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Continuous System Simulation and Neural Network Modeling

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Abstract: The proposed work consists of mathematical and Artificial Neural Network Modeling and simulation of Dryer subsystem of Paper making process. The dynamics of the Dryer for paper making process has been studied and a transfer function from the state space model is obtained using MATLAB software. Introduction about the Continuous system simulation along with the advantages of using Artificial Neural Network are included. A SIMULINK model of the dryer of paper making process has been developed considering the effects of input steam flow and pressure. Analysis of the Statistical model and neural network has been carried out to find mean, median, standard deviation and covariance. It is observed that both the model and neural network output have almost similar statistics. So, it concluded that the trained Neural Network model can be used in place of the dynamic model for complex system dynamics if some data are not available.

Keywords: paper machine , Dryer, Neural Network

I. INTRODUCTION

Continuous System Simulation describes systematically and methodically how mathematical models of dynamic systems can be simulated on a digital computer. Mathematical models are usually described by sets of either ordinary or partial dif-ferential equations possibly coupled with algebraic equations. Once a mathematical model of a process has been formulated, the modeling and simulation environment compiles and simu-lates the model, and curves of result appear on the users screen. If there is a problem in simulation an error regarding the simulation is displayed on the screen. It is a highly software-oriented text, based on MATLAB. Here we are considering the dynamic model of a dryer of a paper machine.[1]

A.Why to use Neural Network?

Inspiration for Artificial Neural Network comes from the human brain . Like human it has the ability to learn by example i.e it requires no prior knowledge for training. A trained Neural Network can be thought of as an "expert" in the category of information it has been given to analyse. Other advantages include:

- An ability to learn how to do tasks based on the data given for training or initial experience.
- An ANN can create its own organisation or representation of the information it receives during learning time.
- ANN computations may be carried out in parallel, and special hardware devices are being designed and manu-factured which take advantage of this capability.
- Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

B. Paper Making Process -An Overview

The function of the paper machine is to form the paper sheet from the stock or pulp coming out from the headbox and to remove water upto 5% from the sheet so that it become suitable for packaging, printing and many other applications. The paper machine can be devided into following sections.

Forming Section: Commonly called the wet end , where the slurry of fibres filters out fluid in a continuous fabric loop to form a wet web of fibre.

Press Section: The wet fibre web passes between large rolls loaded under high pressure to squeeze out as much water as possible.

Drying Section: Here the pressed sheet passes partly around a series of steam heated drying cylinders. Drying removes the water content down to a level of about 5%.

Calender Section: Here the dried paper is smoothened under high loading and pressure.

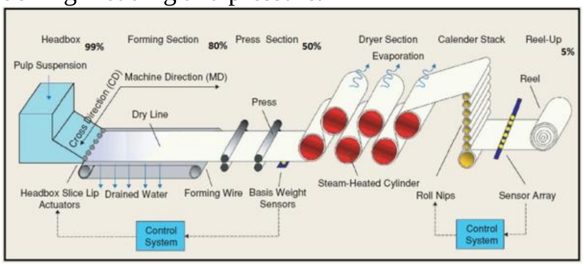

Fig. 1. An Overview of Paper Machine

II. PAPER MAKING DRYING SECTION

In paper making process, steam heated drying cylinders are preferred as a large quantity of heat can be transferred efficiently at a constant temperature and the transferred heat get uniformly distributed throughout the cylinder surface. As the steam condenses inside the drying cylinder latent heat is transferred to the cylinder wall. The condensate are removed with the help of syphon and can be fed back to the boilers for regeneration of steam. The temperature at which steam condenses and the relative amount of latent heat depends on steam pressure.

The primary model of the dryer section of paper making process is a nonlinear differential-algebraic equation set. Re-search

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papers related to drying section of paper machine are reviewed by which we find out the list of variables that affects the final moisture control in the drying section.t hese are:[2]

Input flow of steam Pressure of steam Temperature Dryer speed Tension on the felt Thickness of paper web Stock flow Consistency of stock etc.

In the proposed work, input flow of steam and the steam pressure are chosen as state variables, since both these variables are possible to measure. A Simulink model of the drying process is developed considering the effect of these two major parameters which can give efficient drying of the output product. The simulation is carried out in a MATLAB environment. By drag-and-drop features. It can be used to investigate effects of a rebuild, different controller structures, and different ways to operate the machine.

The standard state-space form of the model of the dryer is :[1]

$\underset{\sim}{x} = Ax + B\ q_s$

$y = Cx + D\ q_s$

Where

$x = [P; T_m]^T$

$C = [10]; D = 0$

$x^{\cdot} = Ax + B\Delta q_s$

$y = Cx + D\Delta q_s$

Where,

$x = [\Delta P, \Delta T_m]^T$

$$A = \alpha_{sc}\begin{bmatrix} \dfrac{-Acyl\frac{dTs}{dP}}{hs\frac{dps}{dP}} & \dfrac{Acyl}{hs\frac{dps}{dP}} \\ \dfrac{-Acyl\frac{dTs}{dP}}{mCp,m} & -\dfrac{Acyl}{mCp,m} \end{bmatrix};$$

$$B = \begin{bmatrix} \dfrac{1}{V\frac{dps}{dP}} \\ 0 \end{bmatrix}; \qquad C = [\ 1\ 0\ ]; \qquad D = 0$$

Now considering the value of the unknown parameters as shown below we can find out the transfer function from steam flow to pressure.

$C_{p,m} = 500J=kg/Kelvin\ A_{cyl} = 37.2$

$Mass(m) = 7610kg\ V\ Volume(V) = 12:6m^3$

$^{\alpha}{}_{sc} = 500$

$h_s = 2675.43kj/kg$

Considering the above value of the parameters we get,

A= [-0.009520 0.29; .00159 -.00488850];

B= [0.042135;0];

C= [1, 0];

D =0;

Using MATLAB we get the following Continuous Transfer Function from steam flow to pressure of the Dryer of Paper making Process:

$$\frac{Q(s)}{P(s)} = \frac{B(s)}{A(s)}$$
$$= \frac{0.0421350000000000s + 0.000205976947500000}{1s^2 + 0.0144085000000000s - 0.000414561480000000}$$

2) Step for acquiring the step response of Transfer Function:

- Open the window of Matlab software Click on simulink icon
- Take different symbols from simulink library Connect all blocks
- Run the simulated model
- For this simulated model, collect the input output data This data can be used for trained Neural Network

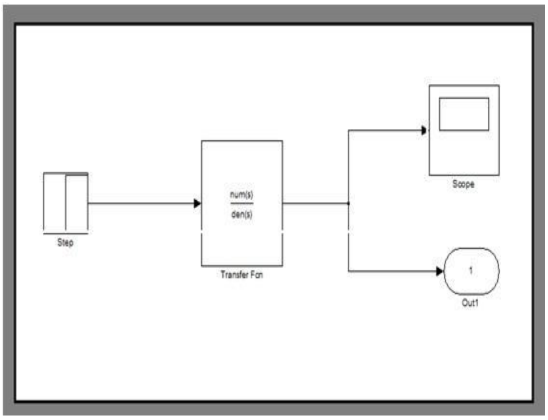

Fig 2 : SIMULINK model

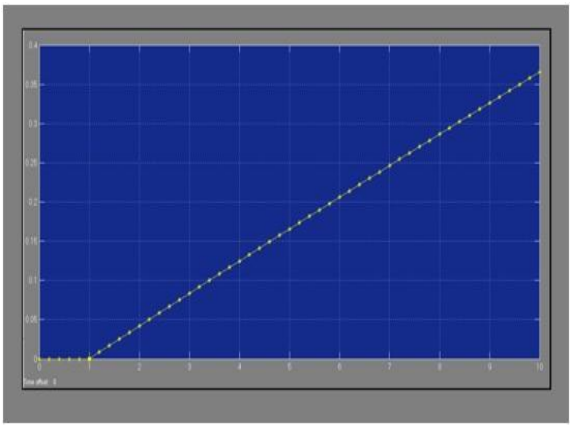

Fig. 3. The Step Response of the Transfer Function Model

The graph shown in fig 3 is the step response of the Dryer Subsystem of Papermaking Process transfer function. Here we are considering the step input as the steam flow and output as the pressure of steam.[2] The input output data from this graph are noted down for the training of the Neural Network.

The Network is trained using the input data and the performance plot, training state and regression plots are observed. In this training, random (dividerand) rule divides the data where 60% data are assigned to training set, 20% to validation and 20% data to test set.

The algorithm choosen here is Levenberg-Marquardt backpropagation (trainlm), trainlm is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. trainlm is often the fastest backpropagation algorithm in the toolbox, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms.

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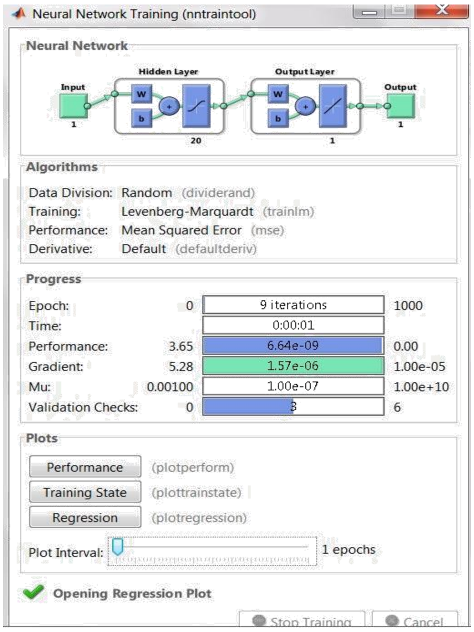

Fig. 4. Neural Network Training

The property tr.best epoch indicates the iteration at which the validation performance reached a minimum. From the training state plot it is seen that training continued for three more iterations before the training stopped. The performance plot shown in fig 6 does not indicate any major problems with the training. The validation and test curves are very similar.

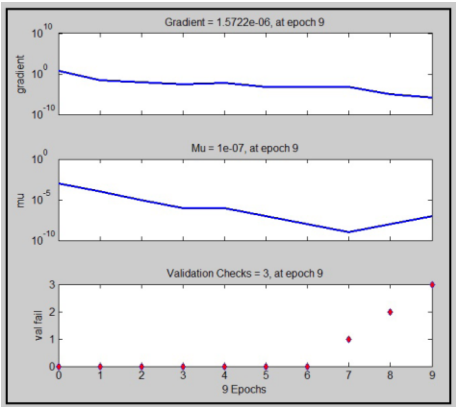

Fig 5: Training plot

If the test curve had increased significantly before the validation curve increased, then it ispossible that some over fitting might have occurred.

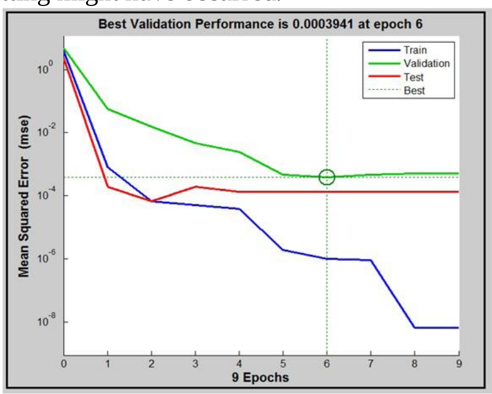

Fig. 6. Performance Plot

The next step in validating the network is to create a regression plot, which shows the relationship between the outputs of the network and the targets. If the training were perfect, the network outputs and the targets would be exactly equal, but the relationship is rarely perfect in practice. Fig 7 represent the training, validation, and testing data. The dashed line in each plot represents the perfect result outputs = targets. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets.

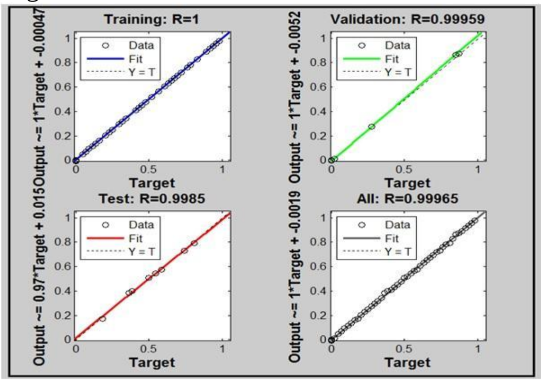

Fig. 7. Regression Plot

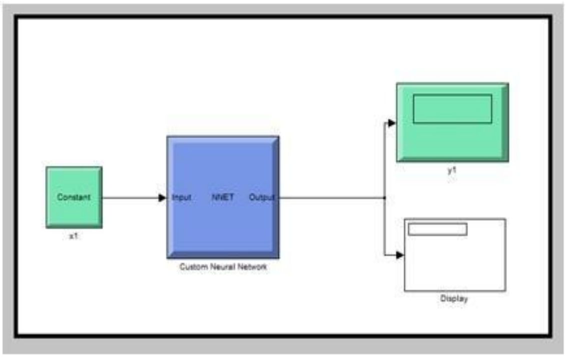

Fig. 8

III. RESULTS AND ANALYSIS

Basic Fitting
Numerical result for input Data
Fit= linear
Coefficient and Norm of Residuals y = p1*x + p223
Coefficients:
p1 = 0.019513
p2 = 0.48491
Norm of residuals = 0.076046
Numerical Result for Model Data
Fit = Linear
Coefficient and Norm of Residuals y = p1*x + p2
Coefficients: p1 = 0.021077 p2 = 0.43865
Norm of residuals = 0.20058
Numerical Result for Neural Network Data
Fit = Linear
Coefficient and Norm of Residuals: y = p1*x + p2
Coefficients: p1 = 0.021223 p2 = 0.43973
Norm of residuals = 0.20991

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DATA STATISTICS:

The statistical data is shown in table 1 and 2 for input and output (Model and NN data).

Table1:Data Statistics for input data

	t	S
Min	-26	0
Max	26	1
Mean	0	0.4849
Median	0	0.48
Mode	-26	0.1
Std	15.44	0.3015
Range	52	1

Table2: Statistic for Model and Neural Network

	t	P	NN
Min	-26	0	-0.0058
Max	26	0.9999	1.053
Mean	0	0.4387	0.4397
Median	0	0.4305	0.4305
Mode	-26	0	0.0003154
Std	15.44	0.3267	0.3291
Range	52	0.9999	1.059
Covariance		0.1067	0.1083

The table above show that the Model and the Neural network data statistics nearly of identical value. The covariance difference between both these data is 0.0016 which is a negligible one. This indicates that both these datasets can be used as a alternative. Thus we can replace the dynamic model by the trained Neural Network model if the system dynamics is complex.

The Model output data and the Neural Network output data all are plotted together in MATLAB for the statistical analysis. It is observed that both the Model output and Neural Network output data are colliding with each other, as shown in fig 9.

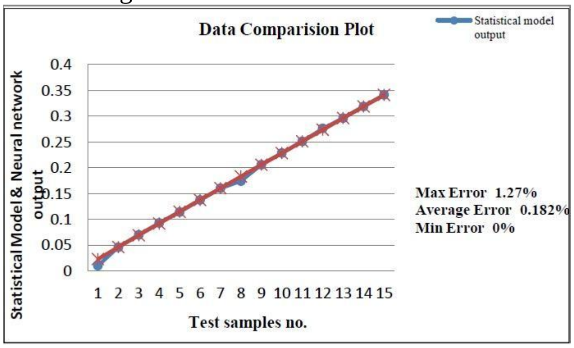

Fig. 9. Model data and Neural Network data comparison plot

C. Improve the result of neural network

If the network is not sufficiently accurate, we can try initializing the network and the training again. Each time we initialize a feed forward network; the network parameters are different and might produce different solutions.

As a second approach, we can increase the number of hidden neurons above 20. Larger numbers of neurons in the hidden layer give the network more flexibility because the network has more parameters it can optimize. (The layer size should be increased gradually. If we make the hidden layer too large, it might cause the problem to be under-characterized and the network must optimize more parameters than there are data vectors to constrain these parameters.)

A third option is to try a different training function. Bayesian regularization training with trainbr, for example, can sometimes produce better generalization capability than using early stopping.Finally, use of additional training data. Providing additional data for the network is more likely to produce a network that generalizes well to new data.

IV. CONCLUSION

Traditional modeling techniques for the modeling of the dryer subsystem of paper machine sometime becomes more complex if some data statistics are not available or the system dynamics is complex. As an alternative, a methodology has been offered where a trained neural network whose statistical analysis shows that it has almost similar statistics with the mathematical model of the dryer subsystem can be used. The appealing attributes of the proposed system are: The system provide empirical model which is based on the data .These model have the ability to learn by example makes them very flexible and powerful. Furthermore there is no need to understand the internal mechanism of the task. They are also very well suited for real time systems because of their fast response and computational times which are due to their parallel architecture. With the addition, many supervisory control opportunities will be available to work with this proposed model.

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