Online Sliding Window Based Self-Organising Fuzzy Neural Network for Cognitive Reasoning

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Abstract **—We propose an online sliding window based self-organising fuzzy neural network (SOFNN) as the core component of a cognitive reasoning system for a smart home environment. The network has the ability to configure its neuronal structure through adding and pruning of neurons while exploring the relationships between the inputs and the desired reasoning outputs, thus enabling continuous learning and reasoning to provide meaningful cognitive understanding of the environment. Initially, the network is trained with environmentally realistic synthesised data thus demonstrating its adaptation capabilities. The network is then validated using unseen data. In the simulation, we have studied the network structures and responses for three different scenarios with and without online sliding window based approaches and the results obtained show the effectiveness of the proposed method.**

Keywords- self-organise; fuzzy logic; neural network; reasoning module

I. INTRODUCTION

Smart home environments are emerging rapidly as sensor rich systems. These systems require substantial computation to extract high level knowledge and understanding from low level sensory information, so as to enable appropriate decisions to be made regarding the state of the environment, i.e., the ecology. The main objectives of introducing intelligence into a smart home environment are to identify events with various degrees of importance and automatically activate suitable responses [1]. The intelligence comes from the adaptive behaviour of the overall ecology as per the requirements of the user. Different aspects of smart home environments have been reported in the literature [2][11]. These include an intelligent just-in-time Activity of Daily Living (ADL) assistance provision within an integrated system architecture [3], a home monitoring system for elderly-care application [2], and a context aware system for smart home applications [9][11][19]. Researchers have used different methods for contextual representations. Mastrogiovanni et al., [5] have integrated ontology and logic based approaches to map numerical data to symbolic representations. Roy et al. [6] have used possibility theory and description logic (DL) as the semantic model of the agent's behaviour for activity recognition.

Detection of anomalous events within a smart home is an important aspect of situation awareness. Jakkula [4] has used One Class Support Vector Machines (OCSVM) techniques to address this issue. In [15], we have shown that the SOFNN based cognitive reasoning module can be utilised to extract knowledge from everyday events occurring within a smart home environment. The SOFNN has a self-organising capability to configure its structure and identify parameters of the fuzzy neural network from data. We explored the potential of the SOFNN as a core component of a cognitive system unfolding the relations of its inputs and the desired reasoning outputs and showed its ability to adapt its neuronal structure through adding and pruning of neurons. In this work, we show that the proposed sliding window based online SOFNN can achieve similar knowledge via a simpler structure with a reduced number of neurons.

The remainder of this paper is organised as follows: Section II presents an overview of the SOFNN. A sliding window based online SOFNN is described in Section III. Section IV presents the implementation results of the proposed work in a smart home environment. We consider three cases: case 1 represents purely offline training and testing; case 2 represents offline initial training and then online training and testing simultaneously during the verification stage with sliding window control; case 3 represents fully online situation utilising the proposed method. Section V presents the overall conclusion of this work.

II. AN OVERVIEW OF THE SOFNN

The self-organising fuzzy neural network (SOFNN) [14], implementing Takagi-Sugeno (TS) fuzzy models [16] online, is a five-layer fuzzy neural network with the ability

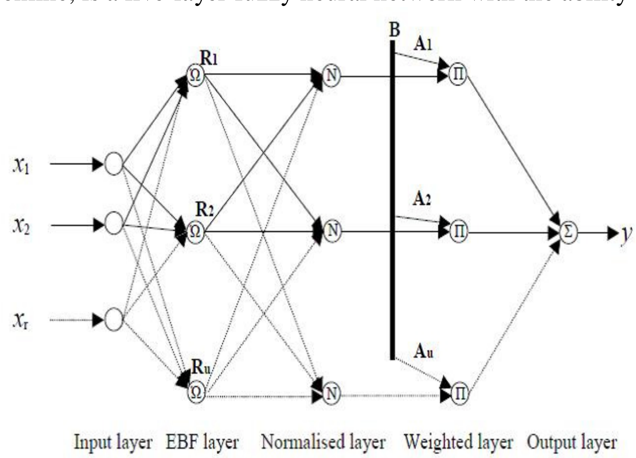

Figure 1. Structure of self-organising fuzzy neural networks

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to self-organise its own structure during the learning process. The structure of SOFNN is shown in Fig. 1.

Consider the t-th observation $(X_t\ d_t)$. We define $X_t = [x_{1t}\ x_{2t}\ \cdots\ x_{rt}]$ as the input vector, r is the number of inputs, d_t is the desired output (target) at time t and y_t is the actual output of the current network at time t. Then, the output in layer 5 is obtained as

$$y(\mathbf{x}) = \frac{\sum_{j=1}^{u} w_{2j} \exp\left[-\sum_{i=1}^{r} \frac{(x_i - c_{ij})^2}{2\sigma_{ij}^2}\right]}{\sum_{k=1}^{u} \exp\left[-\sum_{i=1}^{r} \frac{(x_i - c_{ik})^2}{2\sigma_{ik}^2}\right]}. \quad (1)$$

Here, u is the number of neurons, c_{ij} is the centre of the i-th membership function in the j-th neuron, σ_{ij} is the width of the i-th membership function in the j-th neuron; j and k are variables of the number of neurons and i is the variable of the number of membership functions in each neuron. The row vector $\mathbf{A_j} = [a_{j0}\ a_{j1}\ a_{j2}\ \cdots\cdots\ a_{jr}]$ represents the set of parameters corresponding to the neuron j and w_{2j} is the weighted bias, which is defined for the TS model as

$$w_{2j} = \mathbf{A_j} \times [1\ x_1\ x_2\ \cdots\cdots\ x_r]^T = a_{j0} + a_{j1}x_1 + \cdots + a_{jr}x_r \quad j = 1, 2, \cdots, u. \quad (2)$$

For learning purposes, the output of the network can be described in matrix form as

$$Y = W_2 \Psi \quad (3)$$

$$Y = [y_1\ y_2\ \cdots\ y_n] \quad (4)$$

$$W_2 = \left[a_{10}\ \ a_{11} \cdots a_{1r} \cdots a_{u0}\ \ a_{u1} \cdots a_{ur}\right] \quad (5)$$

$$\Psi = \begin{bmatrix} \psi_{11} & \cdots & \psi_{1n} \\ \psi_{11} x11 & \cdots & \psi_{1n} x1n \\ \vdots & \vdots & \vdots \\ \psi_{11} xr1 & \cdots & \psi_{1n} xrn \\ \vdots & \vdots & \vdots \\ \psi_{u1} & \cdots & \psi_{un} \\ \psi_{u1} x11 & \cdots & \psi_{un} x1n \\ \vdots & \vdots & \vdots \\ \psi_{u1} xr1 & \cdots & \psi_{un} xrn \end{bmatrix} \quad (6)$$

where W_2 is the parameter matrix, ψ_{jt} is the output of the j-th neuron in the normalised layer when the t-th training pattern enters the network.

The learning process of the SOFNN can be divided into structure learning and parameter learning. The structure learning combines adding new EBF (ellipsoidal basis function) neurons and pruning unimportant EBF neurons [14]-[15]. The parameter learning is based on the linear least squares method and the recursive least squares algorithm [17]. The recursive parameter matrix learning algorithm developed in [14] is as follows

$$L(t) = Q(t)p(t) = Q(t-1)p(t)\left[1 + p^T(t)Q(t-1)p(t)\right]^{-1} \quad (7)$$

$$Q(t) = \left[I - \alpha L(t)p^T(t)\right]Q(t-1) \quad (8)$$

$$\hat{\Theta}(t) = \hat{\Theta}(t-1) + \alpha L(t)[d_t - p^T(t)\hat{\Theta}(t-1)] \quad (9)$$

$$\alpha = \begin{cases} 1, & |e(t)| \geq |\varepsilon(t)| \\ 0, & |e(t)| < |\varepsilon(t)| \end{cases} \quad (10)$$

where $Q(t) = \left[P^T(t)P(t)\right]^{-1}$ is an MxM Hermitian matrix (Q-matrix), $P(t) = \Psi^T = \left[p^T(1)\, p^T(2) \cdots p^T(t)\right]^T$, $M = u \times (r+1)$, $\Theta(t) = W_2^T = [\theta_1\ \theta_2 \cdots \theta_M]^T$, $e(t) = d_t - p^T(t)\hat{\Theta}(t-1)$ is the estimation error and $\varepsilon(t) = d_t - y_t = d_t - p^T(t)\hat{\Theta}(t)$ is the approximation error. More details can be found in [14].

III. THE PROPOSED ONLINE APPROACH OF SOFNN

The dynamic structure of a SOFNN enables the cognitive system to learn different situations online via self-adaptation. To facilitate online training a sliding-window (SW) [12][13], as a data pool, has been employed. In this case the Q-matrix has to be updated based on limited historical data and current data.

The proposed online approach implements a first-in-first-out sliding window (FIFO-SW) (Fig. 2) with the SOFNN. When new data are obtained the oldest data will be discarded and the new data will be added to this window. The data in the sliding window include the current input-target learning pair as in (11) and limited historical input-target learning pairs as shown in (12) where W is the width of the sliding window.

$$Data_t = [X_t\ d_t]^T \quad (11)$$

$$Data_{SW} = [Data_{t-W+1}\ Data_{t-W+2}\ \ldots\ Data_t]. \quad (12)$$

Fig. 3 is the block diagram of the proposed online SOFNN. The structure of the SOFNN is self-organised during the

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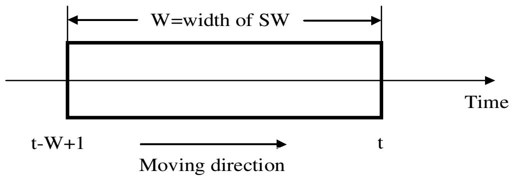

Figure 2. First-in-first-out sliding window

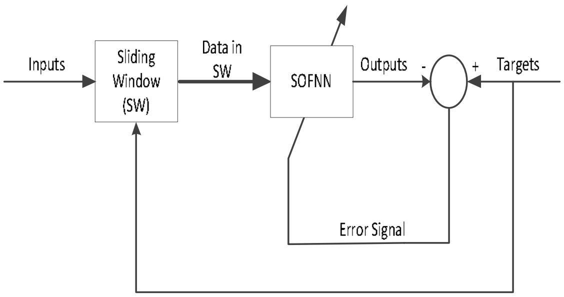

Figure 3. Block diagram of the online SOFNN

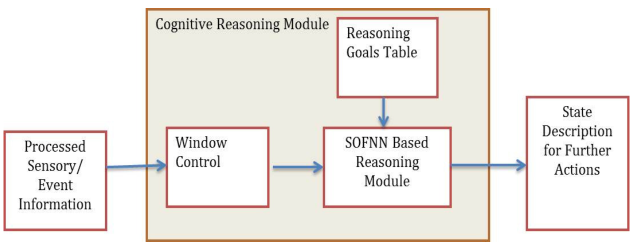

Figure 4. Outline of cognitive reasoning system

learning process. A new SOFNN structure is generated if EBF neurons have been added or pruned in the existing SOFNN structure. In the proposed recursive parameter matrix learning algorithm, the size of the Hermitian matrix (Q-matrix) depends on the number of neurons as $Q(t)=\left[P^{T}(t)P(t)\right]^{-1}$ and $P(t)=\Psi^{T}$. If the number of neurons in the SOFNN structure is changed, the data organized in the sliding window will be used to update the parameter $\hat{\Theta}(t)$ and Q-matrix $Q(t)$ through equations (13) and (14) as follows

$$\hat{\Theta}(t)=\left[P^{T}(t)P(t)\right]^{-1}P^{T}(t)D(t) \tag{13}$$

$$Q(1)=\left[P^{T}(1)P(1)\right]^{-1} \tag{14}$$

where $D(t)=\left[d_{t-W+1}\ d_{t-W+2}\ \cdots\ d_{t}\right]^{T}$. The proposed recursive parameter matrix learning algorithm is then applied to update the parameters during subsequent learning. It is clear that if the width of the sliding window is the same as the number of entire training data, then this can be considered as offline training.

IV. RESULTS

In order to evaluate the proposed approach we consider a smart home environment with different sensors and actuators as in the EU FP7 RUBICON project (contract no. 269914) [7]. There are four technical layers named learning, control, communication and cognitive layers, which explore and support the smart home environment. The learning layer addresses sensory information for event classification, the control layer employs robots for different goals within the ecology whereas the communication layer is responsible for data transmission among the layers. The cognitive layer seeks to acquire knowledge and understanding of the state of the ecology as per the event information, while accurately reflecting its dynamics. The proposed online algorithm is employed in the reasoning module of the cognitive layer as shown in Fig. 4. To demonstrate the cognitive capability, it is necessary to handle multiple events that may occur in the ecology, and in particular extract higher-level intelligence. We have anticipated 19 events as inputs from a home environment reflecting activities of a user and the states of the environment and a set of 10 reasoning goals as outputs are chosen to reflect the network's capabilities of reasoning across user activities and current state of the ecology. Table I and II show the chosen inputs and outputs [15]. Values of inputs and outputs represent confidence levels between 0 and 1. We synthesize 4500 data samples including data for 19 inputs and 10 reasoning outputs. To validate the performance of the proposed online algorithm, three cases have been designed.

A. *Case 1: Offline Training and Learning*

The first 3900 data are chosen as the training data and the last 600 data are used as the testing data. We use the training data to obtain the SOFNN structure. We then test the performance using the testing data based on the obtained SOFNN structure during which the structure is not refined. This is an offline training process without sliding window control.

B. *Case 2: Pseudo Online Training and Learning*

In case 2, the first 3900 data are used as the first group of training data. The remaining 600 data are used as the testing data, as well as the second group of training data. The first phase is offline training without sliding window control. In the testing process using the second group of data, the obtained structure is also updated based on the FIFO sliding window with the size of 300 samples. In this phase, the refining process is based on the proposed online training algorithm as equations (7) to (14). The testing data are used to validate the performance of the obtained SOFNN structure. This case is a combination of offline and online training process (pseudo online). This process also shows that the approach can continue its training and learning from a previously offline trained network.

TABLE I. THE EVENT INPUTS FOR REASONING MODULE

Synthesized Input	Events
1	User in room 1
2	User in room 2
3	User in room 3
4	Visitor detection
5	Phone event
6	Doorbell event
7	Dripping event
8	Music event
9	Fire alarm
10	Microwave usage
11	Dishwasher usage
12	TV usage
13	Cleaning operation
14	Cooking
15	Use of oven
16	Smoke detection
17	Room temperature
18	Burglary alarm
19	Front door usage

TABLE II. TARGETED OUTPUT OF SOFNN REASONING

ID	Potential reasoning outputs
1	User exercise
2	User relaxing
3	User in kitchen
4	Bring phone
5	Open door
6	Cooking activity
7	Fire alert situation
8	Burglary alert situation
9	Dripping alert situation
10	Cleaning situation

C. *Case 3: Fully Online*

In case 3, all 4500 data are used as the training data. The rear 600 data are the testing data used to validate the performance of the obtained SOFNN structure. For this case, we use the training data to train the SOFNN structure, based on the FIFO sliding window with the size of 300 samples from the beginning of the training. No offline training occurs in this case. To compare with case 1 and case 2, the testing data are used to validate the performance of the obtained SOFNN structure. In this testing process, the obtained structure is also continuing its refinement. So, the structure and parameters are also changing based on the proposed online algorithm.

During the training process in all cases, event inputs and reasoning outputs form the training data as presented in (11). However, during the testing phase, only event data are presented to the network and the reasoning outputs are obtained from the trained network. The results achieved for each of the three cases are presented in Tables III, IV and V. It is observed in Table III that case 1 through to case 3 have 42, 42 and 28 neurons respectively to reason across the reasoning outputs for the smart home environment. The root mean square errors (RMSE) of the training are presented in Table IV for the first set of 3900 data. As case 2 incorporates offline training with the first set of data, the RMSEs are same as case 1. RMSEs of testing of case 2 are better than those of case 1 (Table V) as the obtained structure for case 2 has been refined during the testing process. For a number of the reasoning outputs, the RMSEs of the training and testing of cases 1 and 2 are smaller than the corresponding values in case 3. This is because of the sliding window with limited data has been applied in case 3 from the beginning of the training process as opposed to offline training without sliding window in other cases. However, the reduced number of neurons in case 3 than those in case 1 and case 2 highlights the potential for the proposed online sliding window based approach. Fig. 5 shows the change in neuronal structure for each of these cases. It is observed that case 3 has 28 neurons compared to 42 neurons for cases 1 and 2 respectively. Hence in comparison with the offline approach in case 1 and the pseudo online approach in case 2, the fully online approach in case 3 with FIFO sliding window has the capability to generate a simple structure and achieve similar performances.

Fig. 6 presents an example of the online case 3 with the output “User Exercise”. Fig. 6-(a) shows the training process where the network has identified the transitions when the user starts and ends exercising. In this case, the plot shows only data samples from 3301 to 3900 for clarity. It shows the desired state and the training output of the user exercise situation. It is observed that the network is able to learn this situation. For this output, there are two neurons generated during the training process, which are shown in Fig. 7. It also shows that the number of neurons in the network is changed dynamically during the training process illustrating the self-organising capability of the proposed network. The final 600 data, from 3901 to 4500, have been used in the testing process. The testing results are given in Fig. 6-(b). It is observed that the network is capable of identifying the user exercise situation as desired.

Fig. 8 presents an example of the online case 3 for the open door situation. Fig. 8-(a) shows the desired and actual outputs during the training process where the network has identified the requirements to open the door of the home. In

TABLE III. NUMBERS OF NEURONS FOR 3 CASES

Outputs	Case 1	Case 2	Case 3
User Exercise	3	3	2
User Relaxing	9	9	4
User in Kitchen	2	2	2
Bring Phone	2	2	2
Open Door	2	2	2
Cooking Activity	2	2	2
Fire Alert Situation	2	2	2
Burglary Alert Situation	3	3	3
Dripping Alert Situation	14	14	6
Cleaning Situation	3	3	3
Total Number	42	42	28

TABLE IV. RMSES OF THE TRAINING FOR 3 CASES

Outputs	Case 1	Case 2	Case 3
User Exercise	0.0566	0.0566	0.0566
User Relaxing	0.0463	0.0463	0.0478
User in Kitchen	0.0562	0.0562	0.0551
Bring Phone	0.0641	0.0641	0.0596
Open Door	0.0540	0.0540	0.0507
Cooking Activity	0.0629	0.0629	0.0617
Fire Alert Situation	0.0393	0.0393	0.0311
Burglary Alert Situation	0.0395	0.0395	0.0463
Dripping Alert Situation	0.0359	0.0359	0.0378
Cleaning Situation	0.0385	0.0385	0.0481

TABLE V. RMSES OF THE TESTING FOR 3 CASES

Outputs	Case 1	Case 2	Case 3
User Exercise	0.0580	0.0577	0.0631
User Relaxing	0.0492	0.0490	0.0558
User in Kitchen	0.0558	0.0557	0.0555
Bring Phone	0.0652	0.0650	0.0683
Open Door	0.0498	0.0496	0.0533
Cooking Activity	0.0658	0.0650	0.0705
Fire Alert Situation	0.0401	0.0397	0.0432
Burglary Alert Situation	0.0189	0.0184	0.0187
Dripping Alert Situation	0.0484	0.0481	0.0832
Cleaning Situation	0.0443	0.0526	0.0532

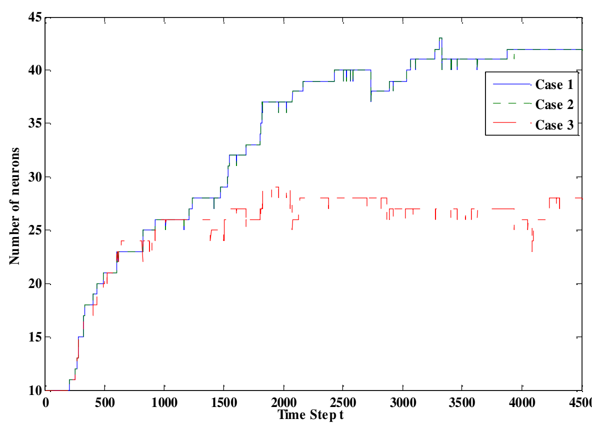

Figure 5. Change of neuronal structure for case 1 through to 3

this case, the plot shows only data samples from 3301 to 3900 for clarity. For this output, there are two neurons generated during the training process, which are shown in Fig. 9. It also shows that the number of neurons in the network is changing dynamically during the training process. The final 600 data, from 3901 to 4500, have been used in the testing process. The testing results are given in Fig. 8-(b). It is observed that the network is capable of identifying the situation as desired.

The Mackey-Glass time-series with a 6-step-ahead prediction model [18] is simulated to show the advantage of the proposed online algorithm in machine learning. This is a benchmark example of a chaotic system. We have chosen the parameters as in [18] for consistency with earlier work.

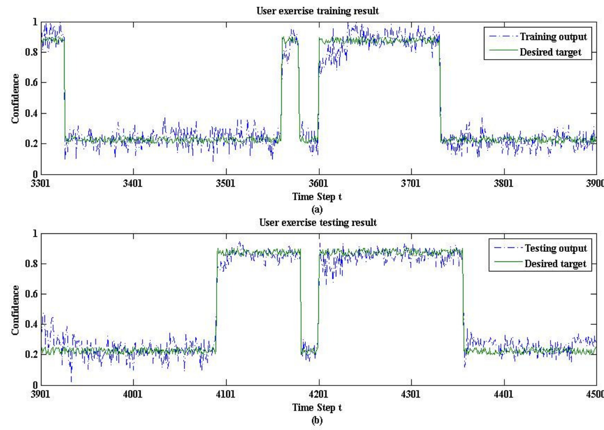

Figure 6. Results of case 3 for user exercise situation

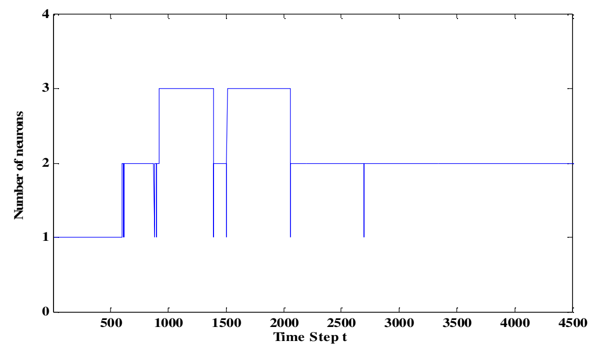

Figure 7. Growth of neurons for user exercise in case 3

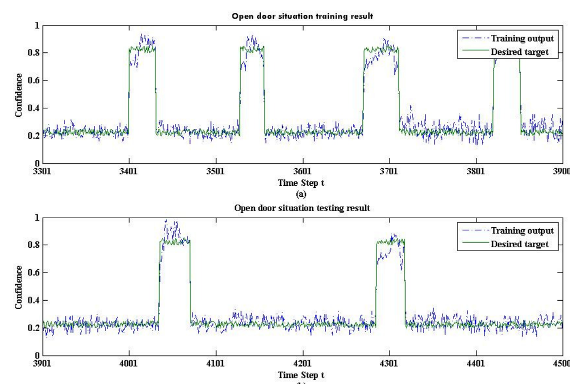

Figure 8. Results of case 3 for open door situation

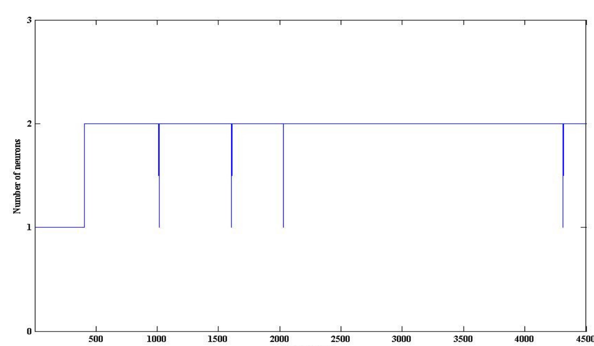

Figure 9. Growth of neurons for open door situation in case 3

TABLE VI. RESULTS OF MACKEY-GLASS TIME-SERIES PREDICTION

Approach	Number of neurons	RMSE of training	RMSE of testing
WNN [18]	4	-	0.0153
Case 1 (no SW)	4	0.0114	0.0116
Case 2 (SW 100 during testing)	4	0.0113	0.0151
Case 2 (SW 200 during testing)	4	0.0114	0.0148
Case 2 (SW 300 during testing)	4	0.0113	0.0123
Case 3 (SW 100)	4	0.0141	0.0151
Case 3 (SW 200)	4	0.0142	0.0148
Case 3 (SW 300)	4	0.0142	0.0123

The results of this simulation are shown in Table VI. We compare our results with the wavelet based neural network (WNN) in [18] which also tabulated further comparative results with other existing methods. It is observed from the RMSE values that our approach produces better results for all three cases presented when compared with the WNN.

V. CONCLUSIONS

This paper presents an online self-organising fuzzy neural network based on the sliding window. The proposed online algorithm has been applied to a smart home situation. The method is also compared with two other designed cases (cases 1 and 2) to show its advantage. A more compact structure and similar performance are obtained using this proposed online algorithm (case 3). Furthermore, we also show through case 2 that the proposed algorithm can be combined with a previously learnt system for continuous learning with new available data. From these results, we can conclude that the proposed method is suitable for online cognitive reasoning. We also consider a benchmark chaotic system prediction using our proposed method and present comparative results with an existing wavelet neural network based approach. The results show that the proposed sliding window based online approach is suitable for machine learning.

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