learning and predicting potential of ANFIS model in applications related to finance [26].

ANFIS was proposed to generate a model for long-term weather forecasting, to predict rainfall. According to the results, ANFIS model was able to seize dynamic behaviour of the rainfall data and satisfactory results were procured, so that it can be beneficial to predict rainfall in the long term [27].

ANFIS was chosen to convert Univariate data to multivariate data, because it carried advantages of both ANN and FIS. It was showed that ANFIS can foretell electricity consumption pretty well with a small MAPE of 0.4002%. [28][29][30][31].

3 hybrid models— Wavelet Packet-ARIMA-BFGS, Wavelet Packet-BFGS, and Wavelet-BFGS—were presented to forecast speed of wind in accordance with wavelet theories, time series analysis, wavelet packet, and ANN. Results indicated that the suggested three hybrid models could accurately estimate wind speed, with the Wavelet Packet-ANN model, being more accurate. [32].

Based on the meteorological data gathered from various places, a multi-model ANFIS technique was utilised to forecast time-dependent values. Results indicated that utilising average weather data as an input variable, averaging predicted values of ten repeated runs produced the finest forecast [33].

To assess the quantity of regional rainfall, a hybrid model based on ANFIS-GA was presented. Training R-value of the recommended ANFIS-GA model was 0.9920, the testing R-value was 0.9840, and the error ratio was 0.0011, according to the result. It was made abundantly clear that it indicated the model's great predictive performance and low error level. Therefore, it is simple to predict meteorological occurrences using hybrid systems like ANFIS-GA [34].

ANFIS was used to estimate the Standardised Precipitation Index (SPI). Authors created a fuzzy logic model utilising Sugeno fuzzy inference technology. For SPI-5 and SPI-6, a variety of ANFIS forecasting models were trained and evaluated. When the ANFIS model results were evaluated, it was discovered that only the models' performances that used precipitation values from an earlier time step performed worse than those of the other models. ANFIS model’s performance and evaluation revealed that, for each entity with SPI 5 and SPI 6, using solely SPI value as an input parameter and combining SPI and rainfall value as an input parameter, respectively, yielded greatest results. ANFIS models can be constructed easily, and the computation time is also comparatively less [35].

Three years' worth of hourly load data from 2005 to 2007 was combined with weather information from the same years, including temperature, wind speed, and humidity. Based on input characteristics at that time, forecasting was done for load demand for the following hour. ANFIS and ANN were combined to create a model to forecast short-term load, favouring the impact of the real-time electricity market on that quantity. The experimental assessments supported the proposed load forecasting scheme's strong practicability, accuracy, feasibility, and efficacy. The outcomes demonstrated how accurate the model was [36].

ANFIS presented a method for employing WT as a feature extraction and classification tool to find the earth fault on synchronous generators. The notion has been shown using Simulink/Matlab to validate WT and ANFIS techniques. The presented system was found to be more efficient to identify and locate the defect starting from more than 0% of the per unit length of the winding to 100% of its length based on various operating and testing simulated situations [37].

**Conclusion:**

The substantial culminating and closing points of this paper include:

(i) Properties of various wavelet bases, along with construction method is briefly summarised.

(ii) Wavelet related algorithms were also discussed.

(iii) As the neural networks develop, the wavelet analysis and neural networks has combination also succeeded. The Combination of WNN, the signal of which is pre-processed is one of the advantages of ANN and WT.

(iv) Wavelet Analysis has an extensive array of applications in signal processing, in terms of de-noising, enhancement, classification and compression.

Thus, time series wavelet analysis have applications for meteorological and medical data.

**References:**

1. L. Cohen, Time-Frequency Analysis. Upper Saddle River, NJ, USA: Prentice-Hall, 1995
2. R. N. Czerwinski and D. L. Jones, ‘‘Adaptive short-time Fourier analysis,’’ IEEE Signal Process. Lett. Vol. 1997. 4(2). pp. 42–45.
3. J. Lei Y. Meyer and R. Ryan, ‘‘Wavelets: Algorithms & applications’’ Math. Comput. 1994. Vol. 63. p. 822.
4. S. G. Mallat, ‘‘A theory for multiresolution signal decomposition: The wavelet representation,’’ IEEE Trans. Pattern Anal. Mach. Intell. 1989. Vol. 11(7). pp. 674–693.
5. A. K. Soman and P. P. Vaidyanathan, ‘‘Paraunitary filter banks and wavelet packets,’’ in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP). 1992. Vol. 4. pp. 397–400.
6. H. Zou and A. H. Tewfik, ‘‘Discrete orthogonal M-band wavelet decompositions,’’ in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process. (ICASSP). 1992. pp. 605–608.
7. T. Goodman and S. L. Lee, ‘‘Wavelets of multiplicity r,’’ Trans. Amer. Math. Soc. 1994. Vol. 342(1). pp. 307–324.

8. J. S. Geronimo, et.al., ‘‘Fractal functions and wavelet expansions based on several scaling functions,’’ J. Approximation Theory. 1994. Vol. 78(3). pp. 373–401.
9. W. Swedens, ‘‘The lifting scheme: A new philosophy in bi-orthogonal wavelet constructions,’’ Proc. SPIE, 1995. Vol. 2569, pp. 68–79.
10. J. Ma and G. Plonka, ‘‘The curvelet transform,’’ IEEE Signal Process. Mag. 2010. Vol. 27(2). pp. 118–133.
11. N. Kingsbury, “The dual-tree complex wavelet transform: A new efficient tool for image restoration and enhancement,” in Proc. 9th Eur. Signal Process. Conf. (EUSIPCO). 1998. pp. 1–4
12. Y. C. Pati and P. S. Krishnaprasad, ‘‘Analysis and synthesis of feedforward neural networks using discrete affine wavelet transformations,’’ IEEE Trans. Neural Netw. 1993. Vol. 4(1). pp. 73–85.
13. Q. Zhang and A. Benveniste, “Wavelet networks”, IEEE Trans. Neural Netw. 1992. Vol. 3(6). pp. 889–898.
14. Z. Zhang, Y. Shi, H. Toda, and T. Akiduki, “A study of a new wavelet neural network for deep learning”, in Proc. Int. Conf. Wavelet Anal. Pattern Recognit. (ICWAPR). 2017. pp. 127–131.
15. H. H. Szu, “Neural network adaptive wavelets for signal representation and classification”, Opt. Eng., 1992. Vol. 31(9). Pp- 1907.
16. B. R. Bakshi and G. Stephanopoulos, “Wave-Net: A multiresolution, hierarchical neural network with localized learning”, AIChE J., 1993. Vol. 39(1). pp. 57–81.
17. Emine Dilek Taylan, et. al., “Hybrid wavelet–artiBcial intelligence models in meteorological drought estimation”, Journal of Earth System Science. 2021. Vol. 130(38).
18. L. Karthikeyan, D. Nagesh Kumar, “Predictability of non-stationary time series using wavelet and EMD based ARMA models”, Journal of Hydrology. 2013. Vol. 502. Pp-103–119.
19. P. Syamala Rao, et. al., “Financial time series forecasting using optimized multistage wavelet regression approach”, Int. j. inf. tecnol. 2022. Vol. 14(4). Pp-2231–224.
20. Devi Munandar, “Wavelet discrete transform, ANFIS and linear regression for short-term time series prediction of air temperature”, International Journal of Advances in Intelligent Informatics. 2017. Vol. 3(2). pp- 68-80.
21. Eduardo Lopez-Arce Vivas, et. al., “Discrete Wavelet transform and ANFIS classifier for Brain-Machine Interface based on EEG”, Conference proceedings. 2013.
22. Shimaa Barakat, et. al., “Fault location in underground cables using ANFIS nets and discrete wavelet transform”, Journal of Electrical Systems and Information Technology. 2014. Pp-198–211.
23. Mojtaba Kadkhodazadeh and Saeed Farzin, “A novel hybrid framework based on the ANFIS, discrete wavelet transform, and optimization algorithm for the estimation of water quality parameters”, Journal of Water and Climate Change. Vol. 13(8). Pp- 2940.
24. Celso A. G. Santos, et. al., “Discrete wavelet transform coupled with ANN for daily discharge forecasting into Três Marias reservoir”, Evolving Water Resources Systems: Understanding, Predicting and Managing Water–Society Interactions Proceedings of ICWRS2014. 2014. Vol. 364.
25. Ani Shabri, “A Hybrid Wavelet Analysis and Adaptive Neuro-Fuzzy Inference System for Drought Forecasting”, Applied Mathematical Sciences. 2014. Vol. 8(139). Pp-6909 – 6918.
26. Jin Xue-bo, et. al., “ANFIS model for time series prediction”, Applied Mechanics and Materials. 2013.
27. Nazim Osman Bushara and Ajith Abraham, “Using Adaptive Neuro-Fuzzy Inference System (ANFIS) to Improve the Long-term Rainfall Forecasting”, Journal of Network and Innovative Computing. 2015. Vol. 3 Pp- 146-158
28. Y. W. Lee, K. G. Tay & Y. Y. Choy, Forecasting Electricity Consumption Using Time Series Model. International Journal of Engineering and Technology. 2018. Vol. 7(4). Pp- 218-223.
29. K. G. Tay, Y. Y. Choy, & C. Y. Chew, Forecasting Electricity Consumption Using Fuzzy Time Series. International Journal of Engineering and Technology. 2018. Vol. 7(4). Pp- 342-346.
30. K. G. Tay, Y. Y. Choy, & A. Huong, Forecasting Electricity Consumption Using Multiple Linear Regression. International Journal of Engineering and Technology. 2018. Vol. 7(4). Pp-3515-3520.
31. K. G. Tay, et. al., “Electricity Consumption Forecasting Using Adaptive Neuro-Fuzzy Inference System (ANFIS)”, Universal Journal of Electrical and Electronic Engineering. 2019. Vol. 6(5B): Pp-37-48.
32. Hui Liu et. al., “Forecasting models for wind speed using wavelet, wavelet packet, time series and Artificial Neural Networks”, Applied Energy. 2013. Vol.107. Pp- 191–208.
33. Donghui Shi, et. al., “A Fuzzy Neural Approach with Multiple Models to Time Dependent Short Term Power Load Forecasting Based on Weather”, International Journal of Multimedia

and Ubiquitous Engineering. 2017. Vol. 12(1). Pp-1-16.

34. M. Hanefi CALP, "A Hybrid ANFIS-GA Approach for Estimation of Regional Rainfall Amount", J Sci. 2019. Vol. 32(1). Pp- 145-162.
35. Fenil R. Gandhi and Jayantilal N. Patel, "Combined Standardized Precipitation Index and ANFIS Approach for Predicting Rainfall in the Tropical Savanna Region". Journal of Soft Computing in Civil Engineering. 2022. Vol. 6(3). Pp- 63-77.
36. J. P. Rothe et. al., "Artificial Neural Network and ANFIS Based Short Term Load Forecasting in Real Time Electrical Load Environment", International Journal of Current Engineering and Technology. 2014. Vol. 4(3).
37. Amany. H. Helal, et. al., Locating Earth Fault of Synchronous Generator using Wavelet Transform and ANFIS. Journal of Advanced Research Design. 2018. Vol. 49(1). Pp- 1-6.