COMPUTATIONAL INTELLIGENCE AND MACHINE LEARNING
e-ISSN: 2582-7464
Computational Intelligence and Machine Learning
Vol-1, Issue-1, August 2020

Collaborative Fuzzy Clustering Mechanism & Data Driven Fuzzy Neural System

Rudra Bhanu Satpathy[1]*, Siddth Kumar Chhajer[2]

[1] M.Tech, Electrical, Electronics and Communications Engineering, St. Peter's University, Chennai, Tamil Nadu, India.
[2] MBA,Marketing, St. Peter's University, Chennai, Tamil Nadu, India.
*Corresponding Author Email: [1] rudra@gmail.com

Abstract

In this Research, Fuzzy Logic guideline move system for self-developing Fuzzy neural deduction systems is anticipated. Highlights of proposed strategy, named (CFCM-DDNFS) Collaborative Fuzzy Clustering Mechanism & Data Driven Fuzzy Neural System mechanism were; (1) Fuzzy guidelines are produced simply by Fuzzy c-means (FCM) and afterward adjusted by the (PCFC)preprocessed synergistic Fuzzy clustering method, and (2) Boundary &Structured learning are accomplished at the same time without choosing the underlying boundaries. The CFCM-DDNFS could implemented to manage enormous information issues by the goodness of the PCFC method, which is fit for managing colossal data-sets while saving the protection and security of data-sets. At first, the whole data-set is composed into two individual data-sets for the PCFC system, where each of the data-set is bunched independently. The information on model factors (bunch focuses) and the lattice of only one divide of data-set across synergistic strategy are sent. CFCM-DDNFS can accomplish consistency within the sight of aggregate information on the PCFC and lift the framework demonstrating procedure by boundary learning capacity of oneself developing neural Fuzzy induction systems (SONFIN). Proposed strategy beats existing strategies for time arrangement forecast issues.

Keywords

Big Data, Collaborative strategy, Fuzzy system, Neural network, On-line learning framework, Privacy & security, Time arrangement expectation.

INTRODUCTION

"Neural systems & Fuzzy frameworks([1], 1996) are two significant innovations which assume an essential job towards acknowledgment of AI and man-made consciousness" ([2], 1994). The combination of Fuzzy deduction frameworks (FISs) and counterfeit neural systems (ANNs) has been broadly sought after by numerous analysts because of the imperative of versatile insightful frameworks for taking care of certifiable issues. The coordinated innovation, called neural Fuzzy strategy, has been applied every now and again in numerous controls identified with building. "Subsequently, numerous scientists have concentrated on framework demonstrating by utilizing neural Fuzzy procedures([3], 1997) ([4], 1996) ([5], 1995), in light of the fact that it has the benefits of both neural systems & Fuzzy frameworks". In addition, configuration distinguishing proof and boundary learning of Fuzzy neural systems help beating the lack of ability of Fuzzy frameworks with boundary learning and neural systems incapable to do understanding of socialawareness. "In Fuzzy neural frameworks, a few information driven methodologies to produce fitting quantities of Fuzzy principles have been presented"([6], 1994) ([7], 1995) ([8], 1995).

"Rong &Sundarajan ([9], 1995) proposed a consecutive versatile Fuzzy deduction framework (SAFIS) in light of the utilitarian identicalness between an outspread premise work arrange and FIS"(Fuzzy inferencesystem). If there's no admittance to Fuzzy trendy by input information, at that point just the limits of the nearest precept are refreshed through using an all-encompassing Kalman channel (EKF) conspire. Dovzan & Skrjan([10], 2011)"anticipated an online TSKtype Fuzzy ideal thatcould be utilized for displaying control framework or mechanical autonomy by blend of a recursive Fuzzy c-means and minimumplaces". This strategy desires more computational expense than the SAFIS due to the Fuzzy covariance framework. "Nonetheless, memory necessities are fixed because of in-elastic digit of groups. Lee &Wang([11], 2002)recommended a self-adaptive neuroFuzzy induction system" (SANFIS), that's satisfactory aimed at self-adjusting and self-sorting out its confined structure to acquire an efficient guideline base for delineating the inward structure from input preparing data-set of the framework. A web established sliding-window-based self-sorting out Fuzzy neural system (SOFNN) was recommended by Leng & Prasad([12], 2004), which is appropriate for AI and furthermore it is relevant for intellectual thinking in shrewd home condition. Er Jr.& Wu([13], 2002)suggested a learning calculation for dynamic Fuzzy neural systems (DFNN) in light of broadened outspread premise work (RBF) neural systems. The highlights of DFNN methodology develop around allowed boundaries that could be balanced and configuration learning instrument related with self-versatile activity over a trimming method.

Fuzzy neural network (FNNs) have 02 groups. Primary group is Fuzzy frameworks with self-tuning capacity yet needs instatement of the quantity of Fuzzy standards. 2nd group of neural Fuzzy systems is capacity to progressively decide Fuzzy rules from given data-set. Be that as it may, the greater part of the current Fuzzy neural frameworks stood up to certain issues, for example, from the earlier calculation to decide the quantity of bunches, conflicting standard base and heuristically characterized hub tasks. Thinking about all lacks, a Fuzzy Logic guideline move instrument for self-developing neural Fuzzy derivation systems, where move Fuzzy principle is utilized as anauxiliary for standard age methodology with which SONFIN is anticipated in the investigation. Proposed strategy advances our learning procedure as well as gives a steady and great exhibition. So as to exhibit the plausibility and adequacy of the proposed technique, a few models, including Mackey Glass time arrangement expectation issue & non-linear unique framework, are utilized to decide the system's presentation. Trial results show that the proposed technique beats different strategies on given arrangements of benchmark information with relatively less rules.

METHODOLOGY:

Self Constructing Neural Fuzzy Inference Networks:

SONFIN (Self constructive neural Fuzzy derivation systems) ([14], 1998) was propositioned by Juang & Lin, that'simplemented to different applications([19], 2013) ([21], 2004) ([24], 2005). The SONFIN consistently brings a successful system structure and accelerates the learning procedure with very much characterized demonstrating capacity contrasted with regular neural systems.

The SONFIN comprises of various layers, every one has a limited fan-in of associations whichis spoken to through weight esteems after different hubs and fan-out of associations with different hubs. The capacity gives the net contribution to hub is meant as follows:

$$net\text{-}input = f[u_1^k, u_2^k, \ldots\ldots\ldots, u_n^k, \ldots.. w_1^k, w_2^k \ldots\ldots\ldots w_n^k] \quad (1)$$

Where u_1^k, u_2^k... u_n^k are inputs to the node and w_1^k, w_2^k ....w_n^k are weights of connected links. The $k$super-script shows amount of layer.

The given output activation function value of each node of its net input is given by:

$$Output = o_i^k = a(net\text{-}input) = a(f) \quad (2)$$

Here a(.) means the function of Activation. Elements of hubs in every one of 05 layers of SONFIN organization are quickly portrayed below:

Layer1: No calculation is acted here, information esteems were legitimately transmitted to following layer.

$$f = u_i^1 \,\&\, a^1 = f \quad (3)$$

Layer2: By means of Gaussian enrollment work yield of 1st layer is determined by:

$$f[u_{ij}^2] = -\frac{[u_{ij}{}^2-\mu_{ij}]^2}{\sigma_{ij}{}^2} \text{ and } a^2 = e^f \quad (4)$$

where μ_{ij} is mean &σ_{ij} is the difference of Gaussian participation capacity of i^{th} input variable u_{ij} for j^{th}division.

Layer3:1 Fuzzy rationale regulation is spoken to by hub in this layer and it plays out a pre-condition coordinating of standard with AND activity by:

$$f[u_i^3] = \prod_{i=1}^{n} u_i{}^3 \text{ and } a^3 = f \quad (5)$$

here$n$ is quantity of 2ndlayer hubs taking part in IF fragment of rule.

Layer4: Regularized terminating quality is determined in 3rdlayer & number of hubs in this layer is equivalent to 3rdLayer.

$$f[u_i^4] = \sum_{i=1}^{r} u_i{}^4 \text{ and } a^4(f) = \frac{u_i{}^4}{f} \quad (6)$$

here r is quantity of rule hubs in 3rdLayer.

Layer5: Hub coordinates all activities suggested in 5thLayer and goes about as de-fuzzifier. Every hub inlayer compares to 1 yield variable.

$$f[u_i^5] = \textstyle\sum_i w_i u_i^5,\ a^5(f)=f \quad (7)$$

For subtleties on boundaries &structures learning of SONFIN, clients can allude to ([18], 1998).

Fuzzy C-means Clustering:

Bezdek,in 1981 presented FCM (Fuzzy c-implies) ([25], 2013), which permits every information point displays to at least one groups that are determined by an enrollment work. Minimization of target which chooses presentation of FCM is characterized as appeared in Equation below:

$$J_M = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}{}^m \left|\left|x_i - v_j\right|\right|^2 \quad (8)$$

here M is genuine digit incredible than 01, u_{ij} is level of enrollment of x_i in bunch j, x_i is the i^{th} information purpose of d-measurement data-set, v_j is d-measurement of group and ||*|| is any standard communicating similitude between any deliberate information and center.

FCM'sSystem:

a) Set-up an estimation of number of bunches (c);
b) Beginning group model $V_1, V_2, \ldots, V_c$ from X_i, $_i=1, 2, \ldots, N$;
c) Process separation $||X_i\text{-}V_j||$ among items and models;
d) Process components of Fuzzy parcel framework ($i=1,2,\ldots,N; j=1,2,\ldots c$)

$$u_{ij} = \left[\sum_{i=1}^{c} \left(\frac{||x_i - v_j||}{||x_i - v_l||}\right)\right]^{-1} \quad (9)$$

e) Process bunch models ($j=1,2,\ldots,c$)

$$V_j = \frac{\sum_{i=1}^{N} u_{ij}{}^2 x_i}{\sum_{i=1}^{N} u_{ij}{}^2} \quad (10)$$

f) Halt if assembly is accomplished or quantity of repetitionssurpasses given breaking point.
Else, repeat stage 3

Collective Fuzzy Clustering:

Presented by Pedrycz,CFC (collective Fuzzy bunching) method([51], 2005), in which a few subsets of examples can be prepared along with a goal to finding a structure. Flat synergistic grouping & vertical community oriented bunching are two significant variations of CFC and it's applied in various examination zones to take care of bunching and displaying issues ([52], 2013) ([54], 2014). The overall plans of flat community oriented grouping and vertical collective bunching are appeared in Fig. 1 and Fig. 2 individually.

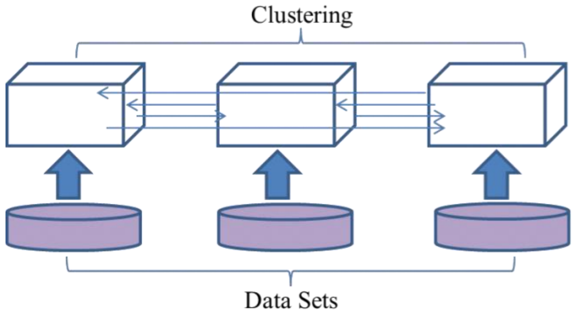


Fig 1: Shows General plan of flat bunching

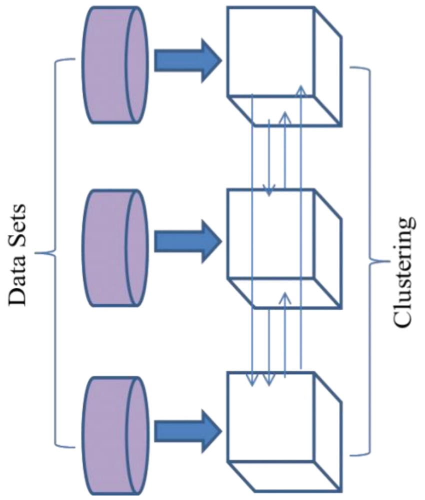


Fig2: Shows General plan of vertical grouping

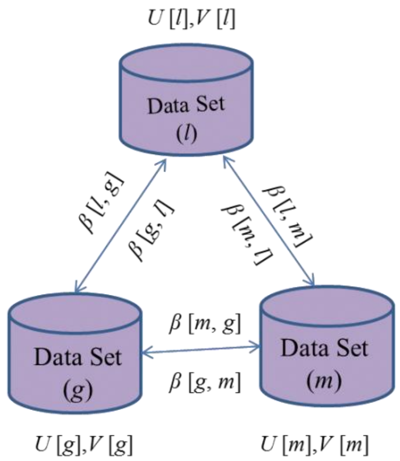


Fig3: Communitarian grouping plan

The target work for coordinated effort procedure is:

$$Q[l] = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{2}[l]\, d_{ij}^{2}[l] + \sum_{\substack{m=1\\ m\neq l}}^{p} \beta[l,m] \sum_{i=1}^{N}\sum_{j=1}^{n} \{u_{ij}[l]-u_{ij}[m]\}^{2} d_{ij}^{2}[l] \quad (11)$$

Here β is a client characterized boundary dependent on data-sets (β>0), β[*l*, *m*] means the communityoriented coefficient with shared impact on data-set l through m, c is the quantity of bunches. *l=1,2,.....,p*. and *p* is quantity of data-sets, and *N* is quantity of examples in data-set, u speaks to parcel framework, where n is quantity of highlights, d is a Euclidean separation among examples & models.

Fig3 shows associations of frameworks so as to achieve coordinated effort between subsets of data-set. In first place, we tackle issue of everydata-set independently then permit outcomes to interface all-inclusive by shaping a synergistic procedure between data-sets. Shared Fuzzy parceling is brought out an iterative advancement of target work as appeared in Equation 11 with an update of parcel grid *u[l]* and model $v_i[l]$.. The estimations of the parcel grid *u[l]* and the model $v_i[l]$ are as per the following:

$$u_{st}[l] = \frac{\varphi_{st}[l]}{1+\psi[l]} + \frac{1}{\sum_{j=1}^{c}\frac{d_{st}^{2}[l]}{d_{jt}^{2}[l]}}\left[1-\sum_{j=1}^{c}\frac{\varphi_{jt}[l]}{1+\psi[l]}\right] \quad (14)$$

Where,

$$\varphi_{st}[l] = \sum_{\substack{m=1\\ m\neq l}}^{p}\beta[l,m]\,u_{st}[m] \quad (15)$$

also,

$$v_{st}[l] = \frac{\sum_{k=1}^{N}u_{sk}^{2}[l]x_{kt}[l] + \sum_{\substack{m=1\\ m\neq l}}^{p}\beta[l,m]\sum_{k=1}^{N}(u_{sk}[l]-u_{sk}[m])^{2}x_{kt}[l]}{\sum_{k=1}^{N}u_{sk}^{2}[l] + \sum_{\substack{m=1\\ m\neq l}}^{p}\beta[l,m]\sum_{k=1}^{N}(u_{sk}[l]-u_{sk}[m])^{2}} \quad (16)$$

Method for CFC:

1. Provided, sub-sets of examples *X1,X2,...,Xp*.
2. Select, separation work, *c*(number of cluster), end condition & coordinated effort β[*l*, *m*]coefficient.
3. Register, haphazardly instate all segment networks *U*[1], *U*[2], ..., *U*[*P*]
4. Stage I

For every information

Repeat

Register, model { $V_j[l]$, *j=1,2,...,c* and parcel frameworks *U*[*l*] for patterns of every sub-sets}

Till an end condition is fulfilled

End of stage I

5. Stage II

Repeat

For network of communitarian joinsβ[*l*, *m*].

Process, model $V_j[l]$ & segment lattices *U*[*l*] utilizing (12) and (15).

Till an end condition is fulfilled

End of stage II

Pre-processed Collaborative Fuzzy Clustering:

PCFC (Pre-processed collective Fuzzy clustering) ([55], 2014) is an improved adaptation of Collaborative Fuzzy clustering (CFC). Issue, which lies by CFC has brought up, a proper arrangement has been given by proposing a bunch place planning instrument earlier then joint effort process.

CFC's Problem:

An immediate deduction of 02 diverse segment grids $u_{ik}[l]$ and $u_{ik}[m]$, we mightdrop valuable data below various parcel frameworks of individual example $X_k$within similar group. Group portrayed by k_{th} column $V_k[l]$ in $u_{ik}[l]$ might be unique in relation to the one depicted by the k_{th} line in $V_k[m]$ in $u_{ik}[m]$. On the off chance that the lines request of one grid changes, the deduction between two networks changes also. For this situation, taking straight deduction amongst02 networks $u_{ik}[l]$&$u_{ik}[m]$ isn't a suitable mode

Explanation by PCFC:

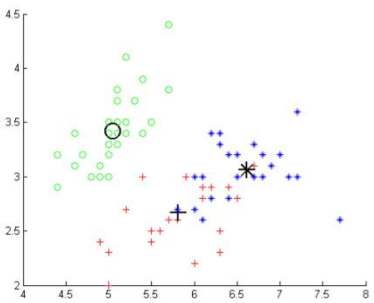
Towards locating anobliging methodology of pre-processing so as to modify column request of u_{ik}[l] comparing to line request of $u_{ik}[m]$ in a sound manner, the coordinating line couple is resolved via:

$$r = \arg \min_{j=1,2\ldots c} \sum_{i=1}^{n} \left(V_{ki}[l] - V_{ji}[m]\right)^2 \qquad (16)$$

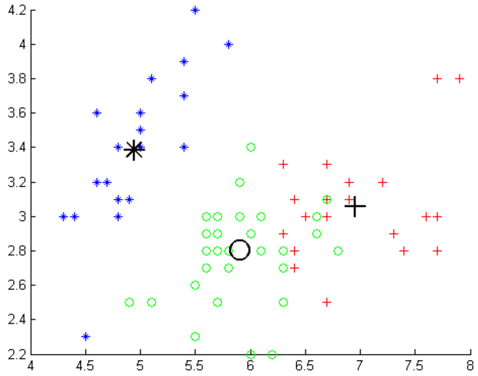
k^{th} line of $V[l]$&r^{th} line of $V[m]$ are viewed as a coordinating line pair $(k=1,2,\ldots, c)$, where $n$signifies quantity of highlights. Likewise, apprise$u_{ik}[l]$&$u_{ik}[m]$ with compare to $V[l]$&$V[m]$.

Discussions:

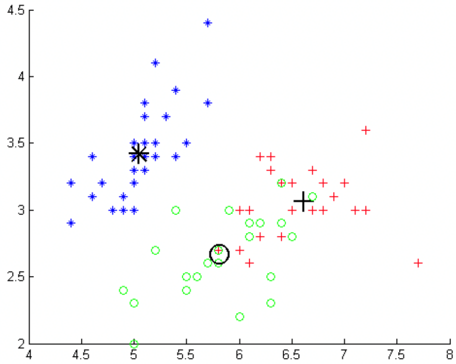
So as near confirm planning component, we have utilized worldview of three classes and afterward partitioned similarly into 02 sub-sets of data-set, in particular data-set1 &data-set2. Fig4 (a) & 4(b) are grouped element vectors of data-set1 and data-set2, individually. As should be obvious, in fig4(a) & 4(b), primary bunch of data-set1 counterparts with 2nd group of data-set2, subsequent group of data-set1 matches with 3rdgroup of data-set2 &3rdgroup of data-set1 matches with main group of data-set2, which are completely befuddled with one another. Fig4(c) & 4(d) show plotting results after planning system, it shows impact of centroid planning for model and line request planning with segment lattice. Presently, we can undoubtedly take differences between columns of data-set1 &data-set2 and effectively do planning between these.



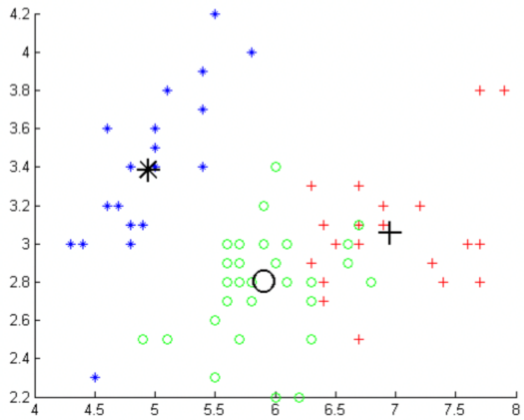
(a) Element vectors luster of data-set1



(b) Element vectors Clusterof data-set2



(c)Component vectorsCluster of data-set1



(d) Element vectorsCluster of data-set2 in Wake of planning

Fig 4: (a, b,c,d) Clustered component vectors of data-set1 and data-set2

PCFC Algorithm:

In light of above conversations & outcomes, we have included 1 more stage named stage III in CFC strategy for pre-processing by:

Technique for PCFC

1. Provided, sub-sets of examples $X1, X2, \ldots, Xp$.

2. Selecting, separation work,c(sum of groups), end condition, coordinated effort coefficient$\beta[l, m]$.

e-ISSN: 2582-7464

3. Register, haphazardly instate altogether segment frameworks U[1],U[2],...,U[P]

4. Stage I

For every information Reprise

Register, model {$V_j[l]$, $j=1,2,...,c$ and parcel frameworks $U[l]$ for all subsections of designs}

Till an end situationis fulfilled

Convey group model from every information put to all others;

End of stage I

5. Stage II

Pick a methodology as given in Eq. (16) for the preprocessing on group model and its comparing parcel grids so as to modify the element line request.

End of stage II

6. Stage III

Repeat

For grid of synergistic connectionsβ $[l, m]$.

Compute, model $V_j[l]$ & parcel grids $U[l]$ by eq. 12 & 15.

Until an end condition is fulfilled

End of stage III

RESULT:

Mackey Glass Time Series Prediction:

Old style benchmark riotous Mackey glass time-arrangement expectations utilized in([45], 2009)([47], 2008)([48], 2006)(Linet al., 2014) is picked for check of anticipated technique.Discrete model of time arrangement by:

$$x(t+1) = (1-a)x(t) + \frac{bx(t-\tau)}{1+x^{10}(t-\tau)} \qquad (18)$$

Here$a$=.10, b=.20, τ=17.0&x(0)= 01.20. Issue is to anticipate worth $x(t+p)$ (p=06.00) from accompanying expectation model:

$$x(t+p)=f\,\{x(t), x(t-6), x(t-12), x(t-18)\} \qquad (19)$$

Sets of thousands examples extricated from Equation 18 for each, preparation & testing reason and these examples utilized for setting up information & yield test information dependent on Equation 19. In this way, preparing data-set is separated into 2data-sets, to be specific data-set1 &data-set2, which contain five hundred examples both. Proposed strategy just uses aggregate information on five hundredexamples of data-set1/data-set2 for neural systems preparing in wake of implementing PCFC component. Boundaries utilized for anticipated technique in this forecast model are: P1=0.70, P2=0.50& P3=500. Table1 displays a presentation examination of proposed strategy with RBF-AFS, GEBF-OSFNN,OLS, and FAOS-PFNN&DFNN. The presentation of proposed strategy as appeared in Table1 is mean worth dependent on ten test preliminaries. The best preparing and testing RMSE esteem during ten trial preliminaries is .00050& .00120, separately. It very well may be effortlessly observed that the proposed strategy accomplishes better execution while utilizing altogether less principles. Fig6 & 8 show the yield estimation of anticipated and wanted model and Fig7 & 9 show the anticipated blunders during preparing and testing stage, separately. It very well may be effectively observed from Table1 that exhibition accomplished by proposed strategy is better than recently proposed techniques.

Table 1: Execution examination of RBF-AFS, GEBF-OSFNN, OLS, and FAOS-PFNN & DFNN

Method	No. of Rules	Training RMSE	Testing RMSE
RBF-AFS	21	.01070	.01280
OLS	13	.01580	.01620
FAOS-PFNN	11	.00730	.01270
GEBF-OSFNN	10	.00910	.00870
DFNN	10	.00820	.01270
DDNFS-CFCM	06	.00090	.00340

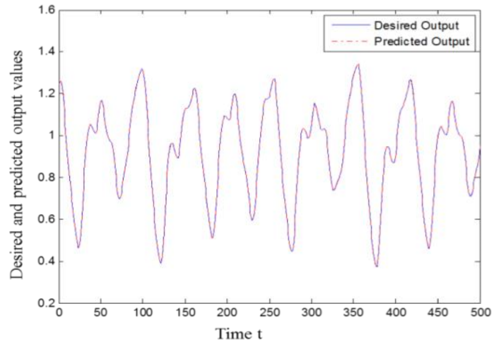


Fig 6: Wanted and anticipated yields during preparing

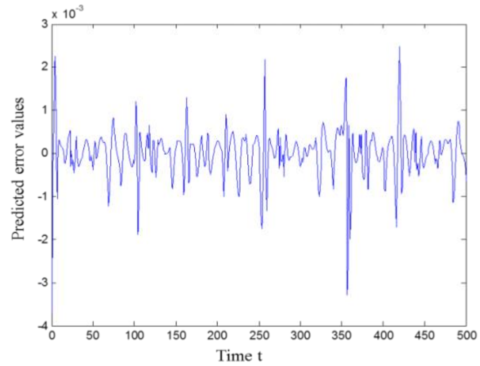


Fig 7: Anticipated mistake during preparing

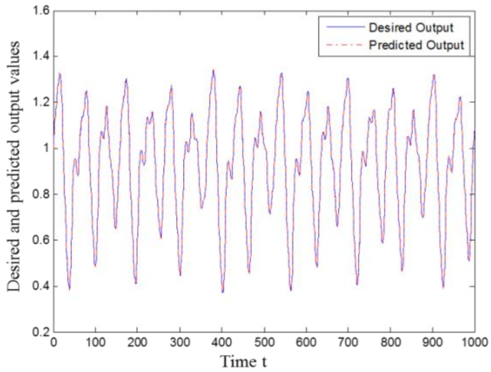


Fig. 8. Wanted and anticipated yields in testing

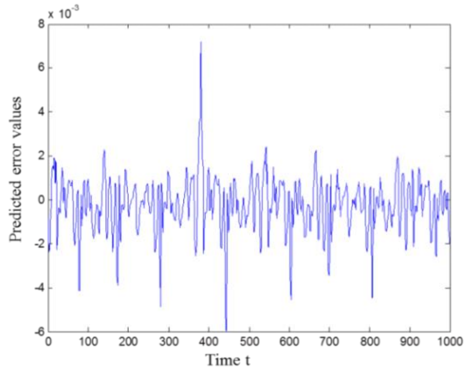


Fig. 9. Anticipated mistake in testing

Table2 displays exhibition of anticipated technique with introductory condition x (0)=.30& p=50.00. The boundaries utilized for proposed strategy in this expectation model are: P1=.040, P2=.50& P3=500. In light of these qualities, proposed technique additionally accomplishes better outcomes regarding RMSE. An examination of proposed strategy with RAN,GEBF-OSFNN, MRAN, RANEKF,GGAP-RBF, and FAOS-PFNN &OS-ELM is displayed in Table2. The best preparing &RMSE testing esteem throughout 10 test preliminaries is .00830& .01720, individually. Fig10 & 12 show ideal and anticipated yields while Fig11 & 13 shows anticipated blunders during preparation & testing stage, individually. It is notices that proposed strategy beats past offered strategies as requiring noteworthy less standards.

Table 2: Execution examination of DDNFS-CFCM, RAN, GEBF-OSFNN, MRAN, RANEKF, GGAP-RBF, and FAOS-PFNN & OS-ELM

Method	No. of Rules	Training RMSE	Testing RMSE
OS-ELM	120	.01840	.01860
RAN	39	.10060	.04660
RANEKF	23	.07260	.02400
MRAN	16	.11010	.03370
GGAP-RBF	13	.07000	.03680
DDNFS-CFCM	09	.01050	.02600

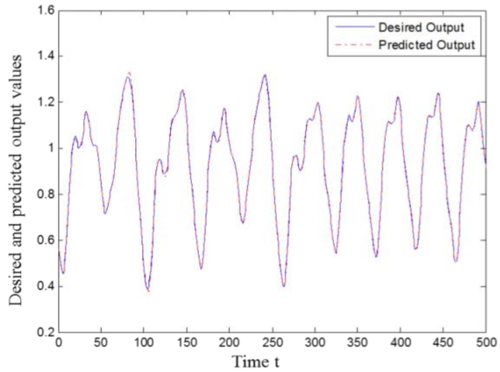


Fig. 10. Wanted &anticipated yields during preparing

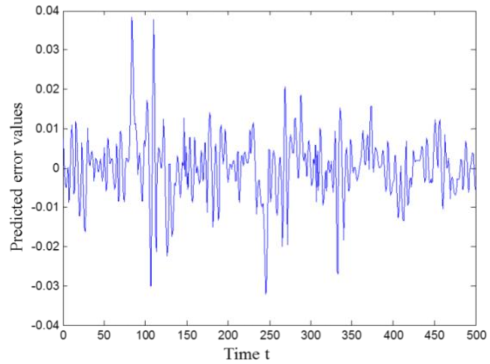


Fig. 11. Anticipated mistake during preparing

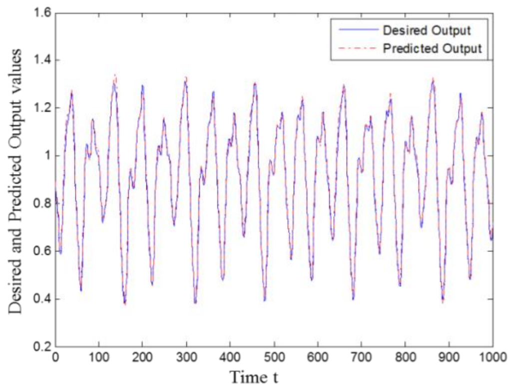


Fig. 12. Wanted and anticipated yields in testing

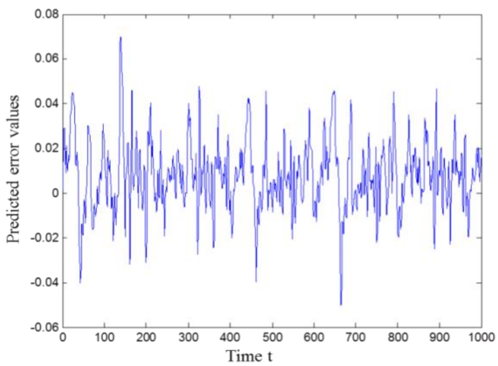


Fig. 13. Anticipated mistake in testing

Nonlinear elements framework recognizable proof issue I the plant to be distinguished remains portrayed in Eq. 20:

$$y(t+1) = \frac{y(t)y(t-1)[y(t)+2.5]}{1+y^2(t)+y^2(t-1)} + u(t) \qquad (20)$$

On the off chance that an arrangement equal recognizable proof model is utilized for distinguishing plant, model could be depicted via Equation 21:

$$\hat{y}(t+1) = f\{y(t), y(t-1), u(t)\} \qquad (21)$$

Here info $u(t)$=sin($2\pi t/25$) and $y(t+1)$ is yield, this system comprises03 data sources &01 yield. The underlying information esteems $y(0)$=0 &$y(1)$=0 is utilized. Set of 200 informationremains produced for every, preparation & testing data-set. In this way, preparing data-set is partitioned into two data-sets, in particular data-set1 and data-set2, which contain hundred examples each. The proposed technique just uses aggregate information on hundred examples of *data-set1/data-set2* for neural systems preparing in wake of applying PCFC instrument. The boundaries utilized for anticipated technique in this forecast model are: *P1*=.20, *P2*=.50&*P3*=500. The exhibition of proposed strategy as appeared in Table3 is mean worth dependent on 30 exploratory preliminaries. The best preparing & testing RMSE esteem during 30 trial preliminaries is .00230& .00200, separately. Table3 shows presentation examination of offered technique with KNN strategy, Mean shift strategy, Khayat's model, Space dividing strategy, SOFNN &SOFNNGA.

Table 3: Execution correlation of strategy, Meanshift strategy, Khayat's model, DDNFS-CFCM, KNN, Space dividing strategy, SOFNN & SOFNNGA

Method	No. of Rules	Training RMSE	Testing RMSE
Space partitioning method	09	.00650	.00550
OSFNN	05	.01570	.01510
Mean shift method	05	.01370	.01270
SOFNNGA	04	.01590	.01460
Khayat's model	04	.01470	.01410
KNN method	04	.01500	.01310
DDNFS-CFCM	04	.00360	.00310

Nonlinear elements framework recognizable proof issue is communicated for example:

$$y(t+1) = \frac{y(t)}{1+y^2(t)} + u^3(t) \qquad (20)$$

here $u(t)$ is info sign, which remains created via utilizing sin capacity specified by $u(t)$=sin($2\pi t$)/100. Lot of two hundred information is produced for every, preparation & testing data-set. In this way, preparing data-set is isolated into two data-sets, to be specific *data-set1&data-set2*, which contain hundred examples each. The proposed strategy just uses aggregate information on hundred examples of *data-set1/data-set2* for neural systems preparing in the wake of employing PCFC component.

Boundaries utilized for suggested technique in this forecast model are: *P1*=.20, *P2*=.50&*P3*=300. The anticipated technique just utilize 30000 information focuses (100 information designs with 300 quantities of cycle) to prepare the framework while, different strategies appeared in Table 4 utilize 50000 information focuses. The data sources *y(t)&u(t)* follow uniform example dispersion in span [-1.50,1.50] & [-01,01] separately. The presentation of proposed technique as appeared in Table4 is mean worth dependent on 30 trial preliminaries. Best testing RMSE esteem during 30 test preliminaries is .00450. Table4 shows an exhibition examination of proposed technique with OS-Fuzzy ELM,SAFIS, simpleLeTS&eTS. Fig18 & 19 show anticipated & wanted yield esteems and anticipated blunders during the testing stage, individually. It very well may be handily observed that the proposed technique beats different strategies as far as RSMS while keeping essentially less standards.

Table 4: Execution examination of OS-Fuzzy ELM, SAFIS, simpleLeTS, eTS&DDNFS-CFCM

Method	No. of Rules	Testing RMSE
eTS	19	.00820
simpleLeTS	18	.01220
RANEKF	11	.01840
MRAN	10	.01290
SAFIS	08	.01160
DDNFS-CFCM	05	.00460

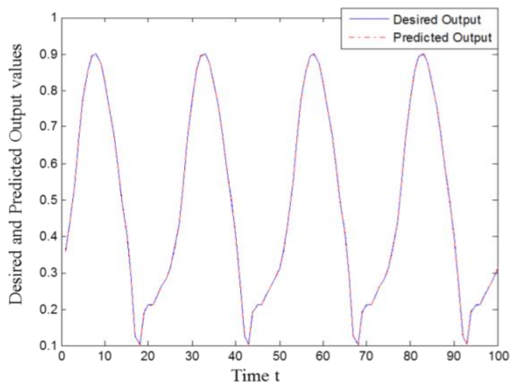


Fig. 14: Wanted and anticipated yields during preparing

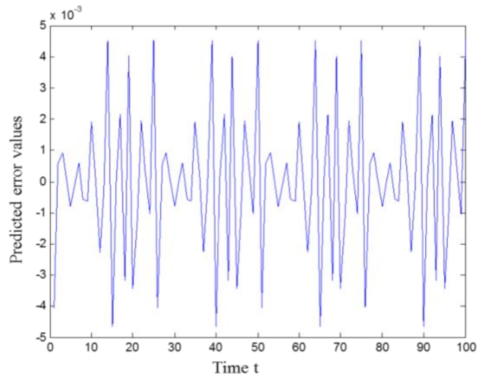


Fig. 15: Anticipated mistake during preparing

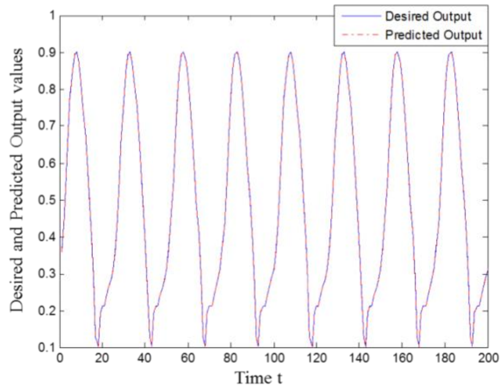


Fig. 16: Wanted and anticipated yields in testing

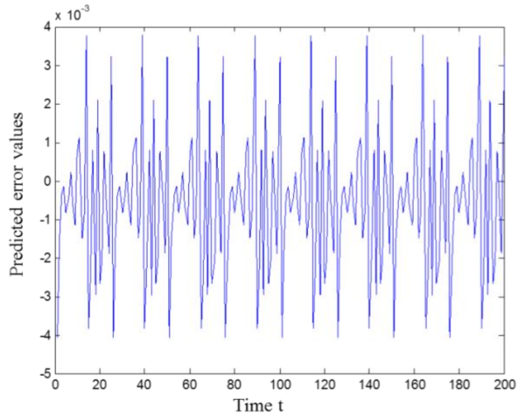


Fig 17: Anticipated mistake in testing

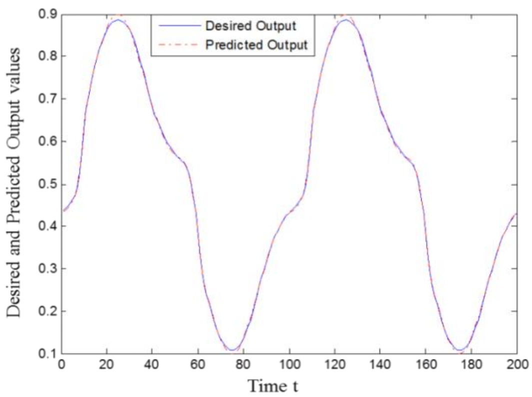


Fig 18: Wanted & anticipated yields in testing

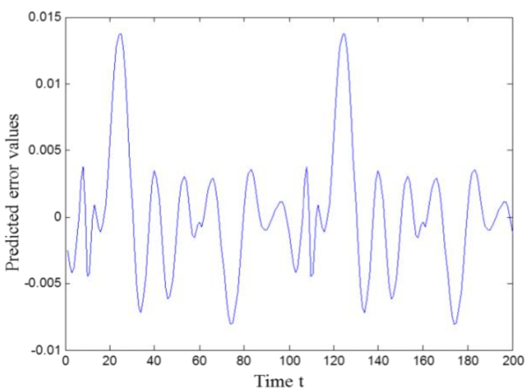


Fig 19: Anticipated mistake in testing

CONCLUSION

In this paper, a Fuzzy Logic guideline move component for self-building neural Fuzzy deduction systems is offered. The highlights of anticipated strategy are: a) Fuzzy standards are produced easily by FCM (Fuzzy c-mean), afterward adjusted by PCFC (pre-processed communitarian Fuzzy clustering) method, b) Boundary & Structure learning are performed at same time without choosing introductory boundaries. In view of the trial results, the proposed technique has demonstrated palatable outcomes as far as computational intricacy with essentially less rules while mulling over of protection & security of data-sets. The proposed technique is better than current cutting edge strategies as exhibited on the arrangement of benchmark issues.

REFERENCES:

[1] C. T. Lin and C. S. G. Lee, Neural Fuzzy Systems: a Neural-Fuzzy Synergism to Intelligent Systems, Englewood Cliffs, NJ: Prentice-Hall, (1996).

[2] L. X. Wang, Adaptive Fuzzy Systems and Control: Design and Stability Analysis, Prentice-Hall, Englewood Cliffs (1994).

[3] J. S. R. Jang, C. T. Sun, and E. Mizutani, Neuro-fuzzy and Soft Computing, Prentice-Hall, Englewood Cliffs, NJ, (1997).

[4] K. B. Cho and B. H. Wang, Radial basis function based adaptive fuzzy systems and their applications to system identification and prediction, Fuzzy Sets and Systems, vol. 83, no.3, pp. 325-339, (1996).

[5] K. Tanaka, M. Sano, and H. Watanabe, Modeling and control of carbon monoxide concentration using a neuro- fuzzy technique, IEEE Transactions on Fuzzy Systems, vol. 3, no. 3, pp. 271-279, (1995).

[6] J. J. Buckley and Y. Hayashi, Fuzzy neural networks: A survey, Fuzzy Sets and Systems, vol. 66, no. 1, pp. 1– 13, (1994).

[7] J. J. Shann and H. C. Fu, A fuzzy neural networks for rule acquiring on fuzzy control systems, Fuzzy Sets and Systems, vol. 71, no. 3, pp. 345–357, (1995).

[8] A. Abraham, Neuro Fuzzy Systems: State-of-the-art Modeling Techniques, Connectionist Models of Neurons, Learning Processes, and Artificial Intelligence Lecture Notes in Computer Science, vol 2084, pp 269-276, (2001).

[9] H. J. Rong, N. Sundararajan, G. B. Huang, and P. Saratchandran, Sequential Adaptive Fuzzy Inference System (SAFIS) for nonlinear system identification and prediction, vol. 157, no. 9, pp. 1260-1275, (2006).

[10] D. Dovzan and I. Skrjanc, Recursive fuzzy c-means clustering for recursive fuzzy identification of time-varying processes, vol. 50, no. 2, pp. 159-169, (2011).

[11] J. S. Wang and C. S. G. Lee, Self-Adaptive Neuro-Fuzzy Inference Systems for Classification Applications, IEEE Transaction on Fuzzy Systems, vol. 10, no. 6, pp. 790-802, (2002).

[12] G. Leng, G. Prasad, and T. M. McGinnity, An on-line algorithm for creating self-organizing fuzzy neural networks, Neural Network, vol. 17, no. 10, pp. 1477-1493, (2004).

[13] M. J. Er and S. Wu, A fast learning algorithm for parsimonious fuzzy neural systems, Fuzzy Sets and Systems, vol. 126, no. 3, pp. 337-351, (2002).

[14] N. Wang, A Generalized Ellipsoidal Basis Function Based Online Self-constructing Fuzzy Neural Network, Neural Processing Letters, vol. 34, no. 1, pp. 13-37, (2011).
[15] H. Han and J. Qiao, A Self-Organizing Fuzzy Neural Network Based on a Growing-and-Pruning Algorithm, IEEE Transaction on Fuzzy Systems, vol. 18, no. 6, pp. 1129-1143, (2010.)
[16] C. J. Lin and C. H. Chen, Nonlinear system control using self-evolving neural fuzzy inference networks with reinforcement evolutionary learning, Applied Soft Computing, vol. 11, no. 8, pp. 5463-5476, (2011).
[17] H. Malek, M. M. Ebadzadeh, and M. Rahmati, Three new fuzzy neural networks learning algorithms based on clustering, training error and genetic algorithm, Applied Intelligence, vol. 37, no. 2, pp. 280-289, (2012).
[18] C. F. Juang and C. T. Lin, An On-Line Self-Constructing Neural Fuzzy Inference Network and Its Applications, IEEE Transaction on Fuzzy Systems, vol. 6, no. 1, pp. 12-32, (1998).
[19] C. T. Lin, S. F. Tsai, and L. W. Ko, EEG-Based Learning System for Online Motion Sickness Level Estimation in a Dynamic Vehicle Environment, IEEE Transaction on Neural Network and Learning Systems, vol. 24, no. 10, pp. 1689-1700, (2013).
[20] C. F. Juang, T. C. Chen, and W. Y. Cheng, Speedup of Implementing Fuzzy Neural Networks With High-Dimensional Inputs Through Parallel Processing on Graphic Processing Units, IEEE Transaction on Fuzzy Systems, vol. 19, no. 4, pp. 717-728, (2011).
[21] R. C. Wu, C. T. Lin, S. F. Liang, T. Y. Huang, Y. C. Chen, and T. P. Jung, Estimating Driving Performance Based on EEG Spectrum and Fuzzy Neural Network, IEEE International Joint Conference on Neural Networks, (2004).
[22] G. D. Wu and C. T. Lin, A Recurrent Neural Fuzzy Network for Word Boundary Detection in Variable Noise- Level Environments, IEEE Transaction on Systems Man and Cybernetics-Part B: Cybernetics, vol. 31, no. 1, pp. 84-97, (2001).
[23] W. J. Lee, C. S. Sen, and S. J. Lee, Constructing Neuro-Fuzzy Systems with TSK Fuzzy Rules and Hybrid SVD-Based Learning, IEEE International Conference on Fuzzy System, (2002).
[24] C. F. Juang, H. S. Perng, and S. K. Chen, Skin Color Segmentation by Histogram-Based Neural Fuzzy Network, IEEE International Joint Conference on Neural Networks, (2005).
[25] J. C. Bezdek, Pattern recognition with fuzzy objective function algorithms, Plenum Press, New York, (1981).
[26] M. Prasad, C. T. Lin, C. T Yang, and A. Saxena, Vertical Collaborative Fuzzy C-Means for Multiple EEG Data Sets, Springer Lecture Notes in Computer Science, vol. 8102, pp. 246-257, (2013).
[27] K. B. Cho and B. H. Wang, Radial basis function based adaptive fuzzy systems and their applications to system identification and prediction, Fuzzy Sets and Systems, vol. 83, no. 3, pp. 25–339, (1996).
[28] S. Chen, C. F. N. Cowan, and P. M. Grant, Orthogonal least squares learning algorithm for radial basis function network, IEEE Transaction on Neural Networks, vol. 2, no. 14, pp. 11–1423, (1991).
[29] S. Q. Wu and M. J. Er, Dynamic fuzzy neural networks—a novel approach to function approximation, IEEE Transaction and Systems Man and Cybernetics-Part B: Cybernetics, vol. 30, no. 3, pp. 58–364, (2000).
[30] N. Wang, M. J. Er, and X. Y. Meng, A fast and accurate online self-organizing scheme for parsimonious fuzzy neural networks, Neurocomputing, vol. 72, no. 38, pp. 3818–3829, (2009).
[31] J. Platt, A resource-allocating network for function interpolation, Neural Computation, vol. 3, no. 2, pp. 213– 225, (1991).
[32] C. S. Velayutham and S. Kumar, Asymmetric Subsethood-Product Fuzzy Neural Inference System
[33] (ASuPFuNIS), IEEE Transaction on Neural Networks, vol. 16, no. 1, pp 160–174, (2005).
[34] G. B. Huang, P. Saratchandran, and N. Sundararajan, A generalized growing and pruning RBF (GGAPRBF) neural network for function approximation, IEEE Transaction on Neural Networks, vol. 16, no. 1, pp. 57–67, (2005).
[35] N. Y. Liang, G. B. Huang, P. Saratchandran, and N Sundararajan, A fast and accurate online sequential learning algorithm for feedforward networks, IEEE Transaction on Neural Networks, vol. 17, no. 6, pp. 1411–1423, (2006).
[36] L. Yingwei, N. Sundararajan, and P. Saratchandran, A sequential learning scheme for function approximation using minimal radial basis function (RBF) neural networks, Neural Computation, vol. 9, no. 4, pp. 461–478, (1997).
[37] G. Leng, G. Prasad, and T.M. McGinnity, An On-line Algorithm for Creating Self-organizing Fuzzy Neural Networks, Neural Networks, vol. 17, pp. 1477-1493, (2004).
[38] G. Leng, T. M. McGinnity, and G. Prasad, Design for Self Organizing Fuzzy Neural Network Based on Genetic Algorithm, IEEE Transaction on Fuzzy Systems, vol. 14, no. 6, pp. 755-766, (2006).
[39] O. Khayat, M. M. Ebadzadeh, H. R. Shahdoosti, R. Rajaei, and I. Khajehnasiri, A Novel Hybrid Algorithm for Creating Self-organizing Fuzzy Neural Networks, Neurocomputing, vol. 73, pp. 517-524, (2009).
[40] H. J. Rong, N. Sundararajan, G. B. Huang, and P. Saratchandran, Sequential adaptive fuzzy inference system (SAFIS) for non-linear system identification and prediction, Fuzzy Sets and Systems, vol. 157, no. 9, pp. 1260– 1275, (2006).
[41] P. Angelov and D. Filev, An approach to online identification of Takagi–Sugeno fuzzy models, IEEE Transactions on Systems Man and Cybernetics, Part B: Cybernetics, vol. 34, no. 1, pp 484–498, (2004).
[42] H. Malek, M. M. Ebadzadeh, and M. Rahmati, Three New Fuzzy Neural Networks Learning Algorithms Based on Clustering, Training Error and Genetic Algorithm, Springer Science and Business Media, Applied Intelligence, vol. 37, no. 2, pp. 280-289, (2012).
[43] P. Angelov and D. Filev, SIMPL eTS: a simplified method for learning evolving Takagi–Sugeno fuzzy models, IEEE International Conference on Fuzzy Systems, (2005).
[44] W. Klimesch, EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis, Brain Research Reviews, vol. 29, nos. 2–3, pp. 169–195, (1999).
[45] S. Hengjie, M. Chunyan, S. Zhiqi, M. Yuan, and B. S. Lee, A fuzzy neural network with fuzzy impact grades, Neurocomputing, vol. 72, nos. 13–15, pp. 3098–3122, (2009).
[46] I. Rojas, H. Pomares, J. L. Bernier, J. Ortega, B. Pino, F. J. Pelayo, and A. Prieto, Time series analysis using normalized PG-RBF network with regression weights, Neurocomputing, vol. 42, nos.1–4, pp. 267–285, (2002).
[47] C. F. Juang and Y. W. Tsao, A self-evolving interval type-2 fuzzy neural network with online structure and parameter learning, IEEE Transaction on Fuzzy Systems, vol. 16, no. 6, pp. 1411– 1424, (2008).

[48] Y. Chen, B. Yang, and J. Dong, Time-series prediction using a local linear wavelet neural network, Neurocomputing, vol. 69, nos. 4–6, pp. 449–465, (2006).

[49] Y. Y. Lin, J. Y. Chang and C. T. Lin, A TSK-type-based Self-Evolving Compensatory Interval Type-2 Fuzzy Neural Network (TSCIT2FNN) and Its Applications, IEEE Transaction on Industrial Electronics, vol. 61, no. 1, (2014).

[50] W. Pedrycz, Collaborative fuzzy clustering, Pattern Recognition Letters, vol. 23, no. 14, pp. 1675–1686, (2002).

[51] W. Pedrycz, Knowledge-based clustering: from data to information granules, A John Wiley &Sons, Inc., Publication, (2005).

[52] C.T. Lin, M. Prasad, and J. Y. Chang, Designing Mamdani Type Fuzzy Rule Using a Collaborative FCM Scheme, International Conference on Fuzzy Theory and Its Application (iFuzzy), Taipei, Taiwan, Dec. 6-8, (2013).

[53] M. Prasad, K. P. Chou, A. Saxena, O. P. Kawrtiya, D. L. Li, and C. T. Lin, Collaborative Fuzzy Rule Learning for Mamdani type Fuzzy Inference System with Mapping of Cluster Centers, IEEE Symposium on Computational Intelligence in Control and Automation (CICA), Orlando, FL, Dec. 9-12, (2014).

[54] K. P. Chou, M. Prasad, Y. Y. Lin, S. Joshi, C. T. Lin, and J. Y. Chang, Takagi-Sugeno-Kang type Collaborative Fuzzy Rule Based System, IEEE symposium on Computational Intelligence and Data Mining (CIDM), Orlando, FL, Dec. 9-12, (2014).

[55] M. Prasad, D. L. Li, Y. T. Liu, L. Siana, C. T. Lin, and A. Saxena, A Preprocessed Induced Partition Matrix Based Collaborative Fuzzy Clustering for Data Analysis, IEEE International Conference of Fuzzy Systems (FUZZ-IEEE), Beijing, China, July 6-11, (2014).