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ANN Based Direct Modeling of Permanent Magnet DC Tachogenerator Sensor

Ashu Gautam[1] and Nidhi Sharma[2]

[1,2]Department of EECE NCU Gurgaon
[1]ashusharma@ncuindia.edu, [2]nidhisharma@ncuindia.edu

Abstract

Non-linearity coupled by all of the sensors and transducers gives set to either difficulties for direct digital readout, on-chip interface, testing, calibration and control. Also, the performance of a transducer is affected adversely by variations in working environments over them. Under the sovereignty of ANN based transducer modeling, the use of single layer ANN has been proposed in two separate studies with quite affluent results. The first existing model is based on the architecture of an adaptive linear (ADALINE) network trained with Widrow-Hoff's learning algorithm. The other is based on the concept of Functional Link Artificial Neural Network (FLANN) designed on the architecture of a single layer linear ANN trained with Gradient-descent with momentum based learning algorithm. To have an optimal solution, it is proposed to amalgamate the direct model of the transducers using the concept of a Polynomial-ANN trained with BFGS Quasi-Newton Learning algorithm. The proposed Polynomial-ANN oriented transducer model is implemented based on the topology of a single-layer feed-forward back-propagation network. The proposed transducer modeling technique provides an extremely fast convergence speed with increased accuracy for the assessment of static input-output characteristics of the transducers and also for the solution of linearizing the non-linear transducers.

Keywords: *DAS (Data acquisition System),SLFF-ANN(Single Layer Feed forward Artificial neural Network),FFBP(Feed forward Back Propagation)*

1. Introduction

The industrial automation requires more and more accurate, sensitive, linear measurement sensors. Sensors and transducers are integral elements in all told instruments and systems considerably applied for measurement, as well as control, in systematic and industrial fields. The crave for righteous sensors is particularly acute in computer/processor-based systems, where sensor knowledge is considered to pace system applications [1].First, an accurate mathematical model including all the error sources is rarely known. Then, further sensors, each one monitoring an interfering parameter, are needed. Soft computing based versatile modeling techniques have been demonstrated to have great potentials and diverse applications in the following broad areas of measurement, instrumentation and control [2]. One way the brain seems to have managed to achieve this performance is by exploiting massive hardware parallelism. Somehow the weak computing powers of a large numbers of slow elements are combined to produce a powerful resultant [3].Web-based instrumentation has facilitated the real-time monitoring and control of any data at anytime from anywhere on this globe. It is stated to be a common tool in the near future that will convert even a sophisticated sensor into a plug-and–play device [4-5]. Plants or process monitoring systems depend on many sets of sensors and transducers. All physically stable systems including sensors and transducers are basically be modeled as integrators and sensor static response characteristic is generally highly non-linear [6]. Therefore, the issues related with the transducer's

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nonlinearity and its self-compensation are required to be addressed in a collective sense in DAS-connected computer-based measurement systems, taking into consideration the nonlinearity associated with the sensor as well as that of its signal conditioning module [4]. The section II explains the general concepts of the importance of Artificial Neural Networks for modeling the transducer's characteristics, in which most of the transducers fall. During first part of the chapter explains the basics of the curve –fitting and the Least Mean Square Principal. The Section III reports the development of a new artificial neural network (ANN) based direct model as well as inverse model using Polynomial ANN trained with BFGS Quasi-Newton method for different types of transducers having characteristics of different orders [17]. The importance of neural network as a function approximator and the reason for neural modeling was studied. The SLFF-ANN (Single Layer Feed Forward Artificial Neural Network) is modified and trained with different learning algorithms and finally with the proposed BFGS Algorithm for achieving an extremely fast convergence in comparison to the existing models. The section IV includes the results of implementation of different types of algorithms for modeling the transducers direct as well as inverse model. Learning characteristics of different algorithms have been shown along with the absolute and percentage errors

2. Mathematical Modeling

A mathematical model is the apply of mathematical interpretation to illustrate the behavior of a system. With digital processing methods now, more readily available general techniques are there to be used for the purpose. One very common technique is to refer to (a) lookup tables; in the look up table method, the sensor characteristics is described by a number of reference points very close to each other which are stored in ROM with linearized values. (b) The polygon interpolation is intended for soft nonlinearity where sectionalized linearization can be adopted. This assumes that the non-linear range is made into few linear sections and hence a fewer reference points serve the purpose of linearization as between these stored reference points, the sensor is considered to behave linearly. For hard non-linearity, the technique fails because the reference points are to be very many. The following Figure shows the technique:

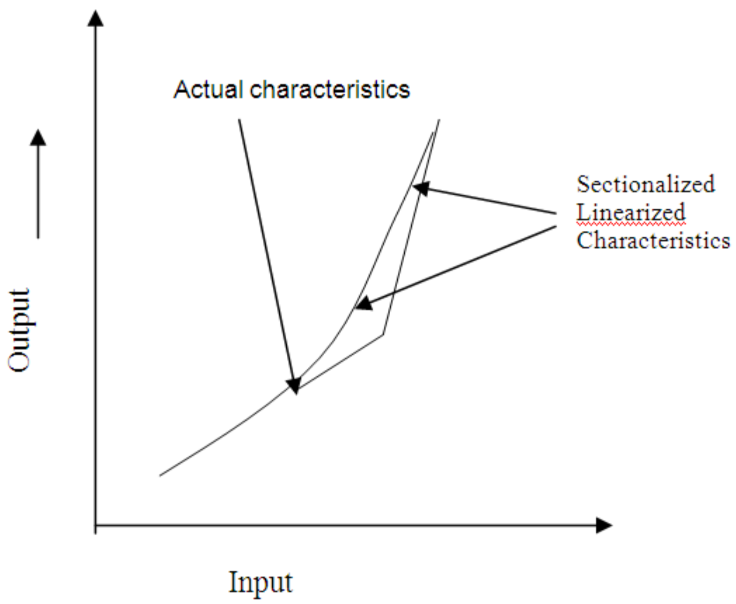

Figure 1. Polygon Interpolation Technique

(c) The Lagrange polynomial interpolation technique is again a standard technique which is based on the functional relationship between n selected measured points on the sensor characteristic and a polynomial of order ≤ (n -1) over the range covering the characteristic. The curve is represented

$$y = \sum_{i=0}^{m} a_i x^i \tag{1}$$

The modification of this method for full scale linearization is to generate a complementary curve of this characteristic

$$y_c = \sum_{j=o}^{m} b_j x^j \tag{2}$$

and then obtain the mean, arithmetic, geometric or root mean square,

$$y_{linear} = (1/2)(y + y_c) \tag{3}$$

$$y_{linear} = (yy_c)^{1/2} \tag{4}$$

$$y_{linear} = \{(y^2 + y_c{}^2)/2\}^{1/2} \tag{5}$$

The Figure 2 shows the linearization principle graphically. Increase in order often leads to oscillations.

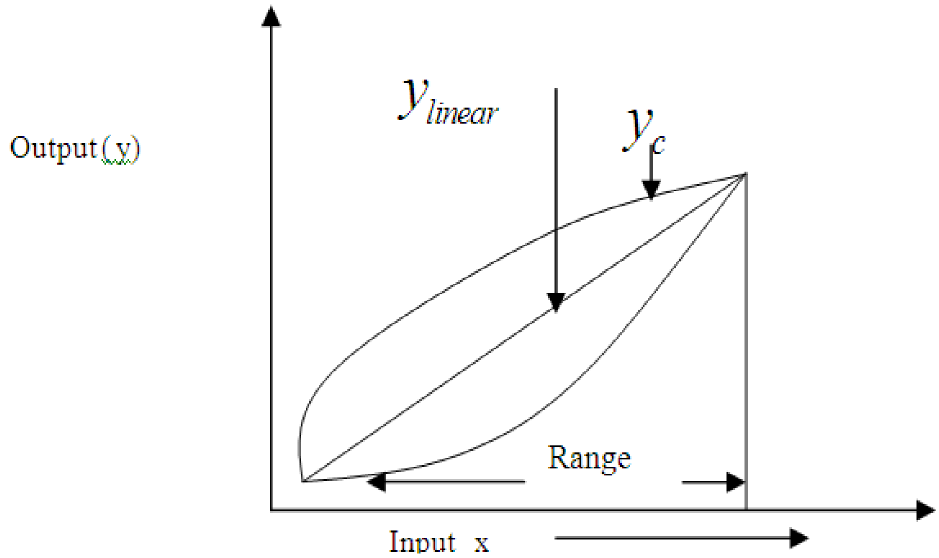

Figure 2. Linearization Techniques Using Complementary Function

(d) The cubic spline interpolation is so named as the sections of the characteristic curve of the sensor between a selected pair of reference (measured) points are represented b cubic spline functions

$$S_i(x) = a_i + b_i(x - x_i) + c_i(x - x_i)^2 + d_i(x - x_i)^3 \tag{6}$$

with $x \in [x_i, x_{i+1}]$, and i =0, 1,2,…,[n-1]

Each section on two sides, except the first and the last sections which have one end free, have junction points that are also represented by the adjacent spline functions, both these functions must coincide with each other in function values, gradient and curvature at these points, from which ,conditions for the polynomials are derived. Basically, interpolation is to fit a polynomial through the points around the point y where the function value is to be found.. Assuming a second order polynomial of the form

$$f(x) = a_1(x - x_1)(x - x_3) + a_2(x - x_1)(x - x_3) + a_3(x - x_1)(x - x_2) \tag{7}$$

one easily gets ,even by inspection,

$$a_1 = f(x_1)/((x_1 - x_2)(x_1 - x_3)), \tag{8}$$

$$a_2 = f(x_2)/((x_2 - x_1)(x_2 - x_3)) \tag{9}$$

and

$$a_3 = f(x_3)/((x_3 - x_1)(x_3 - x_2)) \tag{10}$$

so that the nth order polynomial can be expressed as

$$f(x) = \sum_{i=1}^{n+1} f(x_i) \prod_{\substack{j \neq i \\ j=1}}^{n+1} \frac{(x - x_j)}{(x_i - x_j)} \tag{11}$$

which is known as Lagrange's polynomial

2.1 Artificial Neural Network Based Modeling

Modeling processes involving the serve of neural networks fixate on machine learning which is based on the work of self-adjustment of internal approach parameters. The artificial neural conglomerate environment consists of five prime components; learning domain, neural nets, learning strategies, learning behavior, and analysis process [7, 8]. Accordingly, neural network based modeling process involves five main aspects which are: a) data acquisition, analysis and problem representation; b) architecture determination; c) learning process determination; d) training of the network; and e) testing of the trained network for generalization evaluation.

3. Direct Modeling of Transducers Using ANN

Neural Networks are used experimentally to model the transducer and sensors system [12, 13]. Model of an individual's transducers system must mimic the relationship among variables (*i.e.*, temperature, pressure, angular movement.) and the corresponding outputs in voltage., *i.e.*, they possess the power to approximate any real value non-linear function to any desired degree of accuracy [9]. Supervised neural networks for a given application is specified by the network architecture, topology, and neuron characteristics and learning rule it uses. Neural networks provide a simple and straightforward approach for direct as well as inverse modeling of different type of transducers. The objective is to develop an ANN based modeling of transducers as a powerful tool for use as a software sensor to give reasonable response to unknown inputs. This scheme is analogous to the system identification problem in control engineering. A set of known value of applied inputs and corresponding outputs forms the training set for the proposed neural network. Typically a new will lead to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. Artificial neural networks mimic information processing capability of nervous system.

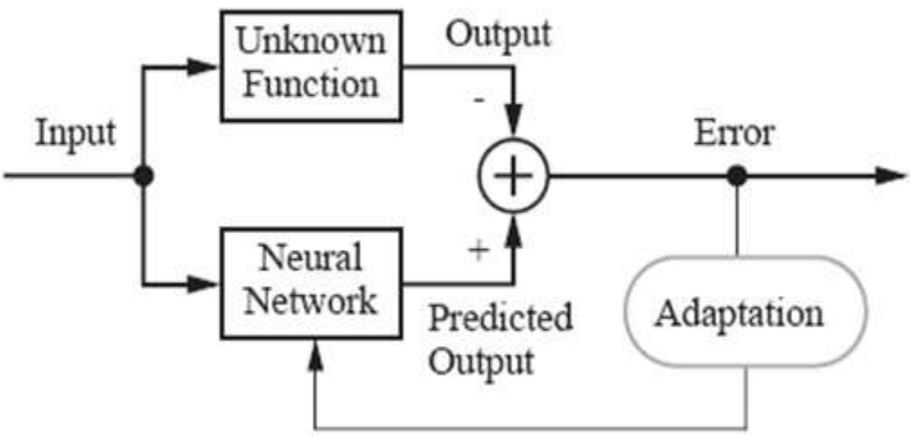

Figure 3. Neural Networks as Universal Approximator

The epitome of the non-linear transducer is represented by the direct model equation [10-11].The consider model equation is complacent for fault estimation and for assessing any fluctuation in the performance of the transducers. In the present work, the nonlinear response characteristics of a transducer for a given range of its operation are modeled based on a power series expansion [10-11]. Adaptive systems provide an alternative to traditional system design: instead of creating a mechanism to perform function F, we create a mechanism that will learn or adapt itself in order to perform F. The least mean square (LMS) and recursive least squares are two a well known algorithms which are used for estimating the parameters of different digital systems in behind mentioned applications. As manifest in Figure3, we have several unknown function that we prospect to approximate. We desire to adjust the parameters of the network so that it will express the much the same response as the unknown function, if the alike input is applied to both systems as manifest in Figure 4.

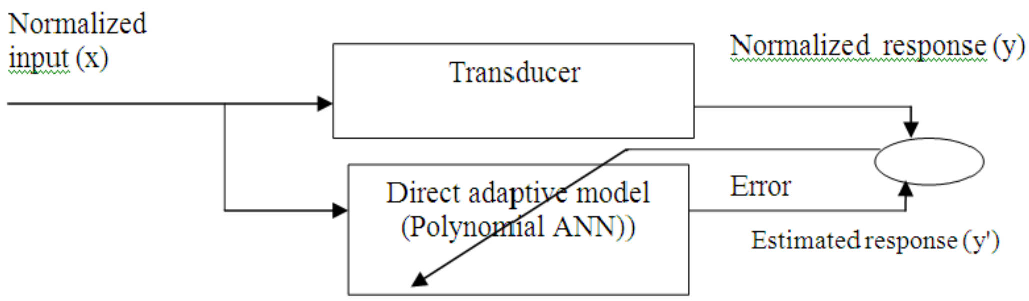

Figure 4. Learning Procedure of Polynomial-ANN for Implementing Direct Model Equation (*x*: Applied Normalized Input; *y*: Actual Normalized Response; *y′*: Estimated Normalized Response; and *e*: Error Signal

In 1970, an alternative inverse Hessian update formula was suggested independently by

In 1970 Broyden, Fletcher, Goldfarb and Shanno (BFGS) [15-16], formula originated a new Quasi Newton method. Under this we will discuss the most popular quasi-Newton method, the BFGS method, together with its precursor & close relative, the DFP algorithm. In the BFGS method, the Hessian matrix is updated iteratively rather than the inverse of the Hessian matrix. Since the inverse of the Hessian matrix is approximated, the BFGS method can be called an indirect update method was not very useful in practice.

3.1.1 Implementation of Proposed Polynomial-ANN Trained with BFGS Quasi Newton Learning Algorithm to Simulate Direct Model of Transducer

In present work a single layer feed forward has been modified by the proposed algorithm [15, 16]. The modified single layer ANN model of the transducer is built around a single neuron of a single layer FFBP-ANN as shown in Figure 5. Which basically represents learning procedure of a single layer linear ANN in direct modeling Network (ANN) by proposed method. The resultant ANN structure is called Polynomial-ANN with degree, d, and one dimensional input pattern. We have chosen single layer FFBP-ANN to model the transducer response characteristics because it offers less computational complexity as compared with multilayer ANN [10]. The use of multilayer ANN may accurately match the desired nonlinear response. However, the parameters cannot be estimated because of large number of associated weight and bias values [11]. The hyperbolic nonlinear sensor characteristics may be modeled by estimating the coefficients a's in the system identification configuration. In quasi–Newton method the idea is to use matrices which approximate the Hessian matrix or its inverse, instead of the Hessian matrix or its inverse in Newton's equation. The basic equation used in the development of Newton method, (eq.15) can be expressed as the

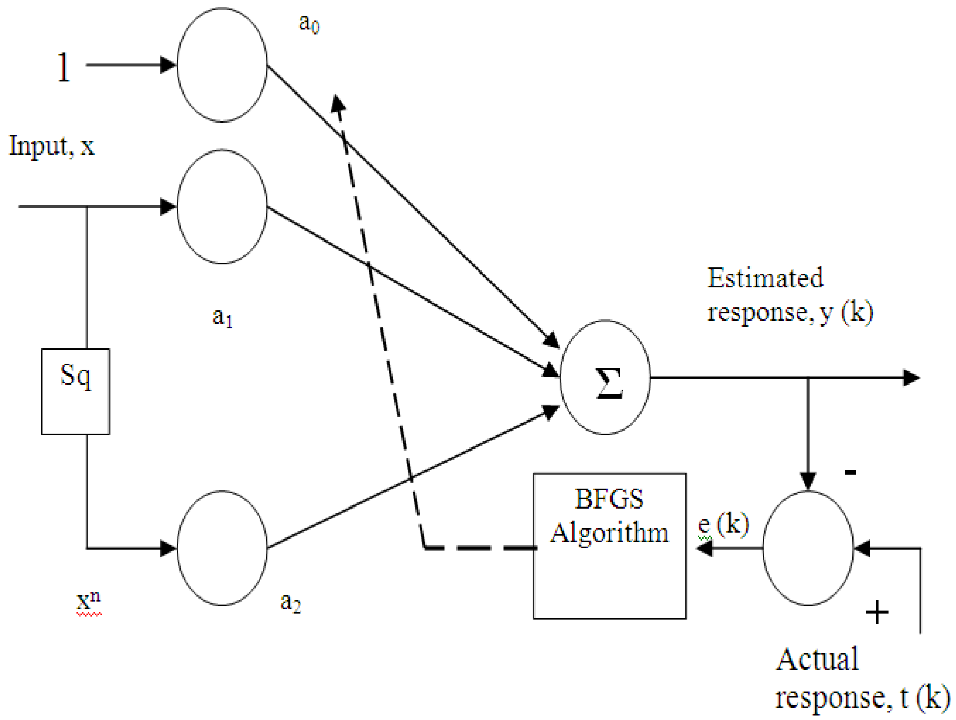

Figure 5. Learning Procedure of a Polynomial ANN Trained with BFGS – Quasi Newton for Direct Modeling of Transducers

Newton's approach constantly converges faster than conjugate gradient methods. Unfortunately, it is complicated and valuable to reckon the Hessian matrix for feed forward neural networks. There is a category of algorithms specially based on Newton's method, for all that which doesn't demand calculation of instant derivatives. These are called quasi-Newton (or secant) methods. They update an relate Hessian matrix at each iteration of the algorithm. The update is computed as a function of the gradient. The quasi-Newton method that has been most successful in published studies is the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) update. This algorithm has been implemented in the trainbfg routine. The training parameters for trainbfg are the same as those for traincgf. The approximate Hessian must be stored, and its dimension is $n \times n$, where n is equal to the number of weights and biases in the network. For smaller networks, however, trainbfg can be an efficient training function.

4. Results and Discussions

In this context, pairs of data are selected covering the entire range of operation of the sensor to train the proposed Polynomial ANN trained with BFGS (one of the Quasi Newton method) Algorithm based direct model of Figure 5, then the two existing model based on the Adaptive linear(ADALINE) trained with Widrow-Hoff's learning algorithm [33]and Functional Link ANN[10-11] trained with Gradient Descent with Momentum based learning algorithm were utilized for the training of Polynomial ANN. The results given below shows that the Polynomial ANN was best trained by the BFGS Algorithm in comparison to the existing algorithms in terms of the time required for the training as well in terms of the absolute error between actual and the estimated values. The transducer characteristics represent the third order degree. The True and estimated static response obtained from direct modeling of Permanent Magnet DC Tachogenerator sensor are as shown in figures 6,10,4.14obtained from training of ANN with three different algorithms respectively. While the learning characteristics of LMS algorithm-ANN based direct model of Permanent Magnet DC Tachogenerator are shown in figures 7, 11 and 15 respectively.

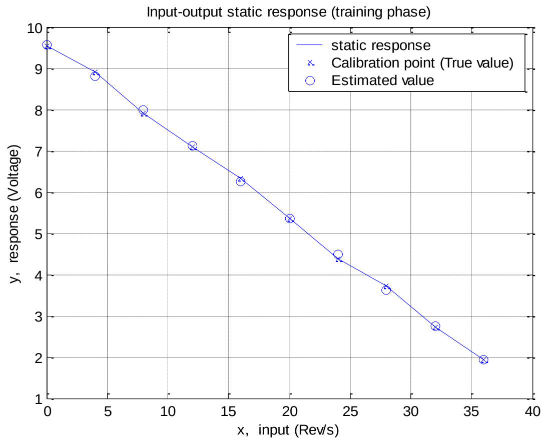

Figure 6. True and Estimated Static Response Obtained from Direct Modeling of Permanent Magnet DC Tachogenerator Sensor Using ADALINE with Widrow-Hoff's Learning Algorithm

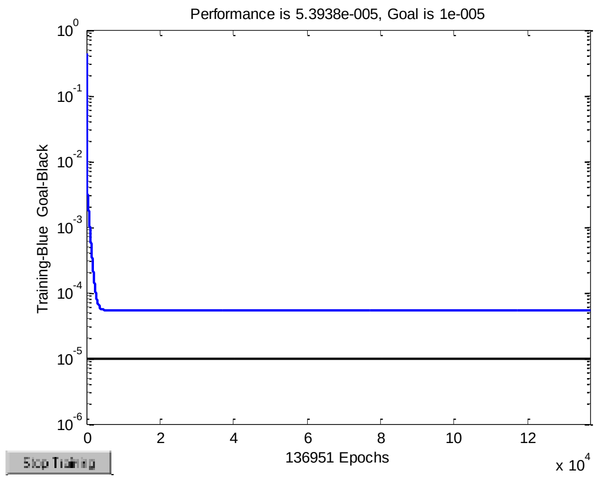

Figure 7. Learning Characteristics of ADALINE Based Direct Model of Permanent Magnet DC Tachogenerator Sensor

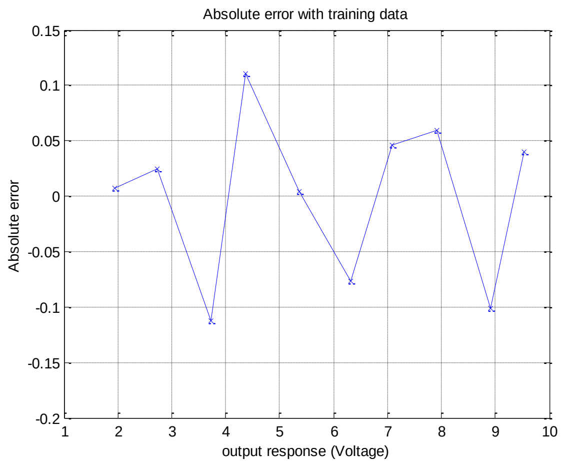

Figure 8. Absolute Error between Actual and Estimated Response with Training Data Obtained from the use of ADALINE Model

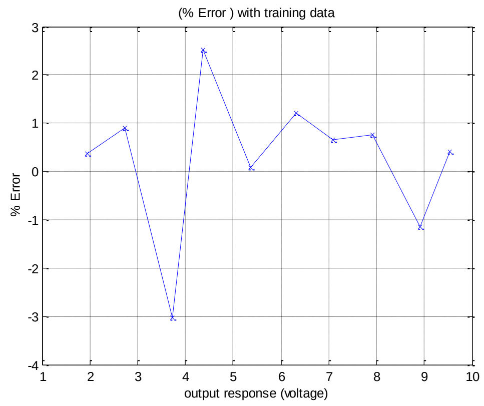

Figure 9. Error (%FS) between Actual and Estimated Response Obtained by ADALINE Based Model Trained with Widrow Hoff's Learning Algorithm

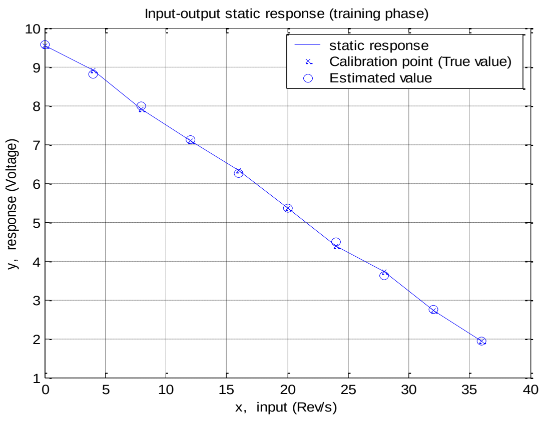

Figure10. True and Estimated Static Response Obtained from Direct Modeling of Permanent Magnet DC Tachogenerator using FLANN Trained with Gradient Descent with Momentum Based Learning Algorithm

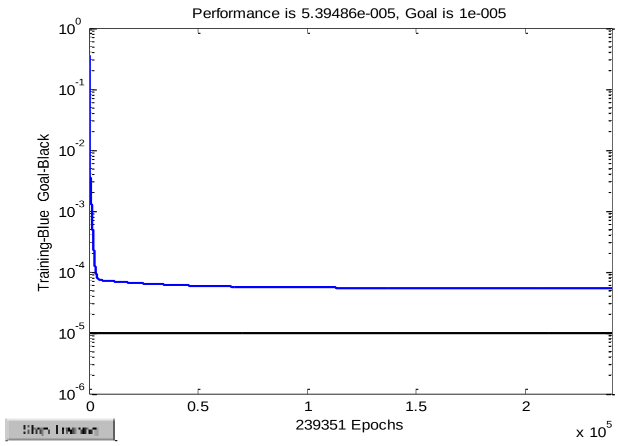

Figure 11. Learning Characteristics of FLANN Based Direct Model of Permanent Magnet DC Tachogenerator Transducer

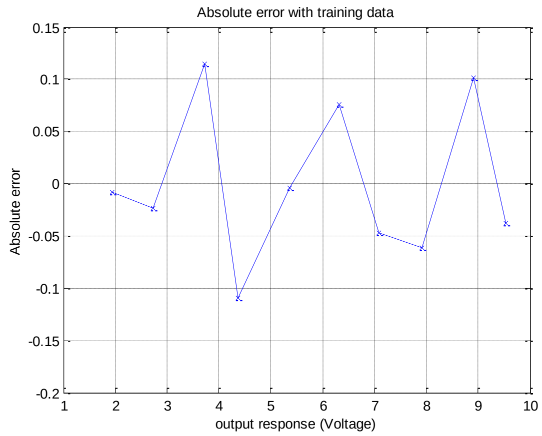

Figure 12. Absolute Error between Actual and Estimated Response with Training Data from the use of FLANN Based Model

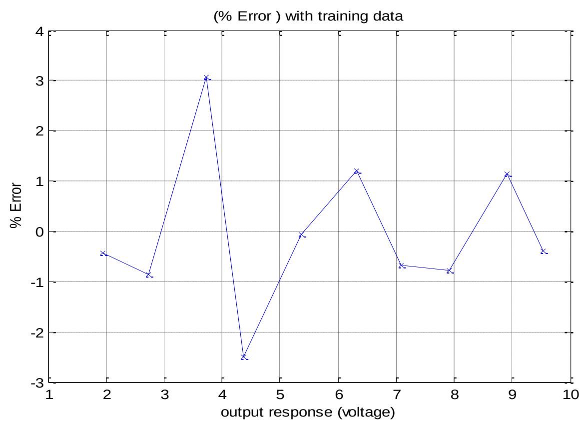

Figure 13. Error (%FS) between Actual and Estimated Response by the FLANN Based Model Trained with Gradient Descent with Momentum Based Learning Algorithm

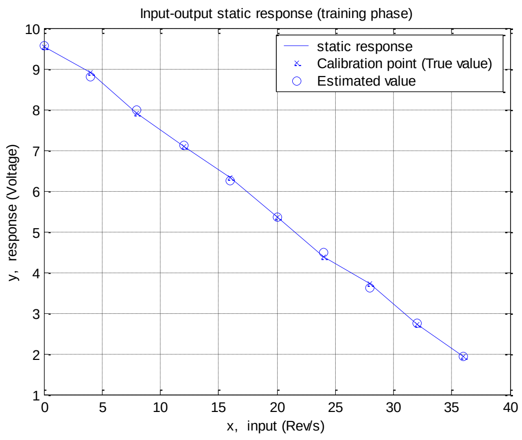

Figure 14. True and Estimated Static Response Obtained from Direct Modeling of Permanent Magnet DC Tachogenerator Sensor Using the Polynomial ANN Trained with BFGS Quasi-Newton Learning Algorithm

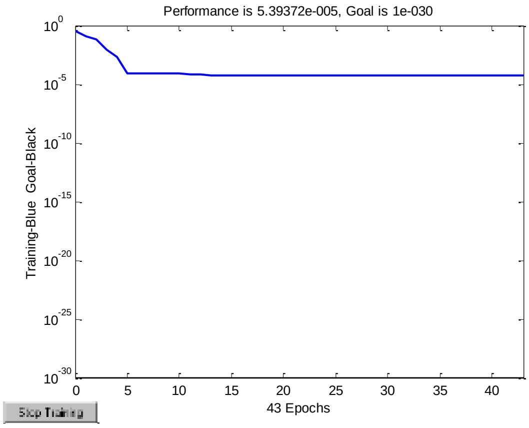

Figure 15. Learning Characteristics of Polynomial ANN Based Direct Model of Permanent Magnet DC Tachogenerator Sensor

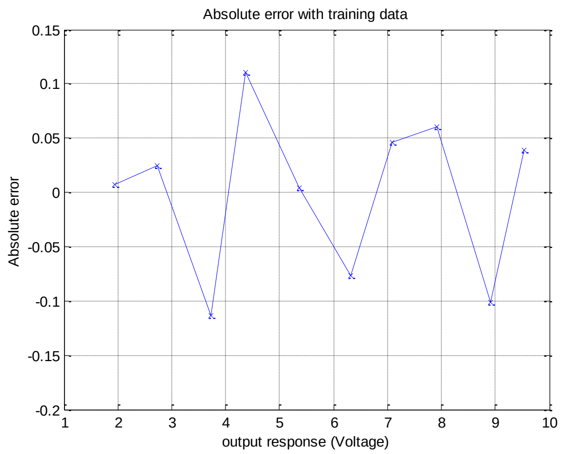

Figure 16. Absolute Error between Actual and Estimated Response with Training Data Using the Polynomial ANN Trained with BFGS Quasi-Newton Learning Algorithm

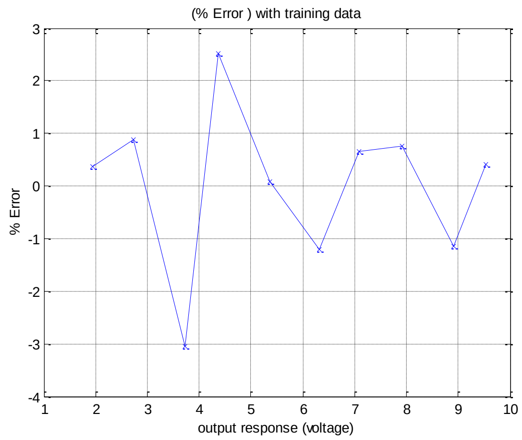

Figure 17. Error (%FS) between Actual and Estimated Response Obtained by Polynomial ANN Trained with BFGS Quasi-Newton Based Learning Algorithm

Table 1. Comparison of Results of Direct Modeling of Permanent Magnet DC Tachogenerator Sensor

Algorithm	Epochs	M.S.E	Maximum absolute error	Maximum %F.S error.	Co-efficients	Estimated value
ADALINE	136951	5.3938e-005	0.1105	3.0299	a_0	1.0042
					a_1	-0.7077
					a_2	-0.2368
					a_3	0.1442
FLANN	239351	5.39486e-005	0.1142	3.0690	a_0	1.0039
					a_1	-0.7043
					a_2	-0.2454
					a_3	0.1498
Polynomial-ANN trained with BFGS	43	5.39372e-005	0.0252	3.0382	a_0	1.0041
					a_1	-0.7070
					a_2	-0.2386
					a_3	0.1454

5. Conclusion

This work proposes a simple approach for direct modeling of transducers using Polynomial-ANN designed around a single layer network trained BFGS-Quasi-Newton learning algorithm. From the present study, it is revealed that the proposed learning algorithm is extremely fast and highly efficient for the simulation of neural models of transducers. The estimated sensor characteristics obtained from the direct modeling are in close agreement with the measured characteristics. This fact justifies the effectiveness of the proposed method. The overall experimental results from the presented technique indicate that this technique is a useful alternative to the existing ANN based techniques for estimating the direct models of transducers.

Appendix

Table 2. Results of Direct Modeling of Permanent Magnet DC Tachogenerator using ADALINE trained with Widrow Hoff's learning algorithm (Training Phase)

Sr No.	Input in Rev/s	Response in volts (y)	Normalized Input (x)	Normalized Output (t)	Normalized Estimated response by ANN (dn)	Estimated Response in millivolts (d)	Error (d-y)	Error(%FS) ((d-y)./y).*100)

1	0	9.5361	0	1.0000	1.0042	9.5758	0.0397	0.4160
1	4	8.9014	0.1111	0.9334	0.9228	8.7999	-0.1015	-1.1399
2	8	7.9199	0.2222	0.8305	0.8368	7.9797	0.0598	0.7545
3	12	7.0805	0.3333	0.7425	0.7473	7.1263	0.0458	0.6464
4	16	6.3281	0.4444	0.6636	0.6555	6.2511	-0.0770	-1.2171
5	20	5.3613	0.5556	0.5622	0.5626	5.3654	0.0041	0.0768
6	24	4.3701	0.6667	0.4583	0.4699	4.4806	0.1105	2.5287
7	28	3.7207	0.7778	0.3902	0.3783	3.6080	-0.1127	-3.0299
8	32	2.7344	0.8889	0.2867	0.2893	2.7588	0.0244	0.8929
9	36	1.9375	1.0000	0.2032	0.2039	1.9445	0.0070	0.3601

Table 3. Results of Direct Modeling of Permanent Magnet DC Tachognerator using FLANN Trained with Gradient Descent with Momentum based Learning Algorithm (Training Phase)

Sr N o.	Inpu t in Rev/ s	Respo nse in volts (y)	Normalize d Input (x)	Normalize d Output (t)	Normalized Estimated response by ANN (dn)	Estimated Response in millivolts (d)	Error (d-y)	Error(%FS) ((d-y) ./y) .*100)
1	0	9.5361	0	1.0000	1.0039	9.5736	0.0375	0.3931
1	4	8.9014	0.1111	0.9334	0.9229	8.8004	-0.1010	-1.1345
2	8	7.9199	0.2222	0.8305	0.8369	7.9812	0.0613	0.7743
3	12	7.0805	0.3333	0.7425	0.7475	7.1278	0.0473	0.6677
4	16	6.3281	0.4444	0.6636	0.6556	6.2518	-0.0763	-1.2054
5	20	5.3613	0.5556	0.5622	0.5626	5.3651	0.0038	0.0713
6	24	4.3701	0.6667	0.4583	0.4697	4.4794	0.1093	2.5019
7	28	3.7207	0.7778	0.3902	0.3782	3.6065	-0.1142	-3.0690
8	32	2.7344	0.8889	0.2867	0.2892	2.7581	0.0237	-0.8673
9	36	1.9375	1.0000	0.2032	0.2041	1.9460	0.0085	0.4386

Table 4. Results of Direct Modeling of Permanent Magnet DC

Tachogenerator using Polynomial-ANN trained with BFGS Quasi-Newton Learning Algorithm (Training Phase)

Sr No.	Input in Rev/s	Response in volts (y)	Normalized Input (x)	Normalized Output (t)	Normalized Estimated response by ANN (dn)	Estimated Response in millivolts (d)	Error (d-y)	Error(%FS) ((d-y)./y).*100)
1	4	8.9014	0.1111	0.9334	0.9228	8.8000	-0.1014	-1.1387
2	8	7.9199	0.2222	0.8305	0.8368	7.9800	0.0601	0.7587
3	12	7.0805	0.3333	0.7425	0.7473	7.1266	0.0461	0.6509
4	16	6.3281	0.4444	0.6636	0.6555	6.2512	-0.0769	-1.2146
5	20	5.3613	0.5556	0.5622	0.5626	5.3654	0.0041	0.0757
6	24	4.3701	0.6667	0.4583	0.4698	4.4804	0.1103	2.5231
7	28	3.7207	0.7778	0.3902	0.3783	3.6077	-0.1130	-3.0382
8	32	2.7344	0.8889	0.2867	0.2893	2.7587	0.0243	0.8875
9	36	1.9375	1.0000	0.2032	0.2039	1.9448	0.0073	0.3767

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Authors

Ashu Gautam, Assistant Professor (Sr.Scale) in the Department of Electrical, Electronics and Communication Engineering, NCU, Gurgaon, (Haryana), India. She has received his M.Tech and B. Tech. from Sant Longowal Institute of Engg. & Tech., Longowal, Sangrur (Punjab) in the year of 2005 and 2003 respectively. Her main research interests are in Control systems, Bio medical Instrumentaion, Instrumentation and Measurements. She is a lifetime member of ISTE and has teaching experience of over 10years.

Nidhi Sharma, Assistant Professor in the Department of Electrical, Electronics and Communication Engineering, NCU, Gurgaon, (Haryana), India. She has received his M.Tech from U.I.E.T. Chandigarh and B.Tech from Sant Longowal Institute of Engg. & Tech., Longowal, Sangrur (Punjab) in the year of 2008 and 2005 respectively. Her main research interests are in Image Processing, Embedded System Design, Digital Signal Processing. She is a lifetime member of ISTE and has teaching experience of over 7 years

