Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7657218

SUGENO FUZZY LOGIC-BASED DATA AGGLOMERATION MODEL FOR SMART AQUACULTURE DEVELOPMENT

G. Shahana[1], P.Ezhilarasi[2] AND S. Rajesh Kannan[3]
[1]Department of Electronics and Communication Engineering, St. Joseph's College Engineering, Tamil Nadu, India
[2]Department of Electronics and Communication Engineering, St. Joseph's College Engineering, Tamil Nadu, India
[3]Department of Electronics and Communication Engineering, St. Joseph's College Engineering, Tamil Nadu, India

ABSTRACT
In this research, a data agglomeration model for smart aquaculture system has been developed and validated using a sugeno fuzzy based machine learning approach. In order to increase production, machine learning (ML) techniques are employed in fisheries and aquaculture to detect and monitor a variety of environmental parameters, including temperature, salinity, dissolved oxygen, and other factors. In the era of developing technology, these metrics are gathered utilizing sensor-based network systems. The input from various sensors must thus be extracted and combined in the cluster head using sophisticated machine learning techniques such as neural networks, mamdani fuzzy system, sugeno fuzzy system etc. to provide more accurate information. Trapezoidal membership functions are used for defining input variables, such as pollution, organic carbon, salinity, dissolved oxygen and pH. In this, triangular membership function is used for defining the output variable (Aggregation). The input values are aggregated using the logical AND operator, truncation implication, weighted average defuzzification, and 1875 fuzzy rules. This model assigns a grade of poor, good, very good, or excellent (on a scale of 1 to 4), depending on the aggregate area of each aqua site in the datasets. The performance of the sugeno model is validated by aquaculture experts classifying the same datasets. The result shows that 96 % of the outputs of the created fuzzy model accord with the conclusions of the aquaculture expert and also it respond to complete aggregate value range, [1-4]. The results show that the sugeno fuzzy based data aggregation model improves the accuracy and reliability of sensed data for the development of smart aquaculture by the planners and decision makers.
Keywords: Machine Learning; Sugeno fuzzy inference system; data aggregation model; aquaculture.

1. INTRODUCTION
Research in agriculture, fisheries, and aquaculture has evolved as a result of the introduction of machine learning (ML). In order to increase production, ML approaches are used in fisheries and allied sectors to measure and track a variety of environmental parameters, such as soil moisture, temperature, pH, water salinity, dissolved oxygen, and so forth. Increasing total crop yield is the aim of fisheries/aquaculture sensor network system. Numerous soil, water, and environmental parameters may be measured with the use of sensors, which can increase

productivity. The sensor may gather information on a range of traits and then analyze the information to enhance farming.

In the era of new technologies, sensor networks areused to collect the dynamic natural factors influencing cultural activities. Finding methods to enhance the sensor network system's information flow will be essential for enhancing its processing capabilities. To improve communication activity, sophisticated machine learning approaches such as neural networks, deep learning, sugeno fuzzy inference system (SFIS)and mamdani fuzzy inference system (MFIS)are needed for the data aggregation process in the cluster head. This has been demonstrated to be useful for tracking rapid changes in environmental factors, particularly in aqua/fish ponds.

Moreover ML techniques like mamdani FIS (Malboget.al., 2020; Alomar and Alazzam, 2018; Kuanr et.al., 2018; Nithiya and Annapurani, 2021; Mahalakshmi and Ganesan, 2015; and Shahana et.al., 2020) sugeno FIS (Cavallaro, 2015; Yulianto, et.al., 2017; and Limbong, 2020) are increasingly used in fisheries, aquaculture and agriculture, however, has not yet gotten its share of dynamic factors and real-time data. Additionally, research demonstrating the growth of data aggregation models utilising Sugeno FIS are seldom ever seen in the aquaculture industries. In this backdrop, we developed and evaluated a data aggregation model using sugeno fuzzy logic for the growth of smart aquaculture system. The proposed model also improves the accuracy and reliability of sensed data for the development of smart aquaculture by the planners and decision makers.

2. PROPOSED FUZZY BASED DATA AGGREGATION MODEL

The experts used language variables like moderately suitable1 (MS1), unsuitable1 (US1), moderately suitable2 (MS2), unsuitable2 (US2) or suitable (S) to represent the antecedent in the developed fuzzy model, while the consequent part was stated as a constant (zero order). In order to create this model, a Sugeno inference system was applied. Figure 1 represents the proposed model.

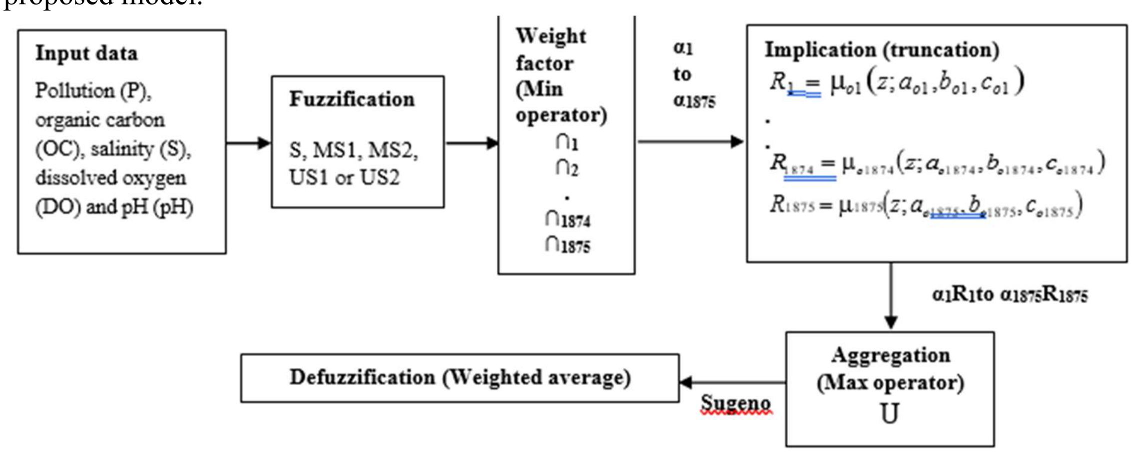


Figure 1.Diagrammatic representation of fuzzy based data aggregation model

2.1 Variables and Datasets

Five variables, including pollution (P), organic carbon (OC), salinity (S), dissolved oxygen (DO) and pH (pH) were chosen after consulting with aquaculture specialists and reviewing the literature (CIBA, 2019; Mahalakshmi and Ganesan, 2009). According to the opinions of aquaculture specialists, modest modifications were made to meet the Indian environment while determining the appropriateness ratings, which included acceptable, moderately acceptable, and not acceptable, for the specified factors. Table 1 lists the variables that were found and their appropriateness ratings. 25 aqua ponds/sites in Andhra Pradesh and Tamil Nadu with sensor-based data collecting systems were used for this study to gather data on P, OC, S, DO and pH.

Table 1. Variables and its suitability range and used sensors

Variables	Range			Sensors
	Acceptable	Moderately acceptable	Not acceptable	
pH (ppt)	[6.5, 8.5]	(5, 6.5) or (8.5, 10)	≤ 5.0 or ≥ 10.0	TCS 3020 (Sensorox)
Dissolved Oxygen (mg/litre)	[5, 10]	(2, 5) or (10, 15)	≤ 2 or ≥ 15	DO6400 (Sensorox)
Salinity	[15, 25]	(5, 15) or (25, 35)	≤ 5 or ≥ 35	S272 pH (Sensorox)
Organic carbon (%)	[1.5, 2]	(0.5, 1.5) or (2, 2.5)	≤ 0.5 or > 2.5	4000 TOCe (Proteus)
Pollution (m)	>3500	(2000,4000)	<2500	Distance measurement

2.2. Membership Functions and Fuzzy Rule Base

In order to aggregate the variables in the aquaculture system, the fuzzy model used five inputs and one output. With the exception of pollution, which is represented by moderately suitable (MS), unsuitable (US) and suitable (S) (Table 2b), input variables, denoted by X, were divided into five linguistic variables: moderately suitable1 (MS1), unsuitable1 (US1), moderately suitable2 (MS2), unsuitable2 (US2) or suitable (S) (Table 2a). The output variables, designated by Z, are assigned values of 4, 3, 2 and 1 for excellent (E), very good (VG), good (G) and poor (P) respectively. The ranges of the triangular and trapezoidal MFs for the input and output variables, respectively, were chosen based on the expertise and experience of experts (Pedrycz, 2001).

Table 2a.Linguistic variables for pH, Dissolved oxygen, Salinity, Organic carbon

Variables	Suitable (S)	Unsuitable1 (US1)	Usuitable2 (US2)	Moderately suitable1 (MS1)	Moderately suitable2 (MS2)
pH	6 < 7 < 8 < 9	4.5 < 5.5	9.5 < 10.5	4.5 < 5.5 < 6 <7	8 < 9 < 9.5 < 10.5
Dissolved oxygen (DO)	4.5 < 5.5 < 9.5 < 10.5	1.5 < 2.5	14.5 < 15.5	1.5 < 2.5 < 14.5 < 15.5	9.5 < 10.5 < 1 4.5 < 15.5
Salinity (S)	13.5 < 16 < 23.5 < 26	3.5 < 6	33.5 < 35.5	3.5 < 6 < 13.5 < 16	23.5 < 26 < 33.5 < 36
Organic carbon (OC)	1 < 1.5 < 1.5 < 2.5	0 < 1	2 < 2.5	0.5 < 1 < 1 < 2	1.5 < 2 < 2 < 3

Table 2b.Linguistic variables for pollution

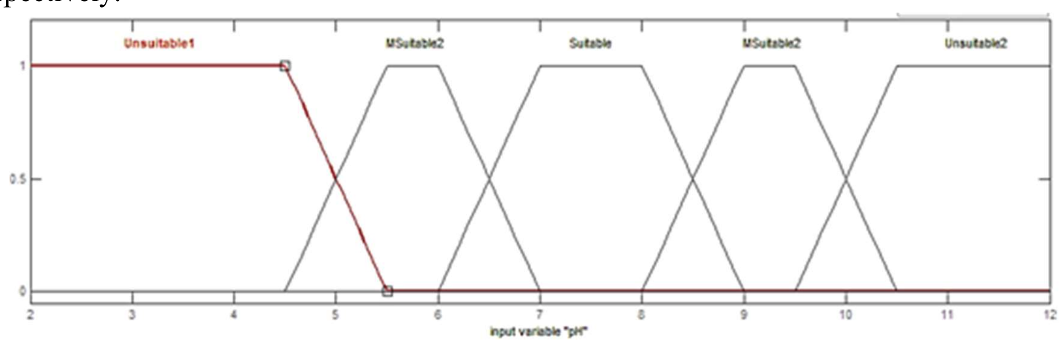
Variables	Suitable (S)	Unsuitable (US)	Moderately Suitable (MS)
Pollution	3500<4000	2000<2500	2000<2500<3500<4000

According to Center and Verma (1998), the order of significance of the variables and their cause and effect relationships were extensively examined with the experts before the criteria for this study were created using an indirect technique. The logical AND operator is used to formulate 5^4 X 3^1 =1875 fuzzy rules. Rule can be represented as if (pH is μ_{ij}) and (DO is μ_{ij}) and (S is μ_{ij}) and (OC is μ_{ij}) and (P is μ_{ij}) then

$R_k = \mu_{ok}(z; a_{ok}, b_{ok}, c_{ok})$ for k = 1, 2, 3,…., 1875 where μ_{ij} is the j^{th} MF of the i^{th} input; μ_{ok} is the k^{th} output MF; R_k is the output of the k^{th} rule; shapes of the output MFs are represented by a_{ok}, b_{ok}, c_{ok}.

2.3. Fuzzification of Input Values

In this phase, input membership functions changes crisp values into fuzzy values. The MF of each class in the input variables overlapped with surrounding classes as a result of decisions being spread across a large number of input classes (Figures 2). Output variables are represented as constants, such as 4, 3, 2, and 1for excellent, very good, good, and poor respectively.



Figures 2.Membership function for 'pH'

2.4. Weight Factor Calculation

The input values were first transformed into fuzzy membership values using the input MFs from the fuzzification stage, and then these membership values were combined using the "AND" operator to create the weighting factor for each rule (α_k). The minimal input membership value corresponds to the "AND" operator. The weighting factor was represented as $\alpha_k = \min_k (\mu_{ij}(pH), \mu_{ij}(DO), \mu_{ij}(S), \mu_{ij}(OC), \mu_{ij}(P))$

k = 1, 2,…., 1875

2.5. Implication and Aggregation

This model shapes the output fuzzy set using the truncation method, which is one of the most common implication methodin the applications (Kim et al., 2001).This was calculated by $\mu_{imp,k} = \min_k (\alpha_k R_k)$ k = 1, 2,…., 1875. Decisions are dependent on the results of testing all of the rules in the model; hence rules must be aggregated in order to make them. The process of aggregation involves combining the truncated output functions into a fuzzy set that representsas output variable.In this model, maximum operator was used for the aggregation process, $\mu_o(k) = \max_k (\mu_{imp,k})$ k = 1,2,….,1875.

2.6. Defuzzification

The weighted average and centre of gravity (COG) methods are the two defuzzification techniques that are most frequently employed in real-time applications than other defuzzification techniques viz.,Centre of biggest area, middle of maxima, first of maxima, and Centre of sums (Kim et al., 2001). In this model, aggregated area was developed using the weighted average method. The computed area provides the aquaculture system's range of aggregation values.

2.7. Validation of the Proposed Model

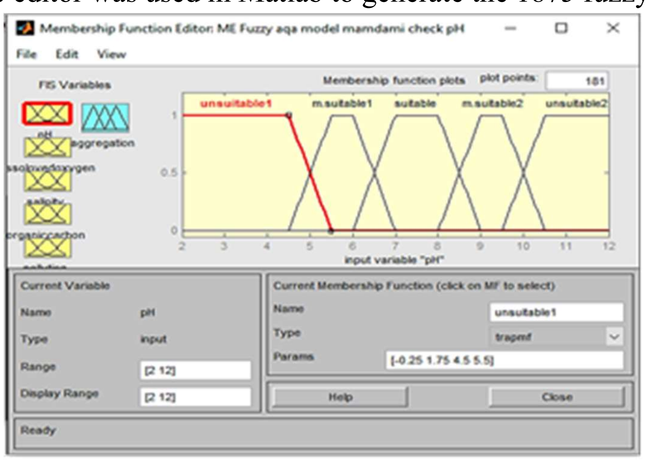
The dataset from 25 aqua ponds/sites was first classified using the computed aggregated area using the developed fuzzy model, and then by an aquaculture specialist for the fuzzy model's validation. Numbers were used to convey the model outputs and expert commentary, and a classification accuracy calculation was made (Lorestani et al., 2006)

$$Accuracy = \frac{n}{N} \times 100$$

Where, n is the number of sites properly categorized by the model and N is the total number of sites evaluated for validation.

3. IMPLEMENTATION OF THE MODEL AND ITS RESULTS

The proposed Sugeno model was implemented in MATLAB (Version R13.a) in which implication phase uses MIN operator and aggregation phase uses MAX operator. Membership functions for each input and output variables were built with membership function editor (Figures 3). The rule editor was used in Matlab to generate the 1875 fuzzy if-then rules.



Figures 3. Example membership function editor toolbox for ‘pH’ input variable

The Sugeno model's working mechanism can be presented via a numerical example illustration with input variables such as pH = 8.16, DO = 2.66, S = 6.97, OC=0.93, and P= 3667.The following fuzzy inputs are generated by Fuzzification step.

Input 1: Membership degree is 0.6 when pH is suitable

Membership degree is 0.3 when pH is moderately suitable 1

Input 2: Membership degree is 1 when Dissolved oxygen is moderately suitable 1 Input 3: Membership degree is 1 when Salinity is moderately suitable 1

Input 4: Membership degree is 0.1 when Organic carbon is unsuitable 1 Membership degree is 0.9 when Organic carbon is moderatelysuitable1

Input 5: Membership degree is0.55 when Pollution is moderately suitable

Membership degree is 0.4 when Pollution is suitable

The necessary weights factor calculation procedures were then activated by the suggested model using the fuzzified inputs. The weights factor was calculated based on the activation rules of 101,95,100,94,851,845,850,844. Based on the weight factor using the MIN operator each rule's fuzzy output was created and using the MAX operator combined into a single fuzzy output as MAX (0.1,0.6,0.1,0.4,0.1,0.3,0.1,0.3).

Finally, in the proposed model the weighted average defuzzification approach was applied for creating an aggregated crisp output value (2.11)(Figure 4). So, its corresponding linguistic value is good. The model performed equivalent steps for all the input values in the dataset (Table 3).The validity of the fuzzy model's output was assessed by comparing the findings of the fuzzy model and aquaculture expert using the test dataset (Table 3).

Figure 4.Sugeno Fuzzy model output

Table 3.Sugeno fuzzy model and aquaculture expert output for the test dataset

Sites or aqua ponds	Input (dataset)					Aggregated area value in sugeno model	Categorization by	
	pH	Dissolved oxygen	Salinity	Organic carbon	Pollution		Sugeno model	Expert
S1	7.73	7.77	5.81	2.08	3988	3.25	VG	VG
S2	8.16	2.66	6.96	0.93	3667	2.11	G	G
S3	7.66	4.86	34.97	1	3496	2.13	G	G
S4	7.94	10.47	30.65	0.96	3970	2.15	G	G
S5	7.89	11.8	3.52	2.83	4074	2.14	G	G

S6	6.93	1.18	18.6	2.75	3163	1	P	P
S7	7.67	15.58	34.67	2.24	2293	1	P	P
S8	5.33	5.72	22.4	1.48	4592	3.49	VG	VG
S9	6.3	5.6	29.38	1.93	3600	3.11	VG	VG
S10	6.73	5.43	17.93	2.19	4941	3.45	VG	VG
S11	6.09	4.18	34.67	1.537	3651	2.14	G	G
S12	5.95	13.8	29.1	1.69	3785	3	VG	VG
S13	6.41	15.4	11.2	1.5	3900	1.19	P	P
S14	7.76	7.34	22	2.8	2345	2.02	G	P
S15	9.32	6.7	5.6	2.4	3710	2.26	G	G
S16	9.44	3.43	15.9	1.6	3995	3	VG	VG
S17	10.1	3.2	5.79	1.52	1910	1.22	P	P
S18	9.17	11.7	10.43	2.42	3655	2.44	G	G
S19	9.48	1.88	25.85	0.4	2480	1.36	P	P
S20	9.57	15.69	11.73	1.4	1963	1	P	P
S21	4.68	2.64	7.2	4	2975	1.18	P	P
S22	3.84	4.5	3.49	2.1	2535	1	P	P
S23	3.81	14.68	36.4	3.7	2105	1	P	P
S24	5.65	6.72	22.4	1.48	4592	4	E	E
S25	9.73	14.1	7	1	3895	2.54	G	G
Accuracy = (24/25)*100 = 96 %								

Accuracy = (24/25)*100 = 96 %

*P-Poor; G- Good; VG- Very Good; E-Excellent

According to the results in Table 3, the fuzzy model accurately categorized 24 of the 25 aqua sites. This demonstrates that the fuzzy model's categorization findings were 96 percent in accord with the aquaculture expert's results. Mazloumzadeh et al., (2010) describes that the degree of agreement between the proposed model and the expert is seldom 100 %, because input variables are defined as class of membership degrees in the fuzzy logic.

4. CONCLUSION

In this study, a data aggregation model was created and validated using a sugeno fuzzy based machine learning approach for the creation of a smart aquaculture system to minimize traffic and improve sensor network efficiency. Sugeno fuzzy based ML model performs well in aquaculture systems based on the performance of the complete range of aggregation values [1-4] and data processing accuracy. The fuzzy model developed in this work will efficiently be combined with an adaptive neuro fuzzy system that will track salinity, temperature, water depth, alkalinity, hardness, and other essential characteristics transmitted by sensor nodes placed in a field in order to regulate cultivation practices. The suggested models offer resources that will aid in the creation of an adaptive neuro fuzzy model for the growth of aquaculture farming techniques by planners and decision-makers.

5. REFERENCES

1. B. Alomar and A. Alazzam, (2018) "A Smart Irrigation System Using IoT and Fuzzy Logic Controller," The Fifth HCT Information Technology Trends (ITT 2018), pp. 175-179, 2018.
2. F. Cavallaro(2015) "A Takagi-Sugeno Fuzzy Inference System for Developing a Sustainability Index of Biomass," Sustainability, vol. 7, pp. 12359-12371, 2015.
3. B. Center and B. Verma, (1998) "Fuzzy logic for biological and agricultural systems," Artificial Intelligence Review, Vol. 12, pp. 213–225, 1998.
4. CIBA (2019) "Recent advances in soil and water management in brackishwater aquaculture CIBA TM- series No. 10," Central Institute of Brackishwater Aquaculture, pp. 136 2019.
5. S. Kim, K. Kim, et.al (2001) "Application of Fuzzy Logic to Vehicle Classification Algorithm in Loop/Piezo-Sensor Fusion Systems," Asian Journal of Control, Vol. 3, No.1, pp. 64-68, 2001.
6. M. Kuanr, B. KesariRath et.al (2018), "Crop Recommender System for the Farmers using Mamdani Fuzzy Inference Model. Int. J. Eng. Technol. Vol. 7, pp. 277-280, 2018.
7. T. Limbong, P. Siagian et.al (2020), "Implementation of the sugeno fuzzy logic method in identifying the quality of coffee beans," IOP Conference Series: Materials Science and Engineering, vol. 725, pp. 1-9, 2020.
8. A.N. Lorestani, M. Omid et.al (2006), Design and Evaluation of a Fuzzy Logic Based Decision Support System for Grading of Golden Delicious Apples,"International Journal of Agriculture and Biology, Vol. 8, pp. 440-444, 2006.
9. P. Mahalakshmi and K. Ganesan, (2009) "Mahalanobis Taguchi System based criteria selection for shrimp aquaculture development," Computers and electronics in agriculture, Vol 65 (2), pp. 192-197, 2009
10. P. Mahalakshmi and K. Ganesan, (2015) "Mamdani fuzzy rule based model to classify sites for aquaculture development,"Indian J. Fish., vol. 62 (1), pp. 110-115, 2015.
11. M.A.F. Malbog, J.A.B. Susa, et.al (2020) "A Fuzzy Rule-Based Approach for Automatic Irrigation System through Controlled Soil Moisture Measurement," Int. J. Adv. Trends Comput. Sci. Eng., vol. 9(2), pp. 2332-2337, 2020.
12. S.M. Mazloumzadeh, M. Shamsi, et.al (2010) "Fuzzy logic to classify date palm trees based on some physical properties related to precision agriculture," Precision Agric., vol. 11(3), pp. 258–273, 2010.
13. S. Nithiya and K. Annapurani (2021)"Optimisedfertiliser suggestion in smart agriculture system based on fuzzy inference rule,"ActaAgricScand B Soil Plant Sci, vol. 71(3), pp. 191-201, 2021.
14. W. Pedrycz,(2001) "Fuzzy equalization in the construction of fuzzy sets,"Fuzzy Sets and Systems, Vol. 119, pp. 329-335, 2001.
15. G. Shahana, V. Deepthi and I.J Stella,"Fuzzy Based Data Conglomeration Model In Multi Sensor For Optimizing Aquafarm,"Int. j. math. comput. appl. res. Vol. 10(2), pp. 69-78, 2020.

16. T. Yulianto, S. Komariyah, et.al (2017)“Application of Fuzzy Inference System by Sugeno Method on Estimating of Salt Production,”International Conference on Mathematics: Pure, Applied and Computation, pp. 020039-1–020039-7, 2017.
17. Danthala, S. W. E. T. H. A., et al. "Robotic manipulator control by using machine learning algorithms: A review." International Journal of Mechanical and Production Engineering Research and Development 8.5 (2018): 305-310.
18. Dehalwar, K. A. V. I. T. A., and J. A. G. D. I. S. H. Singh. "Current State of Water Management System: Case Review of Bhopal, Madhya Pradesh." International Journal of Civil, Structural, Environmental and Infrastructure Engineering Research and Development (IJCSEIERD) 5.6 (2015): 35-40.
19. Hedau, Abhishek L., and S. S. Sanghai. "Development of trip generation model using activity based approach." International Journal of Civil, Structural, Environmental and Infrastructure Engineering Research and Development 4.3 (2014): 61-78.
20. Aryawan, W. A., and T. E. Putranto. "The Hydrodynamics Performance of Aquaculture Fishing Vessel in Variation of Deadrise Angle and Sponson." International Journal of Mechanical and Production 8.2 (2018): 263-272.
21. Malagi, Ravindra R., Sanjeevkumar R. Chougula, and Ravira J. Shetty. "Prediction of cutting force in turning of Ti-6Al-4V under minimum quantity lubrication (MQL) using response surface model and fuzzy logic model." Int. J. Mech. Prod. Eng. Res. Dev 8 (2018): 263-274.
22. Hemachandra, S., and R. V. S. Satyanarayana. "Co-active neuro-fuzzy inference system for prediction of electric load." International Journal of Electrical and Electronics Engineering Research 3.2 (2013): 217-222.