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Distinct Architectures of Feed Forward Neural Network for Implementing A Human Swing Leg System

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Abstract— *The artificial intelligence techniques such as neural networks and fuzzy systems play an important role to disconnect flexion & expansion of the swing leg, the earth response force of the other foot has been redesigned. Underthat paper, we think the fuzzy controller plan issue for yield following flawed genuine investigation of nonlinear systems. For examination, an essential fuzzy control plot has been bristly developed dependent on a current methodology delegate under the field.In this paper, the Feedforward Neural Network has been implemented with integer, fixed point and floating point data representations. Additionally, The Fuzzy Logic Controllers in both analog and digital forms has been implemented in hardware. Both designs use less hardware resources and operate with reasonable speed compared to other existing designs. The digital implementation of Fuzzy Logic Controller has been tested for a simulated first order liquid level process and the performance results have been compared with those of the Matlab version of Fuzzy Logic Controller. Here, Fuzzy Logic Controller is used as the controller and is trained adaptively for the changes in process parameters using recursive k-means clustering algorithm for updating the centers of the hidden layer and Recursive Least Square algorithm for updating the weights of the output layer, the result of the settling time about 20ms and takes 20 iterations, and the squared error reaches zero at approximately 20 µs.*

Index Terms— *Fuzzy Controller, leg interaction force, Prosthetic legs, Human walking, GyroAccelerate,Fuzzy Logic System.*

I. INTRODUCTION

A human-energized vehicle intends to use machines' support to improve human strength power for passing on & dispatching & to succeed typical human activities, for case under point, walking, running, climbing, or skiing. Along the advancement of mechanical methods, the machines have been mechanized and enhanced to turn out to be more flexible, simpler to incorporate into clients, & cannier to situational mindfulness. As a component of this field, a human-robot blend equipped for performing solid& confounded undertakings would give us various expected applications under various spaces, for example, work escalated ventures.

Due to the fact that the human body has been stacked along signal padding, surface EMG signals is likewise exaggeratedthrough non-abrasiveness [1]. As needs is, to build up a force to help the exoskeleton, an insightful control system has beennecessary. A Neuro-fuzzy controller for higher appendages was plannedunder [1-3]. A Neuro-fluffy regulator for a lower farthest point exoskeleton has been depicted under the making [6]. For lower limitations, a power regulator has been arranged through Christian and Günter [7]. Chan et al. depicted a fluffy EMG classifier for prosthesis control [4]. They disengaged their throughput and one more Phony Neural Association (ANN) - based classifier

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utilizing a near educational mix moreover as similar highlights. Their presentations demonstrated that the fluffy classifier was better than the ANN one, considering a more popularity rate, unfaltering quality toward overtraining, likewise as a basically reliable throughput. Thusly, a fluffy based control framework requests the appraisal of its reach ability for organizing a robotized exoskeleton. Per our strategy, such a regulator has not been tended to now. Under these Sensors 2014, paper, a fluffy regulator for sit-to-stand phenomenal arrangement to-sit redesigns has been arranged. Wearable EMG and kinematic sensors is utilized to achieve the appraisal. A doll has been made for information ensuring about & separating of harsh EMG hails correspondingly to accelerometer information. Five discretionarily picked subjects were utilized to help the controller utilizing diligent information. Under human strolling and running, the swing leg turns forward first and in a little while, around the completion of the swing stage, has been descended and turns under opposite before heel-strike. This supposed Swing Leg Retraction (SLR) has been under like route found under animal advances. The benefits of swing leg withdrawal comprise of: building up the reasonableness and controllability zones, decreasing red hot cost, sway power, and the threat of slippage at heel-strike, and so on [8]. Under hate of these increases, past assessments have relatively shown that SLR upgrades the anticipated quality and power of biped strolling. Hobbelen and Wisse focused under on how SLR impacts the fortitude of biped strolling using three models: a point mass imitated model, a sensible rehashed model, and a veritable model. These models walked around a fixed improvement length and a perpetual. Using the eigenvalues of the Poincare map as the level of the generosity under these models, they found that delicate SLR speeds improve the idea of biped strolling [9]. Various evaluations on this issue have used equivalent frameworks and expanded comparable culminations [8] [10] [11]. For work, some biped robots have used SLR under their headway arranging and control [12].Under any case, these assessments have inadequately seen as other determinant highlights of the biped walking venture, for example, the walking development & step-length (another basic cut-off, the development rehash, has been coordinated through the development length & walking speed). Such as showing up under changed evaluations under human and biped strolling (e.g., [11]), the strolling improvement and step-length pick the impacting and security properties of strolling steps. While the copied models and authentic models utilized under the beginning late implied appraisals can basically stroll around a fixed or particularly minimal degree of strolling rate and medium improvement length, people can stroll around a tremendous degree of strolling speeds and step-lengths. Under human strolling, the standard degrees of strolling rates and step-lengths are 0.7 – 1.9 m/s and 0.4 – 0.7 m, self-administering [13]. The past assessments on SLR can't reveal to us whether their decision will regardless of hold under other strolling plans (e.g., human's enthusiastic strolling along enormous progress length, which was not feasible under their models). Thusly, the appraisal question we ask under this assessment has been: How does the SLR impact the consistency of biped strolling plans under the full degree of human strolling rate and step-length? Around the day's end, does SLR improve the idea of biped strolling at any mix of strolling rate and step-length? Loss of legs makes an individual need to utilize an instrument to override the restrictions of the foot. Counterfeit feet are a contraption that has beenunder many cases utilized through an incapacitated individual who disposes of his leg. It has been outstandingly simple to utilize prosthetic furthest points for disposed of legs under the calf under any case, not along those along handicaps who is cut off under the thigh since they have lost their knee joints. Under Indonesia, there has been a little heap of individuals making ordinary prosthetic individuals, anyway since the advancement of the knee joint on standard prosthetic limits just uses a working system of a mechanical turn of events, it has been up to this point hard to use for the bit through bit works out, particularly under exercises up & first floor [14] [15]. There has been an answer under this evaluation, to be unequivocal bionic feet subject to the weight & grade of the thigh point [16] [17]. Load cellhas been used to measure body weight under noticing feet laying on one foot or two feet & the GY-521 sensor have been used to take a gander at the high point. Fuzzy logic has been used to manage the two sensors. Fuzzy yield as a guide changed under

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the PWM motivation toward control the motor direct actuator that moves the knee joint on as far as possible can move along the correct point so the movement of the bionic foot can move like a person along ordinary legs.

The results maintain the study which conveys that the made controller can perceive human development &force the motor under a fundamental manner.Segment 2 depictstheliterature review bases on fuzzy logic control as well as the human swing leg system underthe latest paper.Under session 3Feedforward Neural Network (FFNN) and Fuzzy Logic Control (FLC). The outcomes is introduced & examined under Segment 4. At long last, ends have been drawn through joining the entirety of the significant purposes of the investigation.

II. LITERATURE REVIEW

In [18] researchers arranged a Neuro-fluffy control framework for control of reiterating leg developments of paraplegic subjects. The rehashing leg developments were obliged through three 'swing stage targets', run of the mill for a brand name human walk. The Neuro-fluffy regulator has been a blend of a fluffy rationale regulator and a neural association, which makes the regulator self-tuning and adaptable. In [19] the Author presented the development get framework for bearing masterminding of the leg swing test framework. Notwithstanding, the camera got the identifier that was mounted on the human leg. Identifiers as markers are put to be followed as joints position. The camera has been followed for the orchestrating progress under the course and in like manner put aside under the information base. The virtuoso information of joint position would shape the improvement of overhauls, for example, the advancement of human leg update. The improvement of the marker has been utilized to portray the strolling cycle. To design and diagram of leg swing bearing sorting everything out, the producers propose it through utilizing joint space heading masterminding. The heading strategy was applied to the leg swing test framework model. It has been a robot leg along an essential position covering the three joints: hip, knee, and lower leg. In [20] Authors planned of Fuzzy Logic Controller for a traffic signal system. Best sign settings can be fixed while passages of the excursion & system stream areunder equilibrium. To deal along taking care of & showing information, fuzzy systems is associated along training the right end. This original copy focuses on the basics of Fuzzy Logic & its motivation under Principle Based Systems to make them capable to hold this current assurance issue. Furthermore, a traffic movement control system was anticipated & evaluated using MATLAB. In [21] paper delicate switch regulator for encouraged control frameworks was proposed. Maybe the most principal of created control frameworks has been the stochastic time deferral of information packs under the alliance, which can cause abnormality. This proposed regulator makes the best control signal utilizing the structure of the TSK fluffy framework and neural affiliations dependent on association time yield assessment. In [22] the researchers discussed the arranging technique for FPSS and the introduction of FPSS has been differentiated and the yield response of a Relative Indispensable Subsidiary (PID) controlled framework. A Fuzzy Logic Controller for Force System Stabilizer (FPSS) was made to overhaul the presentation of a Singular Machine Unfathomable Vehicle (SMIB) framework under solid state and dynamic states of the electrical power framework. For improving the presentation of this framework, two data sources FPSS was viewed as which needs to splash the headways under the framework.In [23] Authors built up a versatile issue open-minded controller, under view of a novel K-channels, to address the following manages issue of a class of nonlinear systems. Along the assistance of fuzzy logic systems, a novel K-channels was proposed to gauge the unmeasured system states. It has been demonstrated that the created controller can ensure all the signs were limited & the yield tracks an offered sign to an area, under spite of the presence of outside aggravations, displaying mistakes, & actuator flaws. In [24] the Authors introduced the consequences of exploration under the turn of events & usage of calculations for delicate interpreting of rudimentary signs, under view of the hypothesis of fuzzy sets & fuzzy logic procedures. The utilization of the mathematical

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mechanical get-together of fuzzy sets & fuzzy logic to portray the dynamic system has been communicated.The strategy for delicate disentangling (dynamic) of rudimentary signs has been offered; it has been recreated utilizing the Fuzzy Logic Tool kit. In [25] Authors introduced the versatile fuzzy after control plan issue for multi-input & multi-yield (MIMO) questionable traded constrict-assessment nonlinear systems along self-authoritative switching's. Fuzzy logic systems (FLSs) thought about observing the dull nonlinear cut-off points (concerning state quantifiable case) & model the uncertain nonlinear systems (for state massive case). Together state examination & spectator based yield input control configuration plans is made dependent upon a joined solicitation channel & versatile fuzzy control procedure. Plus, the security of the fuzzy control systems under self-emphatic switching's was exhibited reliant on the fundamental Lyapunov work strategy. Under [26] Autors executed swing-leg retraction, which was a control technique to improve the strength of the model. Despite the fact that a miscreant control technique has been better, swing leg renunciation lessens calculation at every progression & furthermore the requirement for exact actuators. Utilizing Swing-Leg Retraction (SLR) technique doesn't need estimation after each progression & furthermore gives solidness if there should arise an occurrence of dubious territory. From our outcomes, they can say that utilizing SLR was a decent compromise between the ideal precision. In [27] introduced SLR instances of a biped copy covering the full extent of human walking plans (i.e., speeds & step-lengths). The SLR improves the steadfastness even more clearlyunder walking plans like human-supported ones, & impacts the robustness barely or even debilitates it under walking plans that were through & through not quite the same as human-supported ones.In [28] the Authors explored the exhibition of fuzzy logic controllers (FLCs) applied under the framework associated along wind generators to improve exhibitions of control. This reason expected to accomplish great exhibitions of receptive force remuneration. The controller deals along the best stand-out force into the structure at solidarity power factor, while it under like way allows the qualification under responsive force mixed into the affiliation. Under the second period of the examination, FLCs changes PIs controllers to improve the presentation of power control. In [29] broadsheet, two fell fuzzy rationale regulators for direct power controlled inside a ceaseless magnet coordinated engine (IPMSM) drive framework has been introduced. The redirection results show that utilizing a fuzzy adaptable PI speed regulator, the PI regulator cutoff centres can be in this manner tuned web as indicated by the working condition. Essentially, the engine power has been controlled over a wide speed level of activity utilizing the fuzzy Direct power control (DTC) strategy.

III. METHODOLOGY

The basic goal of fuzzy logic control is to ctreate a system for controlling the life's human with his rich practical expertise and without having any idea about the mathematical model of the plant. The control expert specifies the control actions in the form of linguistic rules. The FLC comprises mainly three blocks namely, fuzzification, inference engine and defuzzification.

A. Fuzzification

The map of Fuzzification is the basic parameters into fuzzy groups and is used to calculate the membership function of the observed inputs to the defined linguistic term. The membership function is a graphical representation of the magnitude of the participation of each input and is created by specifying the degree of membership for each possible input value for a given label. The y-axis {μ} values refer to the degree to which the crisp input value applies to each of the membership function labels (low, medium, etc.). The input values can belong to more than one fuzzy set.

The description of crisp inputs in fuzzy terms allows the system to gracefully respond to gradual change in input. For example, as shown in *Fig. 1*, the fuzzification of the input value, x0 = 70 km/h, gives two membership functions μA and μB which characterize a low and a medium fuzzy set,

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respectively. The given input value of x0 = 70 km/h corresponds to a grade of μD (x0) = 0.75 to the fuzzy set 'low' and a grade of μB (x0) = 0.25 to the fuzzy set 'medium'.

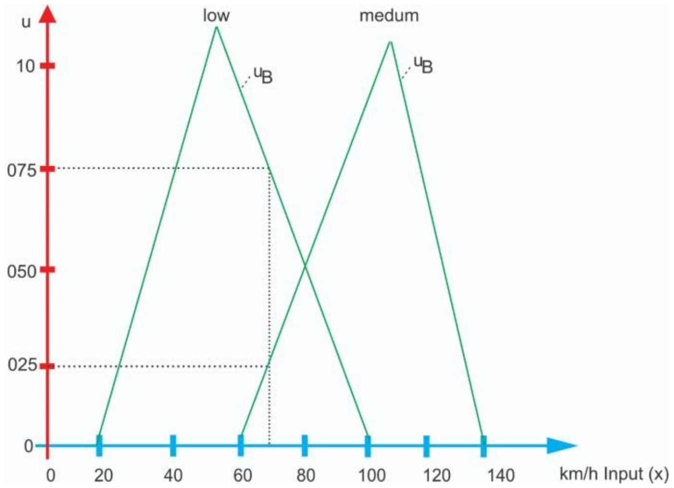

FIG. 1. FUZZIFICATION OF A GIVEN INPUT VALUE.

B. Fuzzy Inference Engine

The vetal form of a fuzzy inference model contains the three theoritical elements:

1- A rule base, that consists the laws of fuzzy.
2- A data base, that shows the relation formulas which depended in the fuzzy laws.
3- A reasoning Algorithm, that achieves the inference structure depending on the laws and existing actuality to get a sensible output.

The application of prediction sensible models has come out as a resonable different in control problems where the model isn't simply reported by an numerical schema. However the inputs are getting via the model, the basics of laws are judged. The condition (IF X AND Y) block experiments each value in the input and products control measures. The result (THEN Z) block of some laws satisfies despite of the others. The control measures are gathered to create logic sum. These control measures provide to the inference operation which the starting power is between (0 to 1) where the output formula is calculated.

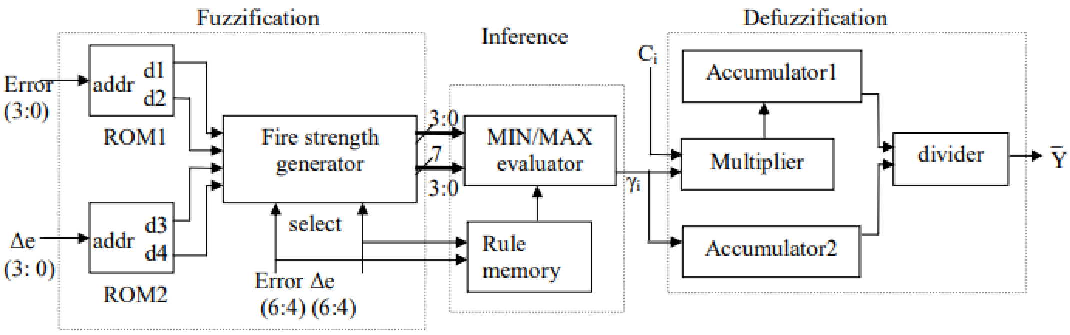

FIG. 2. PROPOSED HARDWARE STRUCTURE OF FUZZY LOGIC CONTROLLER.

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The fuzzifications stage gets a couple of input parameters, called “error and change in error”, Which is generating the fuzzified input (for each 7 bits width), depending upon the relation formula utilized (for each 4 bits width). The input is gotten via the FLC *Fig. 2* is utilized for addressing the ROM memory and acts like a wave for choosing the semantic in the values which start power generators. Many different kinds of relation models related within all fuzzified inputs and fuzzified outputs. In this paper, the symmetric triangular’s relation models are utilized for high response speed to describe input and output.

C. Defuzzification

The output group of fuzzy model are deduced and calculated using the Mamdani-type FIS that performs quite similar, has also an advantage that it can integrated with neural networks and genetic algorithm or other optimization techniques so that the system can adapt to system characteristic efficiently. these are defuzzified to essential outputs which drive the model. Many defuzzification models are varing and they may examined at the last level of FLC. The most popular method of defuzzification is the centroid method. In this method, the conversion of fuzzy data into a crisp output is accomplished by combining the results of the inference process and then computing the fuzzy centroid of the area. The formula used for defuzzification is given by

$$Y = \sum_{i=1}^{n} \gamma_i C_i \sum_{i=1}^{n} \gamma_i$$

where Y is the crisp output, $\gamma_i$is the strength’s weight of ith relation formula from the fuzzy inference engine and C_i is the centre point of the output membership function.

D. Feedforward Neural Network (FFNN)

Back propagation algorithm is the most popular algorithm for training feedforward neural network. The approach contains a couple phase (feedforward phase and backpropagate phase0. In the feedforward phase, firstly, initialize each weight in the network randomly. After that, calculate the network’s outputs. In the backpropagate phase the output is compared to the desired value. Then, the errors are propagating backward then utilized for updating the weights of the preceding layer continously. In the feedforward, the calculations over the allocated weights which got by the back propagate phase then the input values are gotten. The training model of back propagation approach is denoted below:

i. Feedforward Algorithm

1: Initialize the weights of the network in random.
2: Scale the input/output data.
3: Select the structure of the network (such as the number of hidden layers and number of neurons for each layer) and choose activation functions for the different layers.
4: Select the training pair from the training set. Apply the input vector to the network input.
5: Calculate the output of the hidden layer and output layer based on the initial weights and input set. The net input to the jth hidden layer neuron is given by:

$$h_{in_j} = b_j + \sum_{i=1}^{n} x_i V_{ij} \qquad (1)$$

where i = 1,2, …n and j =1,2,…m

$$h_j = f(h_{in\_j}) \qquad (2)$$

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Where xi is the ith input, hj is the output of hidden layer neuron, Vij is the weight on the connection from the ith input neuron to jth hidden layer neuron and bj is the bias. The net input to the k th output layer neuron is given by:

$$y_{netk} = b_k + \sum_{i=1}^{n} h_j w_j k \qquad (3)$$

$$y_k = f(y_{netk}) \qquad (4)$$

where y_k is the network output, w_{jk} is the weight on the connection from the jth hidden layer neuron to kth output layer neuron and b_k is the bias.

ii. Backpropagate Algorithm

1: Calculating the error between output and the desired output (the target vector from the training pair). The error to be minimized is defined as:

$$e = \frac{1}{2}(d - y_k)^2 \qquad (5)$$

where d is the desired value of the output.

2: Propagating the error backward i.e. determine the error correction factors and adjust the weights to minimize the error. The error gradient vector in output layer can be calculated as:

$$\delta_k = (d - y_k) f'(y_{netk}) \qquad (6)$$

Where $f'(y_{netk}) = f((y_{netk})[1 - f((y_{netk}))])$

The weight correction term in output layer is,

$$\Delta w_{jk} = \eta \delta k^h j$$
$$\Delta b_k = \eta \delta k^h \qquad (7)$$

Where η is the learning rate. The error gradient vector in hidden layer is:

$$\delta_j = \sum_{k=1}^{m} \delta k w j k^{f'(h_{in\_j})} \qquad (8)$$

The weight correction term in the hidden layer is,

$$\Delta v_{ij} = \eta \delta j^x \quad i$$
$$\Delta b_j = \eta \delta j \qquad (9)$$

Therefore the weights are updated as

$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij}$$
$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk} \qquad (10)$$

3: Repeat steps 4 to7 for each input vector in the training set until the error is lower than the required minimum error. Equation (1) can be applied for every neuron in hidden and output layers. One of the drawbacks in the back propagation learning algorithm is the long duration of the training period. In order to improve the learning speed, an adaptive learning rate can be chosen.

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A) Recursive K-Means Clustering Algorithm

Clustering algorithm may be depended to seek a group of centers, that is reflecting the exactly spreading of the arguments. The amount of centers 'N' is defined later, and each center Ci is hypothetical to be typical of a set of argument points. The centers in a RBF is conventional artificial (ANNS), the radial basis function network network (RBF) has a more compact structure and consequently it requires less training time compared with other ANNs and neuro- Fuzzy system network are choosed to minimize the whole distance between the aruments and the centers, Thus centers can suitably characterize the arguments. The approach levels are given below

1: The initial centers Ci (i =1,2,3….N) are selected in random.

2: The next input vector X(k) is obtained.

3: The closest center Ci is modified using the equation

$$C_i(k) = C_i(k-1) + \beta(k)[X(k) - C_i(k-1)] \tag{11}$$

4: The sum of squared error (SSE) for the last N sampling periods is computed using the equation

$$SSE = \sum_{i=1}^{M} [Y_p(k-i) - Y_p(k-i)^2] \tag{12}$$

Where $Y_p(k) is\ the\ process\ output\ and Y_p(k)$*is the desired output.*

5: If the SSE is greater than threshold βc*, then the learning rate is maintained at the initial value using the equation*

$$\beta(K+1) = \beta_C \tag{13}$$

Otherwise the learning rate is updated using the equation

$$\beta(K+1) = \gamma\beta_T(k) \quad 0 < \beta(k) < 1, 0 < \gamma < 1 \tag{14}$$

Where $\beta(k)$*is the learning rate,*β_C *is an initial constant value for the learning rate and* γ*is the decay constant. In case the modeling error over a period of time is greater than a selected fixed threshold* ς_C *the adaptive learning rate remains constant, otherwise it decreases to zero.*

B) Recursive Least Square Algorithm

Recursive Least Square (RLS) algorithm is utilized to update the weights of output layer in RBF neural networks. The RLS approach predicts the unknown output layer weights with the help of inputs and outputs and performs recursive computations with exponential forgetting factor. The RLS algorithm estimates the unknown weight parameters recursively for each measurement based on the minimization of the least square error. The matrix equations describing the RLS algorithm are,

$$\in(k) = y(k) - \varphi^T(k-1)w(k-1) \tag{15}$$

$$k(t) = p(k-1)\varphi \quad (k-1)(\lambda\varphi^\tau(k-1)P(k-1)\varphi(\mathrm{k}-1)^{-1} \tag{16}$$

$$w(k) = w(k-1) + K(k) \in (k) \tag{17}$$

$$P(k) = (I - K(k)\varphi^\tau(k-1)P(k-1)/\lambda \tag{18}$$

where λis the forgetting factor, K(k)is the Kalman gain, P(k) is the error covariance, w(k) is the error to be minimised, w(k) is the unknown weight matrix, I is the identity matrix and ε(k) represents the input-output values of RLS block. The components of the vector K(k) are weighting factors that tellhow the correction and the previous estimate should be combined. P(k) is initialized as a diagonal

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matrix at the initial stage. The weights are initialized with small random values and then updated for every iteration.

IV. RESULTS AND CONVERSATION

The feedforward neural network with lookup table based activation function is implemented with integer data representation. The network consists of three input neurons, three neurons in one hidden layer and one output neuron.The simulation signal of the feedforward neural network. In this waveform, IN1, IN2 and IN3 represent the inputs of the network, Y represents the output of the multiplexer placed after hidden layer 116 and Y0 represents the network output. It also shows that the circuit delivers the output at 70 ns with the clock period of 5 ns and then the output is delivered after every 15ns from the network. Thus the design takes 14 clock cycles to perform the feedforward computation.

The summary of device parameters and usage for the FFNN with LUT based activation function is given below:

1. Maximum frequency : 33.33 MHz
2. Number of slices : 591 out of 3072 (19%)
3. Number of slice registers : 368 out of 6,144 (6%)
4. Number of flipflops used : 296 out of 6570 (4%)
5. Number of 4 input LUTs : 965 out of 6,144 (15%)
6. Input/output buffers : 47 out of 142 (33%)
7. Total equivalent gate count for design: 8,926

It may be noted from the synthesis results that the design needs 19% of the CLB slices with the maximum operating frequency of 33.33 MHz. The performance of the neural network is 28.57×106 CPS.

The proposed hardware implementation of 2-3-1 FFNN is simulated with floating point data representation and is examined utilizing the Virtex IV family device 4VLX200ff1513. The neural network has 13 synapse connections including bias connections. The synthesis circuit of a neuron is the same as that given in waveform which except that the arithmetic operations (multiplication and addition) are carried out with floating point representation. The model shows the synthesis circuit of the hidden layer. The simulation waveform of pipelined design of FFNN is used in this waveform, 'ffn_out' indicates the network output and c, d and e indicates hidden layer outputs. The waveform shown that the feedforward computation delivers the output at 11.3 µs with a clock period of 100ns and uses 113 clock cycles. The performance of feedforward computation of pipelined FFNN is 16.88 ×106 CPS.When the design is tested for logical XOR problem, the minimized error is reached at almost 60µs. The design takes 600 clock cycles to reach this error. The learning rate chosen is 0.7 and it is updated every iteration with a decrement of 0.01. The maximum possible frequency of the algorithm is 146.735 MHz and the performance of the learning block is 11.22×106 CUPS. The entire algorithm occupies only 34.58% of CLB slices of the Virtex IV device.

TABLE I . RESULTS OF SYNTHESIS OF FFNN COMPARED WITH EXISTING DESIGNS

Designs	# Data bits	Devic	CLB	Maximum frequency (MHz)	CPS ×106
Coric et al (2000)	8-bit	XC4005	156	30	Not available
Nichols et al (2002)	16-bit	Virtex-E xcv2000e	1239 for 5 neurons	10	Not available
Gilberto Contreras et al (2003)	8-bit	Spartan II XC2s100	855 for 27 neurons	24	150
Ortigosa et al (2006)	8-bit	Virtex-E	3094	21	Not available

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TABLE II. RESULTS OF SYNTHESIS OF FFNN COMPARED WITH PROPOSED DESIGNS

Designs	# Data bits	Devic	CLB	Maximum frequency (MHz)	CPS ×106
FFNN with LUT based activation	8-bit	Spartan IIE Xc2s300e	591 for 7 neuron	34	29.33
FFNN with combinational logic based activation	16-bit	Spartan IIE Xc2s300e	1353 for 6 neurons	14	6.24
FFNN with pipeline design	32-bit	Virtex IV	14636 for 6 neurons	147.46	15.87
Ortigosa et al (2006)	8-bit	Virtex-E	3094	21	Not available

The simulation results of FFNN are compared with those of the existing designs and presented in Table I and Table II it is observed from the table that the hardware implementation of FFNN with 8-bit data representation operates with the maximum frequency of 33.34 MHz compared to other 8-bit designs. The area requirement of FFNN with 32-bit floating point data representation is more compared to other implementations. However, the maximum frequency required for pipelined design of FFNN is the highest among all the known designs.

Fig. 3 shows the variation of sum of squared error as time increases. It may be noted that the squared error reaches zero at approximately 20 µs. At this time the Euclidean distance reaches zero and the center values reaches the input value (at steady state).

The results of the synthesis are obtained using Virtex-II pro device 2VP100ff1704. As given in Table III below, the hardware model of k-means approach involves 15109 CLB slices. The proposed design uses 3036 clock cycles to calculate the four centers in parallel. However, the model uses fewer time for updating the centers.

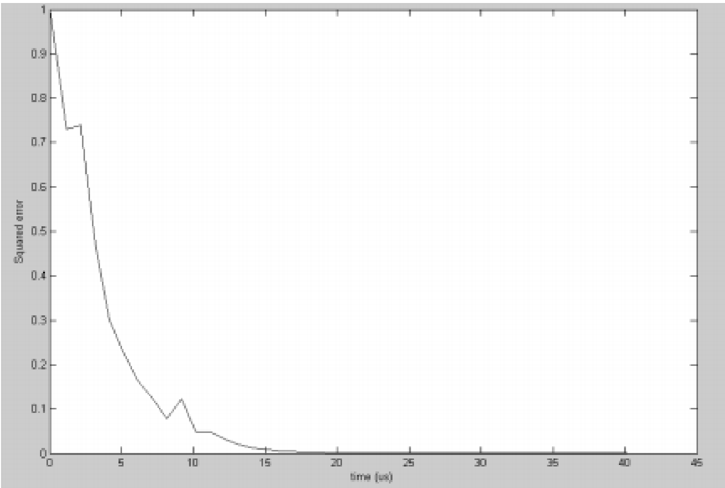

FIG. 3. VARIATION OF SSE IN K-MEANS ALGORITHM.

TABLE III. RESULTS OF SYNTHESIS OF K-MEANS ALGORITHM

Resources	Used	Available	Utilization
IOs	257	1040	24.71%
Global Buffers	1	16	18.75%
Function Generators	30218	88192	34.26%
CLB Slices	15109	44096	34.26%
D-flipflops	18945	91312	20.75%

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V. SIMULATIONRESULTS OF RLS ALGORITHM

The servo response obtained for the Matlab simulated closed loop system is shown in *Fig. 4*

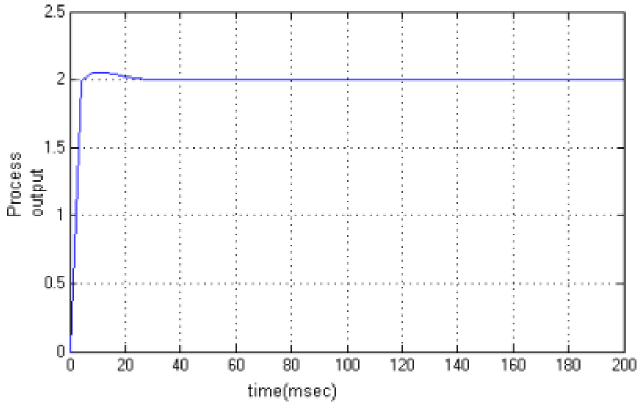
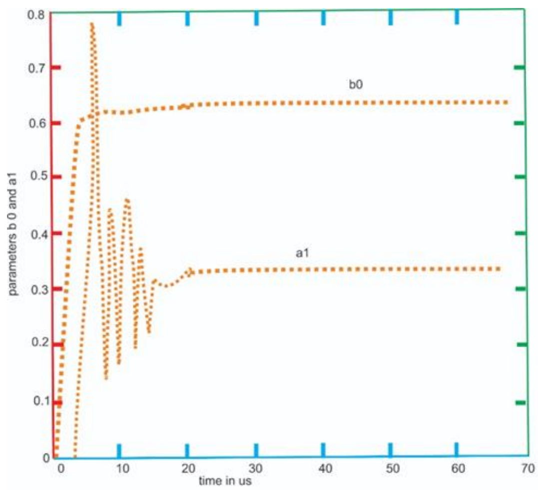


FIG. 4. MATLAB SIMULATION OF LIQUID LEVEL PROCESS.

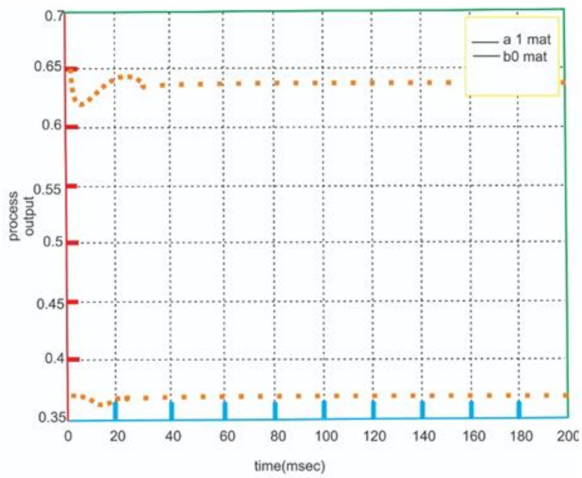
TABLE IV. RESULTS OF SYNTHESIS OF ERROR MATRIX IN RLS ALGORITHM

Resources	Used	Available	Utilization
IOs	324	1040	31.15%
Global Buffers	1	16	6.25%
Function Generators	5387	88192	6.11%
CLB Slices	2694	44096	6.11%
D-flipflops	2709	91312	2.95%

The RLS algorithm delivers the first output (after first iteration) at 2500ns, and delivers subsequent outputs for every 1060ns (for every subsequent iterations). The results of synthesis of error matrix in RLS algorithm is listed in Table IV. The variations of estimated parameters with time are plotted in a graph as shown in *Fig. 5* (a). It is observed that the algorithm takes almost 19 iterations to estimate the parameter b0 (one iteration = 1060 ns) and 30 iterations to estimate the parameter a1. The results of RLS algorithm obtained from the Matlab simulation (where the initial parameters are 0.4 and 0.65) are shown in *Fig. 5* (b). It is observed that the RLS algorithm simulated using Matlab takes more settling time (about 20ms) and takes 20 iterations.



(A)



(B)

FIG. 5. GRAPH OF ESTIMATED PARAMETERS A1 AND B0 IN (A) VHDL AND (B) MATLAB.

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The hardware based RLS approach is examined with a forgetting-factor of 0.9. It is observed that the settling time for a1 is about 75 µs and that of b0 is 67.16 µs. Hence a forgetting factor of one is preferred for the RLS algorithm while designing the STC for second order model. The process model output values are plotted in the graph as shown in *Fig. 6* It denotes that the system output is tracking the input values (setpoint) and it ensures that the predicted sets are acceptable.

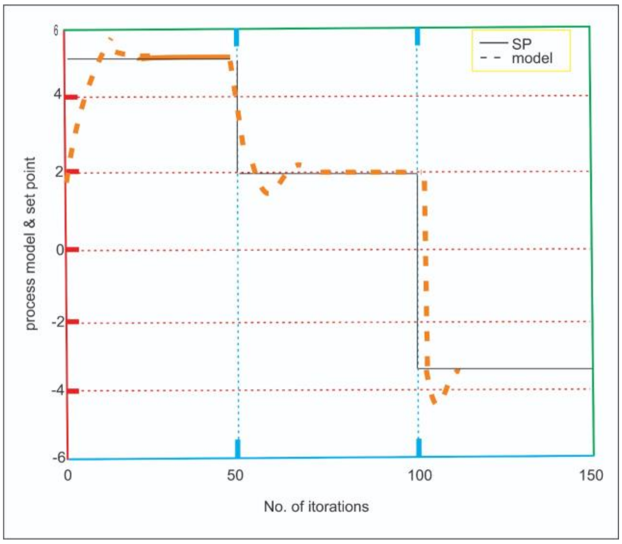

FIG. 6. RESPONSE OF PROCESS MODEL OUTPUT.

The RLS algorithm with forgetting factor of 1 is used to obtain the weights of the output layer of (RBFNN) Radial Basis Function Neural Network. The algorithm uses 130 ns to complete one iteration and 2045 clock cycles (20.45 µs) to update the weight values. The final weight values are 0.4268, 0.1516, 0.3682, and 0.3668.The synthesized results of various bocks of RLS algorithm are given in Tables III.

VI. CONCLUSIONS AND FUTURE WORK

In this research work, distinct hardware architectures of FFNN have been implemented with different data representations. The online training of FFNN has been performed using backpropagation algorithm in floating point data representation. The pipelined architecture of FFNN with floating point hardware gives excellent performance during both online and offline training 177 in terms of area requirement as well as speed of operation. It is observed that the proposed design of digital FLC uses less hardware resources when compared with existing designs. The operational speed of RBFNN is better when compared with existing designs. First of all, the adaptive control values are selected with a hardware depedned on self tuning control system, that utilize the RLS approach to recognize the varing in model values frequently and the MDPP schema for 178 calculating the controller values. The hardware design of adaptive RBFNN based controller has also been implemented by performing the realtime training of RBFNN in adaptive control models. The real time training model of RBFNN has been carried out by employing the recursive k-means clustering approach to update the hidden layer centers and the RLS algorithm for updating the output layer weights, both implemented in hardware.The performance of adaptive RBFNN based controller has been tested for a second order process by varying process parameters and setpoint. In future work for which hardware based online training of neural networks can be implemented with the growing hidden layer neurons depending on the application. Adequate number of neurons should be made available and they have to be available as and when required.

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