An Approach Using Elman Neural Network To Predict The Model For A Nonlinear Process

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Abstract— Most of the industries such as chemical, textile, paper and pharmaceutical use non-linear processes for their production. Generally, the system dynamics of non-linear processes are complex. Due to such complexities, difficulties arise in controlling the plant's operations in desired fashion. In order to ensure desired productivity and safe operation of the plant, it is mandatory to govern the process variables effectively. To achieve such an operation, system identification of the process is essential. But the major problems with system identification is maintaining the stability and observing its dynamic behaviour. For this reason, system identification of a nonlinear process is performed by Elman Recurrent Neural Network (ERNN). In this article, classical approach is used to linearize a conical tank into several regions. These linearized regions are modelled using ERNN. The developed Elman neural network model's performance is analysed with radial basis and feed forward neural networks. Finally the different ERNN models are combined.

Keywords— *Nonlinear process, System dynamics, conical tank, classical approach, Elman recurrent neural network (ERNN), Radial basis and Feed forward neural network.*

I. INTRODUCTION

In process control industries modelling is a necessary scheme to control the specified industry processes in preferred manner. To model a stated process, system identification is an important tool, which involves designing a mathematical model for a process or system using observed data or its physical laws. In many process control industries, processes are fairly difficult to model because of huge delay time and dynamic behaviour. In system identification, classical methodology is the mathematical modelling which gives a system its nonlinearities and dynamics. But this methodology often fails in some areas because in mathematical modelling methodology the physical characteristics about the process should be known. Due to inaccuracies about the physical characteristics of system it is difficult to model the processes. Thus, empirical approach based system identification is preferred here. Empirical approach, considers the process as a block box model. By conducting the experiments on the system the input and output values are obtained. From the input and output information about the process a model is formulated. Numerous studies have been carried out to build a model for controlling a nonlinear process in empirical fashion. Sukanya Warier, SivanandamVenkatesh [1] described, design of controllers based on model predictive control (MPC) for a conical tank level process. In this study, to observe the dynamic behaviour of system in efficient manner the tank is linearized. Then the MPC performance is compared with discrete time PID controller (DTPID). At the result, MPC is proved to be a better controller than DTPID. [2] The Modelling and controlling procedure for conical tank system is well explained by T.Pushpaveni, et.al wherein, the process control action is framed by using model predictive controller (MPC) and conventional PID controller. Then the optimum controller is selected based on the performance of these two controllers. Finally, the MPC controller is found to be the optimum controller. Bhuvaneswari, et.al, [3] carried out their experiments in conical tank level process and its control using artificial neural network approach, where the process model is obtained by ANNs approach based Neuro controller, designed for control action. The similar kind of work is followed by Moonyong Lee, et.al, [4]. In this study, the ANNs based neuro controller and conventional PID controller is designed in a combined fashion for the conical tank level process. In this scheme, if one of the controllers malfunctions, the other one carries out the process. Swati Mohanty [5] designed Model Predictive Controller for floatation column. This study is similar to the previous studies. This paper described the design of a neural network based model predictive controller for controlling the interface level in flotation column. The controller was tested for liquid-gas-solid system and was found to perform satisfactorily. The performance of the controller was compared with that of a conventional PI controller for a two-phase system and was found to be better [1, 2]. Aravind, et.al [6] explained the modelling of conical tank system. Here also the dynamics of the system is recognised by linearization of tank. Nithya, et.al, [7] designed an Intelligent Controller for Non-Linear processes, which provides a solution to the problems raised in an ordinary controller. Every study conducted in this field yielded a unique idea about the system modelling. These studies clearly prove artificial neural networks (ANNs) to be a powerful tool for observing nonlinear processes. The ANNs are classified into many types based on network formation. Elman Recurrent Neural Networks (ERNNs) based ANNs is used here to model a proposed process. The Elman Neural Network of data processing, training and the recurrent neural network working procedures are obtained from recurrent networks by Xiaolin Hu, et.al [8]. The training and its modified algorithm used in Elman network for error minimization work is described in Elman networks and dynamic system modelling [9]. From the above mentioned article, it is evident that there is a difficulty in each type of system modelling and its control. But the neural network techniques have bought extensive attention as they are able to overcome the difficulties in modelling and have offered promising results. ANNs are one of the empirical approach based modelling methods and a prediction tool. It was recently developed and has found widespread approval in many disciplines like chemical industries for modelling the processes, robotics, bio medical instrumentation and share market for prediction. Similar to biological neurons, ANNs are capable of procuring accurate solutions for complicated problems. They can also provide solutions for inaccurately framed problems that can only be understood with experimental data and field observations. ANNs produce complicated nonlinear models by mapping the inputs to the outputs of processes.

Normally ANNs are classified into feed forward ANNs and feedback ANNs. The feed forward ANNs can be used for static behaviour applications like pattern recognition. But ANNs cannot understand the system dynamics when it is in feed forward fashion, hence demanding an alternate approach. This is achieved by recurrent or feedback neural networks (RNNs). RNNs have a memory unit to recall past information about the process. According to the connections between the nodes, the RNNs are characterized as partially recurrent (PRNNs) and fully recurrent networks (FRNNs) [10, 11]. Among these two types, the PRNNs produce good solutions for problems due to its simple structure. But FRNNs are complicated networks since they have more connections between nodes. RNNs temporal behaviour in observing characteristics makes them suitable for mapping non-linear dynamic systems. Hence they are used in wide areas like robotics, bio industries, aircraft, missile technology, etc., In PRNNs, the recurrent connections are established by acquiring input to a selected node as feedback from hidden node output or the output node output of the network. Normally in PRNNs, connections between the nodes are in feed forward fashion, but they differ because of its feedback connections for selected nodes. According to PRNNs recurrence configuration, it is categorized into many types such as Hopfield, Jordon, NARX net and Elman neural network. Among these, Elman neural network concept is used in this paper to perceive the system dynamics and to model the system. Already some articles have been developed for nonlinear system modelling using ANNs [12, 13]. But there are stability related problems occurring due to feed forward and radial basis networks. This study is concentrated on feedback ANNs in Elman neural network, in which the desired response is obtained by mapping the target output with its corresponding appropriate manipulated input. But there is a problem in this apping because the target values can't be provided explicitly. The assumptions about the process dynamics are considered to be unknown. Hence to capture these unknown dynamics of the process, neural networks learning concept are used to give the solution for this problem [12, 13, 14]. By using this learning mechanism, updates about the process dynamics can be obtained and appropriate models for unknown processes can be designed. In this study, conical tank is taken as a process, since it is nonlinear in nature. The proposed idea is to model this conical tank by using Elman recurrent neural network (ERNN). Using ERNN approach the past information of the process can be obtained from its hidden node output at every instant. These previous information's about the system states can be stored in ERNN context node for future prediction and to observe the process dynamics. By this manner of ERNN, the behaviour of the system can be understood easily and is useful in designing an appropriate model. In this study the conical tank is separated into six regions to observe the dynamic behaviour of the process in an appropriate manner [2, 3, and 4] after which it is modelled by Elman recurrent neural network (ERNN). The six region models are compared with classical approach based transfer function model [1, 2]. After that the ERNN performance measurement is analysed with feed forward and radial basis network according to its mean square error (MSE). Finally all the six regions of ERNN model are combined to give an exact model of the conical tank. In the first section, the full description about the conical tank and its mathematical model is described. The procedure to obtain input and output data are explained in detail followed by the system identification part where the classical approach method and Elman neural network method of modelling is explained. In the classical approach, the method to obtain the linearized response of conical tank is explained. In Elman network section, the working principle of Elman recurrent neural network (ERNN) and its data processing [9] are explained. Subsequently, the method to model the conical tank by Elman neural network, radial basis and feed forward networks are described. The subsequent section elucidates how the Elman network is trained to validate the model and how validated model is combined to form combination nonlinear model. Afterwards, the Elman neural network model validation, comparison, combination and performance measurement are derived in the Ease of Use

II. PROCESS DESCRIPTION

The proposed process is a conical tank level process. Generally this conical tank process is nonlinear in nature. In most industries like cement, sugar, etc., the cone shaped kettle is used for process action. Therefore the conical tank process is chosen as the proposed process. The conical tank of mathematical model is described in the following section.

A. Mathematical Model

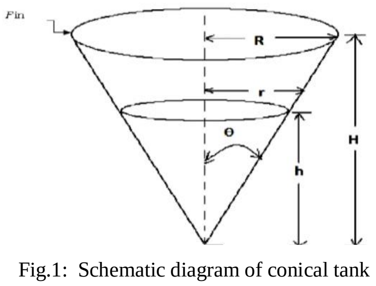

Fig.1: Schematic diagram of conical tank

The process is conical tank level process, in which the liquid level in the tank is maintained at a constant rate. It is done by adjusting the input flow rate into the tank. The block diagram of the conical tank is shown in figure 1.From the law of conservation mass,

$$F_{in} - F_{out} = \frac{Adh}{dt} \qquad (1)$$

$$A = \pi r^2 \qquad (2)$$

Where, F_{in} is inlet flow rate to the tank, F_{out} is the outlet flow rate from the tank, R is the radius of the tank at top level. H is the total height of the tank in cm and r is the radius at any height h in *cm*, then the area of the tank is written as,

$$\tan\theta = \frac{r}{h} = \frac{R}{H} \qquad (3)$$

The conical tank volume in terms of height is

$$V(h) = \pi\left(\frac{R_2}{h_2}\right)h_3 \qquad (4)$$

So, the relation between height and inlet flow of the tank is written as,

$$\frac{dh_3}{dt} = F_{in}(t\text{-}t_d)\text{-}K_v\sqrt{h} \qquad (5)$$

When the flow is considered as gravity flow then, delay time can be calculated as,

$$t_d = (H\text{-}h) + \frac{r}{g} \qquad (6)$$

The radius of the conical tank at any height h is,

$$r = \left(\frac{R}{H}\right)h \qquad (7)$$

When height (h) becomes zero, the area becomes lesser and the rate of change of volume (dV/dt) tends to infinity. Due to the conical tank's outlet flow pipeline, the height never gets to be zero. Considering the initial height, the final mode equation becomes,

$$d\frac{(h+H_{int})3}{dt} = F_{in}(t\text{-}t_d)\text{-}K_v\sqrt{\frac{h+H_{in}}{\pi\left(\frac{R_2}{H_2}\right)}} \qquad (8)$$

Equation (8) is the conical tank for the mathematical model. From the mathematical model the desired control action can be performed. But this mathematical model cannot certainty for all process. Therefore, the empirical approach is applied to system identification.

In system identification task, the conical tank identification (modeling) is done by Elman recurrent neural network (ERNN) based Artificial neural network (ANN) architecture. The ERNN model is obtained by mapping the input and output data histories. To get an appropriate network, have to collect more data. But it is not an easy task to perform experimentally. So, transfer function based classical approach is used [1] to obtain the data histories. In this approach, the system is considered as a block box or unknown system [15]. By conducting the process experiment for random input flow rates, its corresponding output is obtained as level values. From the experimental results, the process response is acquired as a nonlinear curve. To get an accurate model this nonlinear response is linearized according to its equilibrium point. The reason for linearizing the system is to observe the process dynamics efficiently. Finally, the different linearized regions for nonlinear system are obtained. Now the required data are easily obtained from the region wise models. From the data histories, the proposed Elman network model is designed for the conical tank level process.

B. Classical Approach

This approach [1] is used to get the dynamics of the conical tank. The conical tank system which exhibits the property of non-linearity is taken for real time analysis of the designed model and controller. To study the system's non-linearity in good fashion the process is linearized with respect to its equilibrium point [16]. The process dynamics are evaluated in six regions so as to obtain effective models for different operating ranges. We are defining 6 operating regions here [1]. The first region is between 12 to 20cm, second region between 21 to 22cm, third region between 22 to 27cm, fourth region between 27 to 32cm, fifth region between 31 to 35cm, and the final region i.e. the sixth region is set between 34 to 38cm. The inlet and outlet valve is set to a particular restriction. The data obtained from ADAM module are in terms of time and voltage, so it is converted in terms of time and height (level). The height (level), thus obtained is experimental. The calculated height (level) is obtained using process reaction curve method (PRC) and Sudareshan Krishnaswamy Method (SK) method which is a simple method for fitting the dynamic response of systems in terms of first order plus time delay transfer functions. For a change in step function, the PRC method produces a response. From the response, parameters like time delay (τ_d), time constant (τ), and the ultimate gain values are measured. The time constant (τ) is measured when the response reaches at steady state, τ = 63.2 % of the maximum value. The SK method is used to calculates the times t1 and t2 at which the 35.3% and 85.3% of the system response is obtained. Later calculating the t1 and t2, the time delay and process time constant is attained from the subsequent equations (9) & (10) [1, 3].

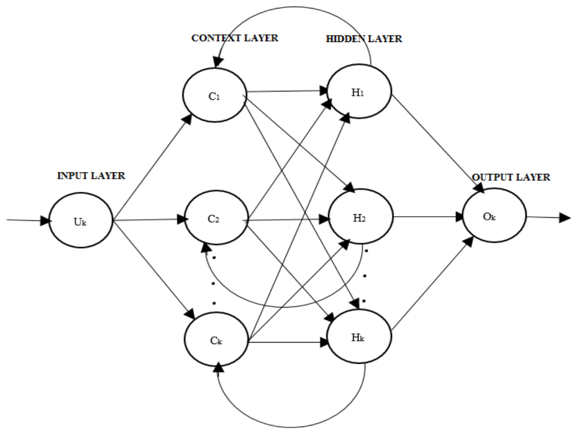

Fig.3: A Simple Elman Neural Network Architecture

$$\tau = 0.67(t_2 - t_1) \quad (9)$$

$$\tau_d = 1.3\, t_1 - 0.29\, t_2 \quad (10)$$

Here, the different linearized regions information are shown in table 1.

From these six different region models of the conical tank, the necessary input and output data are obtained. By using these data histories, the Elman recurrent neural network is designed.

TABLE II. PROCESS PARAMETERS OF CONICAL TANK FOR SIX DIFFERENT OPERATING REGIONS.

Description	Height (cm)	Flow rate (LPH)	Gain (k)	Time constant (τ)	Time Delay (τd)
Region1	12.00 to 20.00	290 to 305	0.02510	46.90	0.10
Region2	19.8 0 to 21.20	305 to 320	0.00490	36.85	10.9
Region3	21.00 to 26.80	320 to 335	0.01780	294.8	4.68
Region4	26.20 to 31.50	335 to 350	0.01550	274.7	3.20
Region5	31.50 to 34.10	370 to 385	0.00689	341.7	1.37
Region6	34.00 to 38.20	385 to 400	0.00994	415.4	2.00

C. Elman Recurrent Neural Network (ERNN)

In this method, the proposed system model is designed with the help of classical approach. The classical method is a source for network construction. The Elman neural network (Elman 1990) is one of the recurrent network types. In this type, the network nodes are partially interconnected [9, 11]. Fig.3 shows the architecture of a simple Elman Recurrent Neural Network (ERNN), in which three layers are combined to give network architecture. The first one is a hidden layer with number of hidden nodes, where the nonlinear data processing is carried out. Another layer is the output layer with output neurons, which gives the final output with linear activation function [17]. Then a special layer to store the past histories of the process, called the context layer is found. It has a number of context neurons. At every instant of time, the input is propagated in a standard feed forward technique, after the hidden node is processed its inputs and its corresponding output values are transferred to output node for further processing to get final output value. At the same time the hidden node output data value is stored in the corresponding context neuron for future prediction [8]. Finally, the output value is obtained from the output node. Then network output is checked with desired value. If any deviation occurs between network output and desired data then, the deviation will be compensated by applying learning rule to network and updating the weights of each node. Then, the next epoch is started, during which the past values of hidden node outputs, stored in the context node are taken for future prediction. Now the hidden node acquires the input node and context node data information simultaneously for further processing. Then, the regular process is carried out.

Generally the ERNN has one input layer, one output layer and one or more hidden layers. In ERNN, each hidden node has a corresponding context node for storing hidden node past values. In this approach a three layered Elman recurrent network is trained through gradient descent with Bayesian regulation learning algorithm. In Elman neural network, selection of neuron in hidden layer is performed by trial and error and with respect to the process complexity. From the neuron selection, the desired process model can be obtained. For more number of hidden neuron selections, the network may be complex and also for the minimum number of hidden neuron selection, the network may not give an appropriate output [18, 19]. Hence the hidden neurons start with reasonable number and with process output its count will be increased or decreased [8, 9, and 10].The adoption of Elman networks is done by using train or adapt function. By using either of the two functions the network error minimization is accomplished. Actually the error is produced by comparing the desired and actual output of network in each of the iteration. According to the error value, the weight factor for the individual neuron is updated. By means of weight updation the error is minimized. Until the desired output is obtained by the network, the error minimization is carried out interms of training [9, 11, and 12].

D.Prediction by Elman Neural Network

The prediction is accomplished in Elman neural network by using the past value information of hidden node output and network input. In Elman neural network, the dynamic behaviours are observed by tracking the network states and used in future prediction. Hence the dynamic behaviour is easily read out by Elman neural network compared to other feed forward neural networks. The data processing of Elman neural network is explained as, at time t=k, the input to network is the combination of the past value of the hidden node (at time t=k-1) and the input value histories (at time t=k) are used, where the previous value of hidden node is stored in context node. If it is the first iteration, then the previous hidden node value is assigned as zero in context node. Now the combinations of these two values are given to hidden node. After the activation of hidden node the output value at time t=k is stored in context node for the t=k+1 data processing [9, 15, 17] and also the hidden node (at time t=k) output is fed to the output node for final result. Here the weight updating is done in usual manner by comparing the actual and desired output. In this network, Bayesian regulation learning algorithm is used instead of Levenberg–Marquardt learning algorithm for network adoption. By this adoption mechanism, the observation of system dynamics is acquired well.

In figure 3, the external input to the network is represented by $\mathrm{U(k)}$ and the network output by $\mathrm{Y(k)}$. The total input to the hidden unit is denoted as $\mathrm{Z(k)}$. The output of the hidden unit is denoted as $\mathrm{X(k)}$. The output of context unit is $\mathrm{C(k)}$ and then W, $\mathrm{W^x}$ and $\mathrm{W^c}$ are the weights from input to hidden unit, hidden to output unit and context to hidden unit respectively. Now, the network prediction is mathematically calculated as,

$$\mathrm{X(k)= f\{Z(k)\}} \qquad (11)$$

$$\mathrm{C(k)= X(k\text{-}1)} \qquad (12)$$

$$\mathrm{Y(k)= W^x(k)X(k)} \qquad (13)$$

$$\mathrm{Z(k)= W^c(k)C(k)+ W(k)U(k)} \qquad (14)$$

When consider n state, it is in the following form,

$$\mathrm{U(k)=}\sum_{\mathrm{k=0}}^{\mathrm{n}}\mathrm{W^x(k)X(k)} \qquad (15)$$

$$\mathrm{Z(k)=}\sum_{\mathrm{k=0}}^{\mathrm{n}}\mathrm{W(k)\,C(k)+}\sum_{\mathrm{k=0}}^{\mathrm{n}}\mathrm{1\,W^x(k)U(k)} \qquad (16)$$

Where substitute $C(k) = X(k-1)$ in (6) and then, consider the hidden unit as linear then,

$$\mathrm{Z(k)=}\sum_{\mathrm{k=0}}^{\mathrm{n}}\mathrm{W(k)\,X(k\text{-}1)+}\sum_{\mathrm{k=0}}^{\mathrm{n}}\mathrm{W^x(k)\,U(k\text{-}1)} \qquad (17)$$

And then,

$$\mathrm{X(k)= Z(k)}$$

Then,

$$\mathrm{Z(k)=}\sum_{\mathrm{k=0}}^{\mathrm{n}}\mathrm{W(k)\,C(k)+}\sum_{\mathrm{k=0}}^{\mathrm{n}}\mathrm{W^x\,(k)U(k)}$$

So,

$$\mathrm{Y(k) = W^x(k)X(k)}$$

$$\mathrm{Y(k)=}\sum_{\mathrm{k=0}}^{\mathrm{n}}\mathrm{W^x\,(k)}\left\{\begin{matrix}\sum_{\mathrm{k=0}}^{\mathrm{n}}\mathrm{W^c(k)\,C(k)+} \\ \sum_{\mathrm{k=0}}^{\mathrm{n}}\mathrm{W(k)\,w(k)U(k)}\end{matrix}\right\} \qquad (18)$$

This $y(k)$ can be expanded in the following format,

$$\mathrm{Y(k)= A_1(k-1)+ A_2Y(k-2)+ ...+ A_nY(k-2)}$$
$$\mathrm{+\quad B_1U(k-1)+\ B_2U(k-2)+ ...+ B_nU(k-n)}$$

(19)

Hence, from the equation (18) and (19), it is clear that by using Elman neural network, any higher order dynamic system can be designed. By training at a repeatable fashion, its dynamics behaviour could be observed [15, 17]. From these mathematical derivations, it is clear that the data mapping is carried out. So obviously the dynamics of nonlinear process could be observed with the help of ERNN.

D. System Identification by Elman Recurrent Neural Network

Due to the behaviours of ERNN, is used as a proposed tool for our system identification of the conical tank. Many empirical approaches are there to model a system. But neural network based approach is more effective when compared to other empirical approaches because of its online learning characteristics and adoption with new environment. So in our system identification part, to model the suggested process the Elman neural network is used.

ERNN based modelling the input output information is obtained from transfer function based classical approach. The classical approach is basic for this study. From that classical approach of model we can obtain our necessary input and output data for neural network design. Then the conical tank is modelled by mapping the input and its corresponding output data histories. In ERNN modelling, the major advantage is the recurrent configuration. The network recurrent connection is configured from the output of hidden node to hidden node input [13]. But in another recurrent neural network like Jordon, Hopfield net, the feedback connection is configured from output of output node to input node as input value. This feature of Elman network enables the intermediate change of system states with effective manner, since the hidden node output is a nonlinear sigmoid activation function. But in Jordon type recurrent network the system dynamics could not be obtained in a desired fashion, as the output node activation is binary or bipolar. Hence the Elman neural network is the best one to model a dynamic process. In this ERNN based modelling there are three neurons used in hidden layer and one neuron used in output layer, since the process is first order plus a single state variable process. Due to this neuron selection, the problem of the network can be avoided from over fitting. Finally the proposed model is designed for the proposed system by using Elman neural network for separate regions. The initial and final conditions of different regions are used to make a combined model for nonlinear conical tank level process without changing its process behaviour [12]. Finally, the planned conical tank level process model is designed by using ERNN approach. The desired Elman neural network architecture is shown in figure 4 with three hidden and three context neurons in addition with one input and oneoutput neuron.

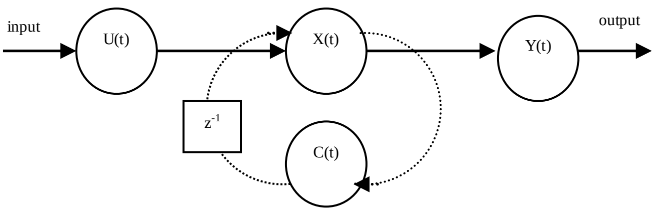

Fig.4: The Proposed Elman Neural Network Architecture

E. System Identification by Radial Basis and Feed Forward Neural Network

The conical tank level process is also modelled by the artificial neural network concept of radial basis and feed forward network for the purpose of comparative analysis and to show that the Elman neural network is better than these network models.

The feed forward network is a simple network, where the data processing is performed in feed forward manner. This network has three layers like input, output and hidden layer filled with its corresponding neurons. The nonlinear activation function is used for hidden neuron processing and linear activation function is used for output neuron processing.

Radial basis network is also one of the feed forward networks, in which the supervised training algorithm is used for network adoption. The only thing that differs from feed forward network is the activation function which is a radial basis activation function. This activation function approximates the value by the difference between the two specified values. The activation function distinguishes the radial basis network from the feed forward network. The radial basis network can be used to perform the time series prediction and control applications. Therefore, in this study both radial basis network modelling and feed forward neural network modelling are performed. The system identification of these two networks is carried out in the same fashions as the Elman neural network modelling. For random input and output information the network is trained and the proposed process model is designed. This network model of both radial basis and feed forward network is compared against transfer function based classical approach model for validation check. The main purpose of this modelling in this article is to implement a performance analysis of ERNN approach.

III. RESULTS OF THE EXPERIMENT

Thus, Elman neural network based model is designed for the conical tank. Here the validation of ERNN based model is done by comparing the ERNN model with classical approach based transfer function model, radial basis and feed forward neural network model. The following figure 5 shows the comparison responses, which displays the comparison between ERNN based model, radial basis, feed forward network model and the classical approach based transfer function model in the sub figure 5a, 5b, 5c, 5d, 5e and 5f respectively for the different six regions of the conical tank. From these following responses, it can be proved that the Elman neural network based modelling approach is superior to dial basis and feed forward neural network approaches.

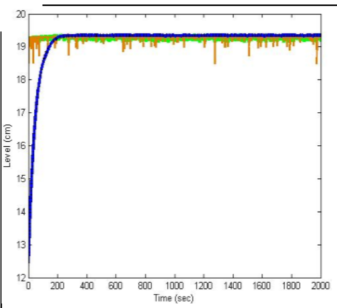

Fig.5a: Response for Operating Region 1

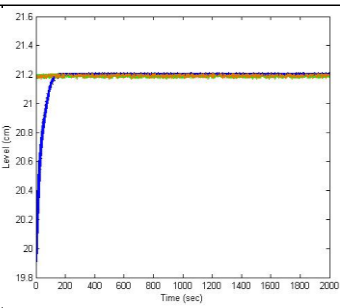

Fig.5b: Response for Operating Region 2

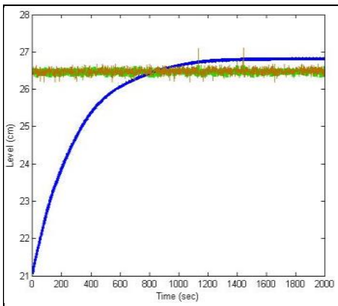

Fig.5c:Response for Operating Region 3

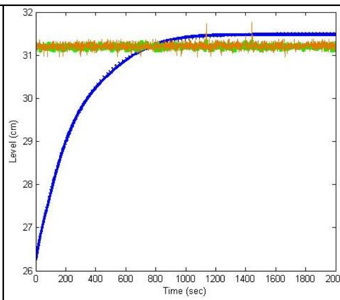

Fig.5d: Response for Operating Region 4

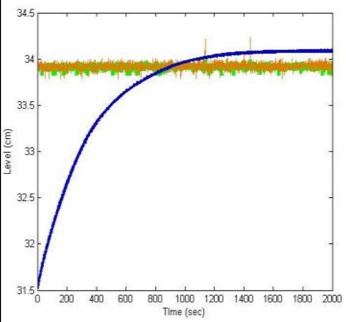

Fig.5e: Response for Operating Region 5

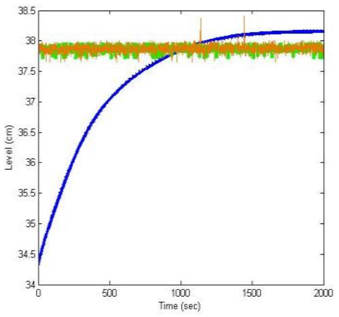

Fig.5f: Response for Operating Region 6

Fig.5: Combined model for Different Six Regions

From the above response of Elman neural network, radial basis and feed forward network with classical approach, it is proved that the Elman neural network approach gives the best model. Also the Elman neural network model gives the exact model like classical approach.

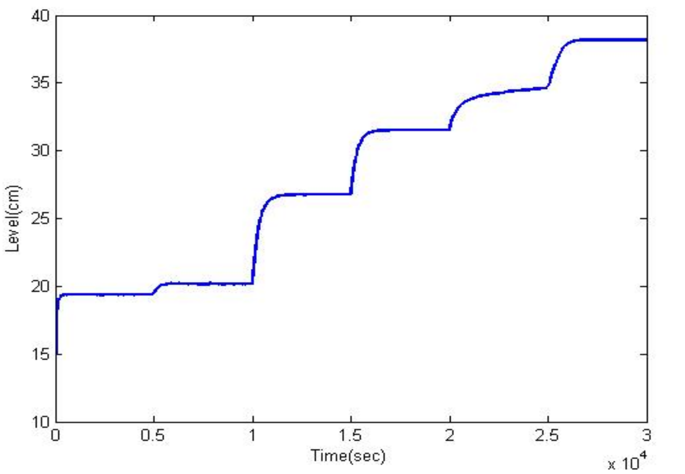

Fig.6: Different Networks Model Responses for Six Dissimilar Operating Regions

Hence Elman neural network model is considered as a proposed network model and this network model is also used for further processing work such as region combination and controller design. After obtaining the model for all six regions, the region combination is performed, where the combination of all six regions is achieved with respect to initial and final conditions of process (shown in table 1). The combination process provides a single combined model of six linearized regions to the nonlinear conical tank process. The grouping model response is shown in figure 6.

Now, to show the Elman neural network performance as the best, the performance measurement of ERNN is carried out with other types of neural networks like feed forward and radial basis network. The performance measurement of ERNN is analysed based on its mean square error (MSE) .These performance measurement analysis is shown in the following tabulation.

From the table 2, the ERNN performance measurement is analysed. The Elman network is provided as the desired response in minimum number of epochs. But at the same number of epochs the other networks like feed forward and radial basis do not give a desired result and also those mean square errors are huge when compared with Elman neural network. From this performance analysis the Elman Recurrent Neural Network (ERNN) gives a better result than other types of neural networks. Hence ERNN is better for nonlinear dynamic process modelling.

TABLE II. DIFFERENT MODELS COMPARISON FOR SIX OPERATING REGIONS WITH MEAN SQUARE ERROR

Description	Network type	Number of Iterations	Mean Square Error
Region 1	**ERNN**	**127**	$\mathbf{5.5 \times 10^{-6}}$
	Feed forward network	153	0.456
	Radial Basis Network	127	0.035
Region 2	**ERNN**	**132**	$\mathbf{2.4 \times 10^{-6}}$
	Feed forward network	138	0.896
	Radial Basis Network	135	0.416
Region 3	**ERNN**	**141**	$\mathbf{1.8 \times 10^{-5}}$
	Feed forward network	141	0.985
	Radial Basis Network	141	0.365
Region 4	**ERNN**	**133**	$\mathbf{3.5 \times 10^{-6}}$
	Feed forward network	140	0.765
	Radial Basis Network	136	0.089
Region 5	**ERNN**	**146**	$\mathbf{1.3 \times 10^{-5}}$
	Feed forward network	186	0.896
	Radial Basis Network	153	0.216
Region 6	**ERNN**	**150**	$\mathbf{4.5 \times 10^{-6}}$
	Feed forward network	150	0.918
	Radial Basis Network	150	0.483

IV. CONCLUSION

Thus, the system identification is successfully carried out for the conical tank level process using Elman neural network approach. In nonlinear process modelling, the major problems are to ensure the stability factor and its dynamic behaviour. These problems were well recognized using Elman neural network approach in addition with classical approach. The ERNN internal states repetition enables investigation of the dynamic behaviour as well as maintains the stability factor of the process. The validation of the Elman neural network model is done by comparing it region wise against the model obtained by transfer function based model. The six different ERNN models and its corresponding initial and final conditions are used to form one equivalent model. Finally the ERNN based model's performance is analysed with feed forward and radial basis neural network based on its mean square error (MSE). From the performance analysis, it is proved that the Elman neural network based model provides better results. Hence the Elman recurrent neural network is well suited for modelling a conical tank nonlinear process.

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