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Condition Monitoring of Special Purpose Transformer Design for Water Pumping Station Using Artificial Neural Network

Shweta Deshmukhh
Department of Electrical and Electronics Engineering
Vindhya Institute of Technology & Science, Indore (M.P.), India
Email:- shwetadeshmukh019@gmail.com

Swati Veleskar
Department of Electrical and Electronics Engineering
Vindhya Institute of Technology & Science, Indore (M.P.), India
Email id

***Abstract* - This paper, deals with condition, monitoring of special purpose transformer that is installed for water pumping application by artificial intelligent techniques. The power transformers are main back bone of power transmission system and its protection is very necessary over various faulty conditions. The healthy conditions of transformer is basically depends on loading factor, power factor, voltage current and harmonics. Proposed paper provides capability to figure out a condition of transformer forecasting model of model. The for-costing is done through the artificial neural network (ANN). In preposed paper Levenberg-Marquard(LM) and Scaled Conjugate Gradient(SCG) function based backpropogation training algorithms are used and then the choice of the most appropriate training algorithm is made to train the model. The used datasets are based on the past data on various working condition of pumping house. Dataset contains data collected between 1 January 2018 to 31 December 2018, a total of 8760 samples at 1 hr time interval is available for used. Samples are for each of the 5 features; those are Frequency, Harmonics, Voltage, Current, and Temperature. For analysis of algorithms and MATLAB software is used.**

***Index Terms* - Artificial neural network (ANN), Levenberg-Marquard(LM), Scaled Conjugate Gradient(SCG), Stepwise regression. Transformer condition monitoring**

I. INTRODUCTION

Earlier the utilization of electrical energy was simple and straight forward; generation of electricity & its consumption was a linear process but now a day's electrical power system is one of the complex networks in the world, increase in demand with diversification, connecting various regional grids and set up of a centralized control like National Load Dispatch Centre (NLDC) are the milestones in this up gradation. Out of all Electrical machines transformer is still maintained its relevance and working methodology same as when it was invented, this is because transformer plays a pivot role in electricity supply system from generation to utilization [1].

Power transformer protection, the key issue lies in Discriminating between transformer magnetizing inrush current and internal fault current. It is natural that relay should be initiated in response to internal fault but not to inrush current or over-excitation/external fault current [2]. Early methods were based on desensitizing or delaying the relay to overcome the transients [3]. These methods are unsatisfactory since the transformer may be exposed for a long unprotected time. Yet another method based on the second harmonic content with respect to the fundamental one was introduced, known as harmonic restraint differential protection [4], which improved security and dependability was appreciated. However, some researchers have reported the existence of a significant amount of the second harmonic in some winding faults [4, 5]. In addition, the new generations of power transformers use of low-loss amorphous material in their core, which can produce inrush current with lower harmonic contents and higher magnitudes [6]. In such cases, some authors have modified the ratio of second harmonic to fundamental restraining criterion by using other ratios defined at a higher frequency [7]. While other researchers proposed wave comparison and error estimation method [8], fuzzy logic based techniques [9], principal component analysis [10], and correlation analysis method [11] to discriminate internal fault condition from non-fault condition. Power flow through the transformer is also be used as an index to detect inrush current. Zero average power during energize and large power consumption during internal fault was the identification key in [12]. However, all the preceding approaches share the same feature, i.e. they depend on a single index. Furthermore, to choose a proper threshold for discrimination is not easy [13].

In this paper condition, monitoring of special purpose transformer that is installed for water pumping application is done by artificial intelligent techniques, for forecasting the healthy and unhealthy conations of transformer Levenberg-Marquard (LM) and Scaled Conjugate Gradient (SCG) function based back propagation training algorithms are used The paper is organized as follows, section II gives the methodology, section III gives results, section IV gives the comparision from obtained results from proposed two training functions, and section V provides conclusions of the work.

II. METHODOLOGY

Proposed ANN based method is tested on 6300KVA 33/6.6KV for condition, monitoring of it. ANN model is basically information processing model that is inspired by the way biological nervous system that means brain, process information. ANNs possess large number of highly interconnected processing elements called as nodes or units or neurons, which usually operate in parallel and are configured in regular architectures. Each connection link is associated with weights which contain information about the input signal. This information is used by the neurons net to solve the particular problem.

To depict the basic operation of a neural net, consider a set of neurons; say X1, X2, X3…. Xn. Transmitting signal to another neuron, Y. Here X1 and X2 are input neurons, which transmit signal, and Y is the output neuron, which receive signal. Input neurons connected to the output neurons via weighted interconnection links (W1 and W2) as shown in Fig.1 and its mathematically expression is given as,

$$Y = W_1X_1 + W_2X_2 + W_3X_3 + ... + W_nX_n \quad (1)$$

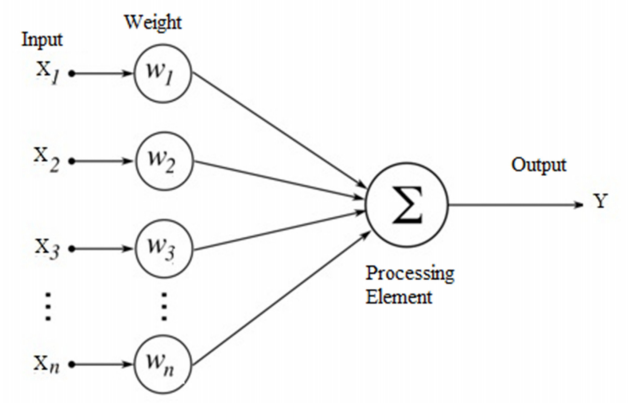

Fig. 1 Mathematical model of artificial neuron

Fig. 1 shows the basic block diagram of ANN model, there are several other types of neural network connection exist. There exist five basic types of neuron connection architecture. They are: Single layer feed-forward network, Multilayer feed-forward network, Single node and with its own feedback, Single layer recurrent network, Multilayer recurrent network

A. *Single Layer Feed-Forward Network*

A layer is formed by taking a processing element and combining it with other processing elements. If all the input stage and the output stage are linked each other. These linked interconnections lead to the formation of various network architectures. This type of connection is called single layer feed-forward network which is shown in Fig 2.

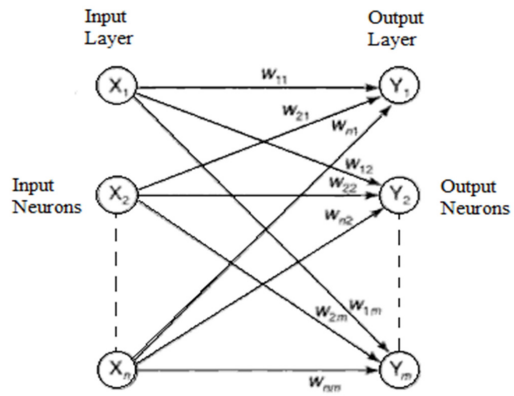

Fig.2. Single layer feed-forward network

B. *Multilayer Feed-Forward Network*

This network is formed by the interconnection of several layers. There are several layers in between input and output layer these layers are known as hidden layers. This hidden layer is internal to the network it has no contact to external environment. This hidden layer can increase from zero to several hidden layer. This network is known as multilayer feed-forward network which is shown in fig. 3.

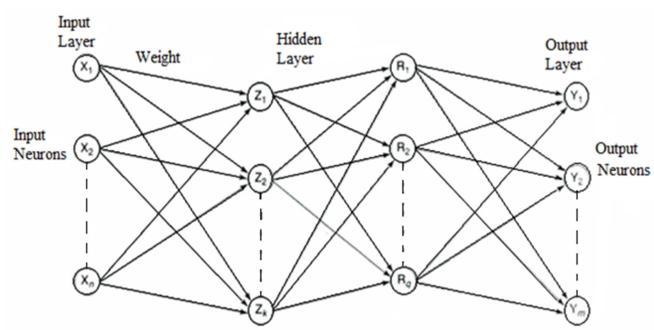

Fig. 3 Multilayer feed-forward network

C. *Single Node With its Own Feedback*

In this type of connection only single node is available. This node is connected to both input and output branches. Through output branches feedback branch is also connected to this node. Single node with its own feedback is shown in Fig. 4

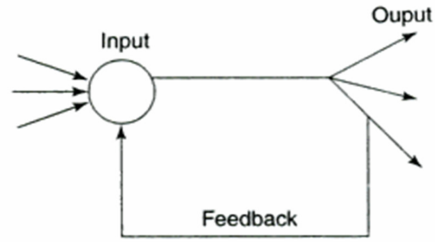

Fig. 4 Single node with its own feedback

D. *Feedback Single layer recurrent network*

In this type of network single layer itself notify that it has only input and output layer. Hidden layer will not present in this connection. If the feedback of the output of the processing element is directed back as an input to processing element then it is known as recurrent feedback. This is also known as lateral feedback. This connection is shown in fig 5.

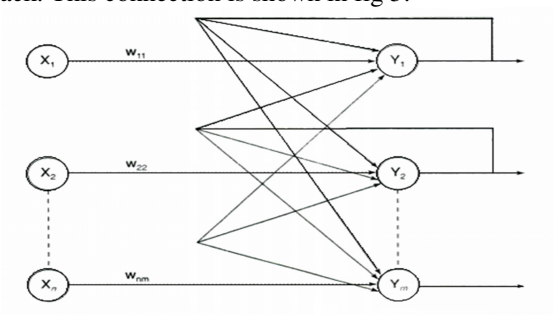

Fig. 5 Single layer recurrent network

E. Multilayer recurrent network

Multilayer recurrent network is same as single layer recurrent network just it has some hidden layer in it. Recurrent feedback is given to hidden layer as shown in fig 6.

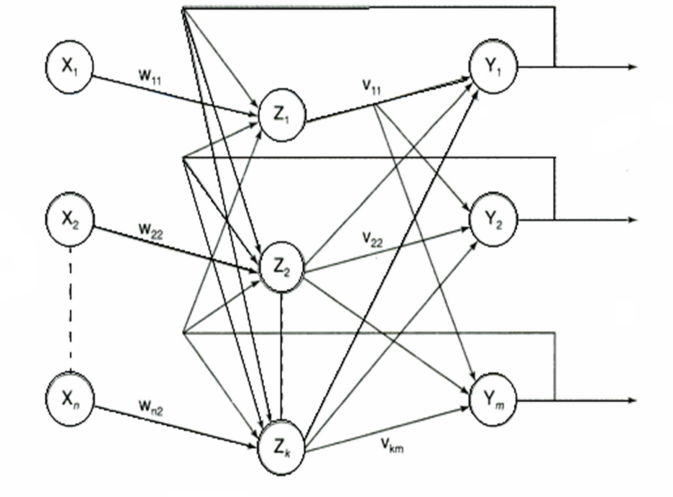

Fig. 6 Multilayer recurrent network

Learning is the main property of ANN. Learning or training is the main process for ANN to simulate, adjust and production of desired output, here back-propagation learning algorithm is used to learning from collecting data's. This learning algorithm is applied to multilayer feed-forward networks consisting of processing element with continuous differentiable activation function. The network associate with this algorithm is called Back-Propagation Network. For a given set of training input-output pair, this algorithm provides a procedure for changing the weights in a BPN to classify the given input patterns correctly. The basic concept for this weight update algorithm is simply the gradient descent method as used in the case of simple perceptron network with differentiable units. This is a methods were the error is propagated back to hidden unit. The training of the BPN is done in three stages feed-forward of the input training pattern, the calculation and back-propagation of the error and updating of weight. The testing of the BPN involves the computation of feed-forward phase only. There can be more than one hidden layer but one hidden layer is sufficient. Even though the training is very slow, once the network is train it can produce its outputs very rapidly. A back-propagation neural network is a multiplier, feed-forward neural network consisting of an input layer, a hidden layer and an output layer. The neurons present in the hidden and output layers have biases, which are the connections from the units whose activation is always 1. The bias term also acts as weights. Fig 7 shows the architecture of a BPN, depicting only the direction of information flow for the feed-forward phase. During the back-propagation phase of learning, signals are sent in the reverse direction.

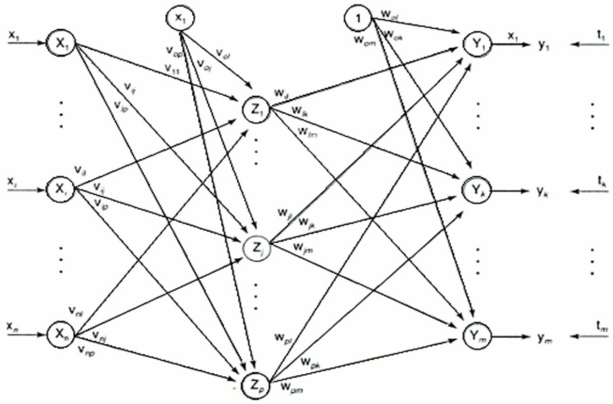

Fig. 7 Architecture of a back-propagation network

III. Results and Descriptions

This section of paper described obtained results from collected data's of transformer such as voltage, current, frequency and temperature by Appling Levenberg-Marquard (LM) and Scaled Conjugate Gradient (SCG) function based back propagation training algorithms

A. Results for Levenberg-Marquardt (LM) Training Function

In Matlab, the command used for training network using Levenberg-Marquardt back propagation algorithm is "trainlm". After observing the results from the Fig. 8, it has been clear that for the data utilized in this study, the best results will be obtained for the hidden layer having no. of neurons will be 10. This is because the priority is given to the one with least MAE and from above table, the least MAE value approx. 60 for 10 hidden layer neurons. Following figures will describe in detail the various network performance factors at this point.

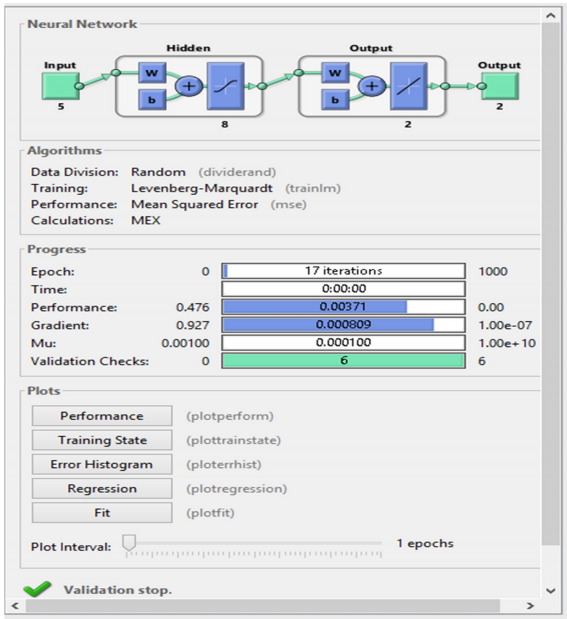

Fig. 8 Graphical Diagram of The Proposed Neural Network for LM Training.

The Fig. 8 shows the Neural Network model diagram with LM based learning. It clearly shows the relationship connection between various layers. W denotes connection branch weights values and b denotes bias values. Here weights are of two types, Input weights (IW) which are weights between input layer and hidden layer neurons and Layer weights (LW) which weights between hidden layer and output layer neurons. Bias are additional neurons for the purpose of activation functions controlling.

Fig. 9 shows the performance plot between the performance function and the number of iterations. The best performance is found out to be MSE 0.021 at 11th epochs. After 11th epoch for next 6 epoch validations is done to check the validity of network for the next sample, once validation proves that no further improvement is possible in present model, training is stopped and results are presented for comparison. Here in this model the training is stopped at 17th epoch.

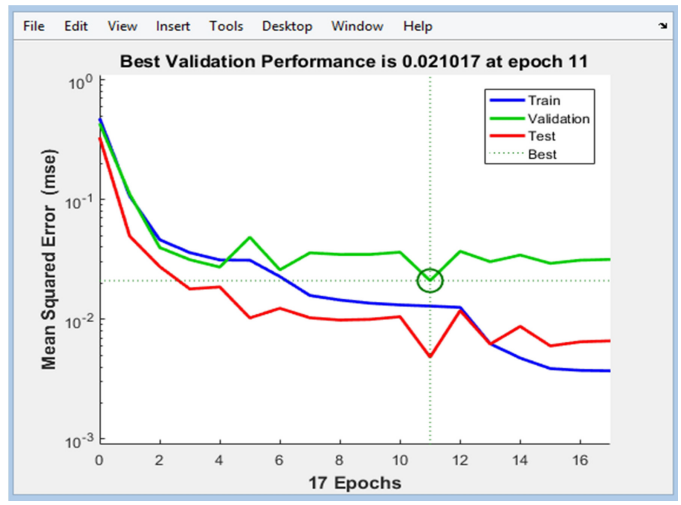

Fig. 9: Comparison among the training, Validation, & testing on employing the proposed model using LM training.

Regression 'R' values measure the correlation between the outputs and the targets. If the value of 'R' is 1, it means there exists a close relationship, and if it is 0, it signifies a random relationship. Regression plot is shown in Fig. 10 during training of neurons.

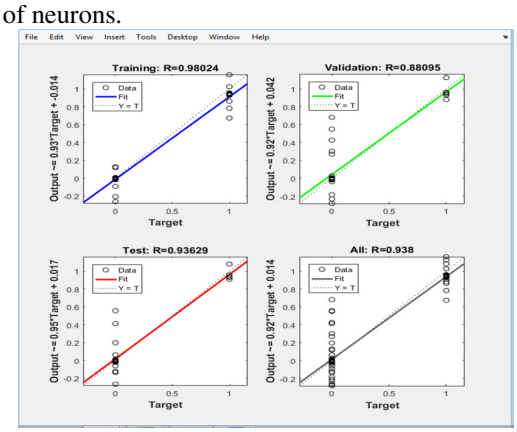

Fig. 10 Regression plot during training, testing & validation for Proposed for Proposed Levenberg-Marquardt (LM) training algorithm.

B. Results for Scaled Conjugate Gradient (SCG) training function

In Matlab, the command used for training network using Scaled Conjugate Gradient (SCG) back propagation algorithm is "trainscg".

After observing the results from the above table, it has been clear that for the data utilized in this study, the best results will be obtained for the hidden layer having no. of neurons will be 17. This is because the priority is given to the one with least MAE and from above table, the least MAE value is ~ 67 for 10 hidden layer neurons.

The Fig. 11 shows the Neural Network model diagram with SCG based learning. It clearly shows the relationship connection between various layers. W denotes connection

branch weights values and b denotes bias values. Here weights are of two types, Input weights (IW) which are weights between input layer and hidden layer neurons and Layer weights (LW) which weights between hidden layer and output layer neurons. Bias are additional neurons for the purpose of activation functions controlling.

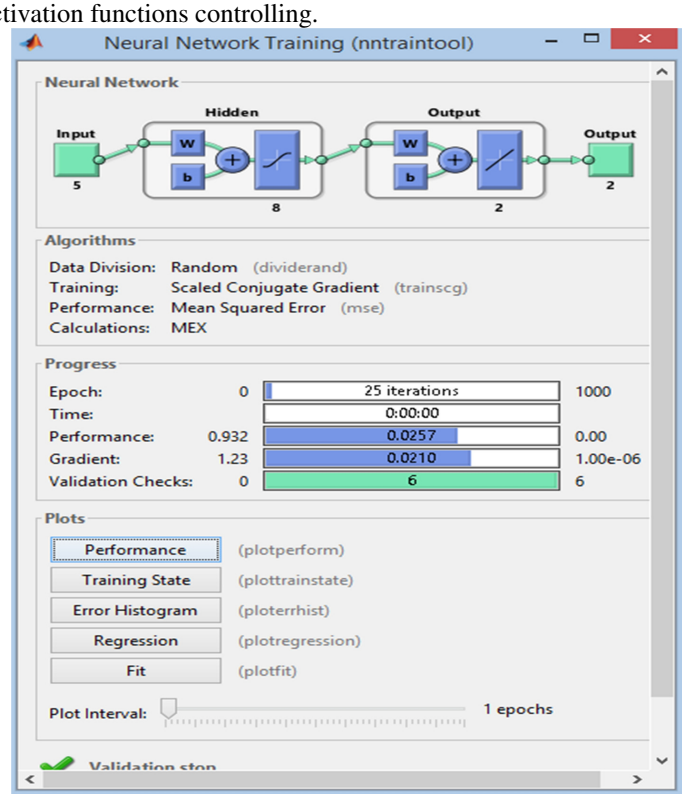

Fig. 11: Graphical Diagram of Proposed for SCG Trained Neural Network.

In Fig.12 Performance plot is plotted between MSE and epochs. The best performance is found out to be MSE of 8686.4853 at 98 epochs. After 98th epoch for next 6 epoch validations is done to check the validity of network for the next sample, once validation proves that no further improvement is possible in present model, training is stopped and results are presented for comparison. Here in this model the training is stopped at 104th epoch. And Regression plot is shown in Fig. 13 during training of neurons.

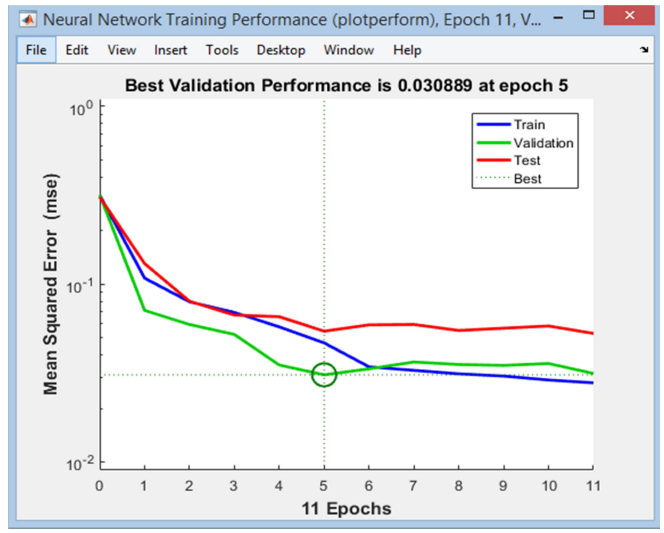

Fig. 12: Computed MSE value using the proposed SCG Trained Neural Network.

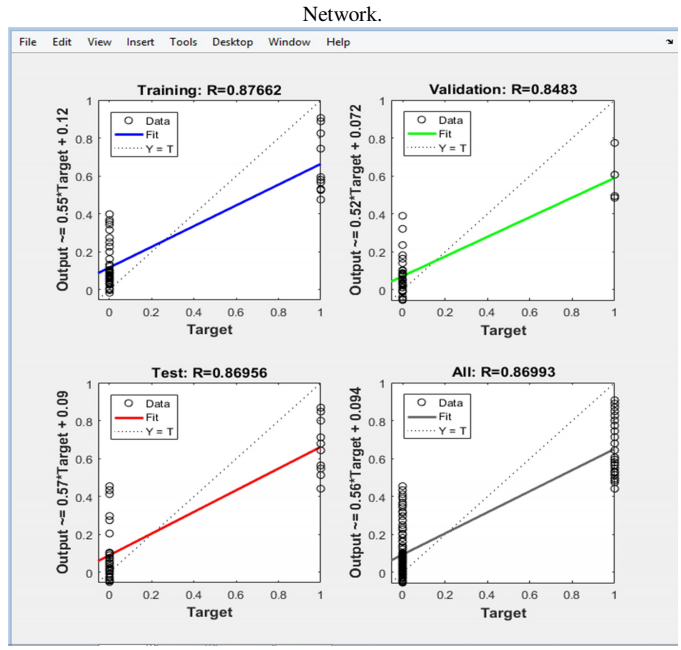

Fig. 13: Regression plot during training, testing & validation for Proposed Scaled Conjugate Gradient (SCG) algorithm.

IV. Comparative Analysis

Here the Attempt is done with two different training methodology named LM training & SCG Training with ANN to train the network. Each methodology was used several times with different hidden layers to obtain the best performance

Table 1

Comparison Of Network performance of proposed model with various neurons using LM training algorithm

Algorithm	No. of Hidden Layer Neurons	Epochs	MSE	Overall Regression
LM	8	11	0.021017	0.938
LM	12	12	0.014964	0.9622
LM	16	11	0.011002	0.9643
LM	20	5	0.01496	0.94568
LM	24	6	0.052912	0.91146

TABLE 2
COMPARISON OF NETWORK PERFORMANCE OF PROPOSED MODEL WITH VARIOUS NEURONS USING SCG TRAINING ALGORITHM

Algorithm	No. of Hidden Layer Neurons	Epochs	MSE	Overall Regression
SCG	8	5	0.030889	0.86993
SCG	12	22	0.033733	0.91763
SCG	16	7	0.034769	0.91088
SCG	20	7	0.033513	0.90557

V. CONCLUSION

As per the result obtained through MATLAB simulation, and observed that model are provide better results with less error, also The models are self-capable to deal worst conditions of working conditions. The methods was required to tackle special situations, more reduction in error & random disturbances

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