

Parameters Estimation of an Electric Fan Using ANN

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Received November 10th, 2009; accepted January 8th, 2010.

ABSTRACT

Electric Fans are very commonly used in the industries, domestic applications and in tunnels for cooling and ventilation purposes. Fan parameters estimation is an important task as far as the reliable operation of a fan system is concerned. Basically, a fan is mainly consisting of a single phase induction motor and therefore fan system parameters are essentially the electrical parameters e.g. resistances, reactances and some load parameters (fan blades). These parameters often change under varying operating conditions and the knowledge of these parameters is necessary to have optimum and efficient operation of the system. Therefore, fan system parameters are required to be estimated. Further, fan system parameters estimation is required to ensure the smooth system operation and to avoid any malfunctioning of the system during abnormal working conditions. In this paper, Artificial Neural Networks (ANN) approach has been used for parameter estimation of a fan system. The simulated and experimental results are compared.

Keywords: Artificial Neural Networks, Fan System, Mathematical Modeling, Parameters Estimation

1. Introduction

A fan system is basically meant for getting air to people occupying a building, office, residential complex, shops or public places etc. and therefore directly impacting the human comfort. Fan circulates the air and provides the pressure required to push it. For many applications like shop ventilation, material handling, boiler usage etc., fans become crucial for process support and human health. In the manufacturing sector, fans use about 78.7 billion kWh of energy every year. This consumption is approximately 15% of the electricity used by motors [1-3].

In manufacturing, fan reliability is critical to plant operation. For example, where fans serve material handling applications, fan failure will immediately create a process stoppage. In industrial ventilation applications, fan failure will often force a process to be shut down. Even in heating and cooling applications, fan operation is essential to maintain a productive work environment. Fan failure leads to conditions in which worker productivity and product quality declines. This is especially true for some production applications e.g. electronic component manufacturing and plastics injection molding.

There are mainly two types of fans namely centrifugal and axial [14]. These types are characterized by the path

of the airflow through the fan. Centrifugal fans use a rotating impeller to increase the velocity of an air stream to gain kinetic energy. Centrifugal fans are capable of generating relatively high pressures. These fans are generally used in “dirty” airstreams (high moisture and particulate content), in material handling applications, and in systems at higher temperatures.

Axial fans move an air stream along the axis of the fan. The air is pressurized by the aerodynamic lift generated by the fan blades. Axial fans are commonly used in “clean air,” low-pressure, high-volume applications.

The components of a fan system must function well in order to ensure efficient operation. The cost-effective operation and maintenance of a fan system requires attention not only to the needs of the individual pieces of equipment, but also to the system as a whole. In this concern, fan system parameters estimation plays a prominent role which addresses the following issues:

- 1) Establishing current conditions and operating parameters.
- 2) Assessing energy consumption with respect to performance.
- 3) Continuing to monitor and optimize the system.
- 4) Continuing to operate and maintain the system for peak performance.

In this paper the method used for determining the fan

parameters is based on on-line methods with the application of artificial neural network algorithm. For the purpose of simulating the fan system and the test conditions, the software Matlab version 7.1 and LabView version 8.0 have been used.

2. Mathematical Modeling of Fan System

Basically, a fan is a single phase induction motor having stator, rotor working on the principle of electromagnetic induction. Stator having two winding and a capacitor to make it self starting. Rotor rotates with fan body. Hence a fan system mainly consists of a single phase induction motor, two to six blades usually made of wood, metal, or plastic; which mount under, on top of, or on the side of the motor. The majority of fans have either four or five blades, while most industrial fans have three. Metal arms, called blade irons (alternately blade brackets, blade arms, blade holders, or flanges), which connect the blades to the motor. Here, we are mainly concerned with the modeling of single phase induction motor which is the main component of a fan system.

The induction motor has only one stator winding (main winding) and operates with a single-phase power supply. In all single-phase induction motors, the rotor is the squirrel cage type [2]. Equivalent Circuit of a Single-Phase Induction Motor is shown in the Figure 1.

There is only a single mmf established by the excited stator coil and, thus, only a single pulsating flux exists. However, one-half of the mmf, hence one-half of the turns, are associated with each of the forward and backward mmf components. A set of slips can be defined for both the forward-revolving and backward-revolving fields as

$$s_f = \frac{\omega_{sf} - \omega_m}{\omega_{sf}} \quad (1)$$

$$s_b = \frac{\omega_{sb} - \omega_m}{\omega_{sb}} \quad (2)$$

Equations (1) and (2) can be solved for ω_m and the resulting expressions equated to yield

$$s_b = 2 - s_f \quad (3)$$

The developed torque can be calculated directly from the equivalent circuit as the power delivered to the energy conversion resistance divided by mechanical speed giving

$$T_d = T_{df} + T_{db}$$

$$T_d = \frac{\frac{1}{2} I_f^2 R_r \frac{(1-s_f)}{s_f}}{\omega_m} - \frac{\frac{1}{2} I_b^2 R_r \frac{(1-s_f)}{(2-s_f)}}{\omega_m} \quad (4)$$

The first term on the right-hand side of Equation (4) is

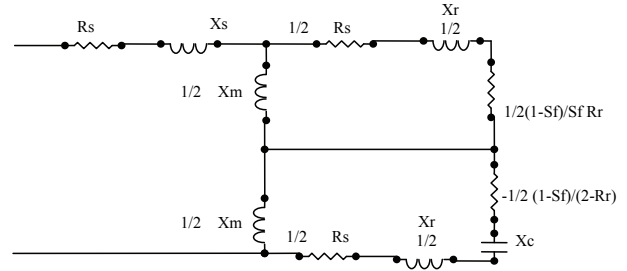


Figure 1. Single-phase induction motor equivalent circuits

the torque (T_{df}) produced by the forward-revolving field while the second term is the torque (T_{db}) resulting from the backward-revolving field. The developed torque can alternately be found as the sum of the power across the air gap divided by the associated synchronous speed.

$$T_d = T_{df} + T_{db}$$

$$T_d = \frac{\frac{1}{2} I_f^2 R_r \frac{1}{s_f}}{\omega_{sf}} + \frac{\frac{1}{2} I_b^2 R_r \frac{1}{(2-s_f)}}{\omega_{sb}} \quad (5)$$

For both cases the second term (T_{db}) is a negative quantity reflecting the fact that the backward-revolving field results in a torque that acts against the direction of rotation.

The impedance of the forward running rotor is

$$Z_f = j \frac{X_m}{2} \left\| \left(\frac{R_r}{2s_f} + \frac{jX_r}{2} \right) \right. \quad (6)$$

The impedance of the backward running rotor is

$$Z_b = j \frac{X_m}{2} \left\| \left(\frac{R_r}{2(2-s_f)} + \frac{jX_r}{2} \right) \right. \quad (7)$$

$$Z_s = R_s + jX_s \quad (8)$$

$$Z_{in} = Z_s + Z_f + Z_b \quad (9)$$

$$I_1 = \frac{V_1}{Z_{in}} \quad (10)$$

By current division, the forward Current is

$$I_f = \frac{\frac{1}{2} jX_m}{Z_f + jX_m} I_1 \quad (11)$$

And backward current is

$$I_b = \frac{\frac{1}{2} jX_m}{Z_b + jX_m} I_1 \quad (12)$$

With I_f and I_b determined, the developed torque

T_d can be readily calculated by Equation (5)

The Load Torque is

$$T_L = k_l + K\omega^2 \quad (13)$$

The accelerating torque is

$$T_{acc} = T - T_L \quad (14)$$

Here $T_{acc} = J\dot{\omega} + B\omega$ and

$$\dot{\omega} = \frac{(T_{acc} - B\omega)}{J}$$

where J=moment of Inertia

B=Damping Coefficient

From the above discussion we find six basic model parameters namely stator resistance (R_s), stator reactance (X_s), rotor resistance (R_r), rotor reactance (X_r), magnetizing reactance (X_m) and capacitive reactance (X_c) and these parameters are required to be estimated for analyzing the overall performance of the system. To determine these parameters Artificial Neural Network (ANN) is used [9].

3. Fan System Parameters Estimation Using ANN

There are three approaches for modeling the fan system: white-box modeling [11], grey-box modeling [10] and black-box modeling [4,7,12]. In the white-box modeling, one assumes a known structure for the system and finds the parameters of the assumed structure using offline tests. In the grey-box modeling, one assumes a known structure for the system and uses the online measurements to estimate the physical parameters. In the black-box modeling, the structure of the model is not assumed to be known a priori. The only concern is to map the input data set to the output data set. Among the three approaches for modeling the fan system, the grey-box modeling of papers assumes a known structure for the fan system, and tries to estimate the physical parameters from online measurements. The main advantage of this category is that it yields the physical parameters. Each parameter has its physical meaning, which sounds good especially for system engineers.

The ANN is used in this paper for estimating the system parameters of a fan manufactured by Crompton Greaves Ltd. India. The ANN structure is suitably selected for this purpose. The block diagram of ANN parameter estimator is shown in Figure 2. The feed-forward back-propagation ANN program is written in Matlab version 7.1 for parameter estimation.

The input vector for ANN is consisting of angular speed (rpm), voltage (V), and current (A) at different delay time. The output vector is consisting of all system

parameters at different operating conditions. The ANN model consisting of four layers namely, one input layer, two hidden layers and one output layer. The number of neurons at input layer is equal to the number of inputs and the number of neurons at output layer is equal to the number of system parameters. The number of neurons for both hidden layers is 8. Although it may be changed but 8 neurons are giving good results. Once, the ANN model is trained off line with these simulated data using Levenberg – Morquate algorithm (the training performance of ANN is shown in Figure 3), then this trained ANN model is used to predict the system parameters for on-line data acquired from the experimental set up. The manufacturer data is shown in Table 1.

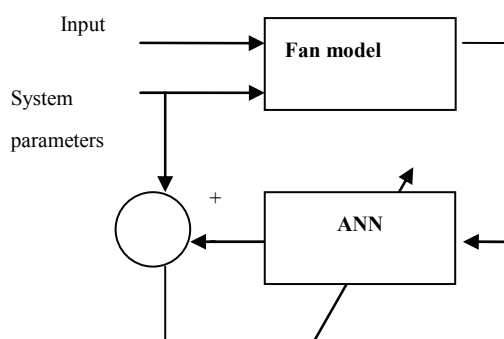


Figure 2. ANN model development for system parameters estimation from simulation results

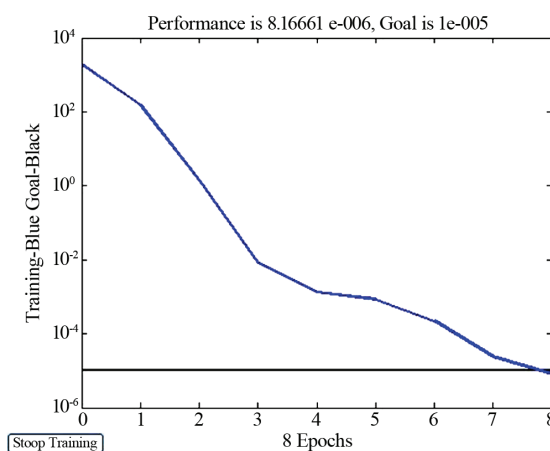


Figure 3. ANN training graph

Table 1. Manufacturer data for fan system

S.No.	System Parameter	Value (Ohms)
1.	R_s	2.02
2.	R_r	4.12
3.	X_s	2.79
4.	X_m	106.8
5.	X_r	2.12
6.	X_c	7.0

4. Experimental Setup

The experimentation is done in Electrical Engineering Lab at Dayalbagh Educational Institute, (Deemed Univ.), Agra, India. The theoretical results are further validated on a physical model. The physical model is consisting of a ceiling fan of Crompton Greaves with the specifications of 1200 mm long blades, 230V, 50Hz, and 60W.

The laboratory model is consisting of a ceiling fan, voltage controller, data acquisition (DAQ) board, and man-machine interface. The real time data acquired with the help of National Instrument Lab-view software and the parameter estimation algorithm is implemented on the real time Matlab software (version7.1) with a 50 ms step size on digital signal processing (DSP) board. The DAQ and DSP boards are installed in a personal computer with the corresponding development software. The analog to digital input channel of the DSP board receives the input signal such as fan speed, supply voltage and current. These input variables are used to calculate the system parameters on-line [9] with the help of ANN as shown in Figure 4. The estimated parameters compared with the manufacturer data under normal operating conditions.

5. Results and Discussion

The random noise is incorporated in the training data to increase the generalization capability (fault tolerant capability) of ANN and the results are shown in Table 2.

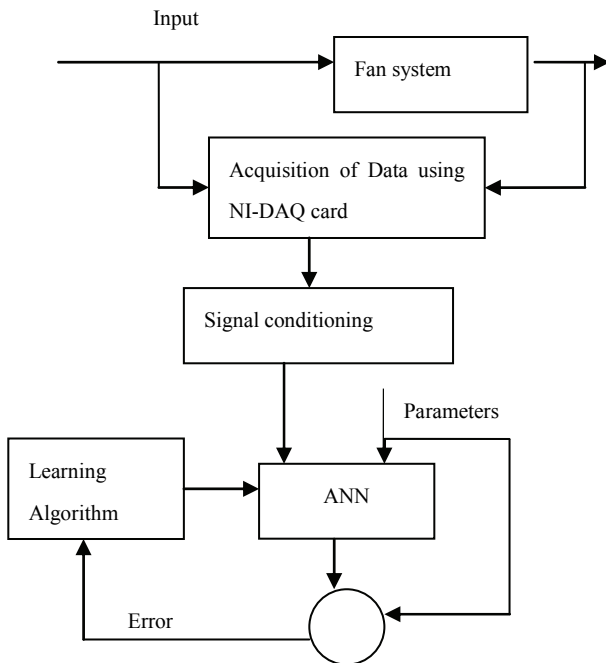


Figure 4. Experimental set up of parameter estimation of fan system using ANN

Further, it is shown that resistances are somewhat increasing while reactances (excluding Xc) are decreasing with increase in supply voltage which is increased from 80V to 230V in the steps of 10 Volts. This is due to the fact that with increase in voltage, the fan temperature gets increased and so does the resistance values while at low voltages, slip being high, the inductive reactance values are high and then with the rise in voltage the speed raises. But these variations get stabilized at near about normal voltage as the fan attains its rated speed.

From the results shown in Figure 5 and Table 2 the

Table 2. Parameter estimation using ANN

Fan Parameters in Ohms	Test data (without noise)	Test data (with noise)	Manufacturer data
Rs	2.0194	2.1835	2.02
Xs	2.7095	2.7975	2.79
Xm	106.7839	104.8351	106.8
Rr	4.1199	3.9647	4.12
Xr	2.1188	1.9660	2.12
Xc	6.9993	6.8436	7.00

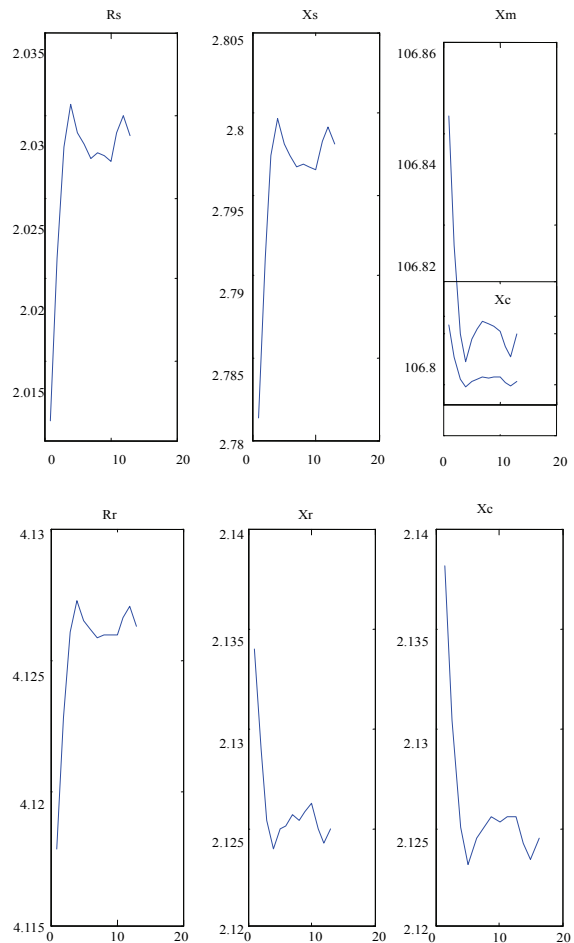


Figure 5. Variation in system parameters

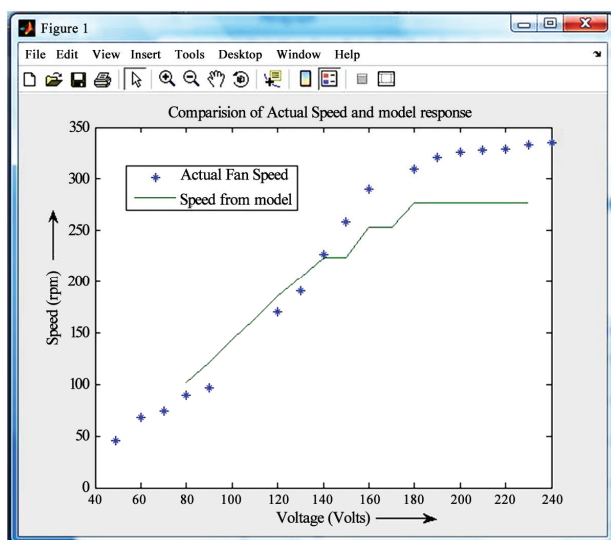


Figure 6. Comparison of simulated and experimental fan speed at different voltages

system parameters are very much dependent upon the operating conditions i.e. the applied voltage, temperature, humidity etc. If there is any abnormality in the system, the parameter changes to a great extent and that abnormality could be recognized and system may be protected from the major fault. The simulation and experimental results for the fan system are compared as shown in Figure 6.

6. Conclusions

In this paper, the mathematical model for fan system is developed and matlab code is written to validate it. Then the experimental data acquired using LABVIEW from fan system in the laboratory and used to estimate the system parameters using ANN approach under different operating voltages and the results have been compared. The results show that the ANN on-line parameter estimation method is fairly good and quite useful for monitoring the system conditions.

It is clear from the experimental results that the performance characteristics obtained from experimental data and those from the simulated data using artificial neural networks (ANN) are in close proximity. So the method used for parameter estimation, performance prediction is almost accurate for all practical purposes.

As the model development is based on the dimensional information, the method is applicable to different types of electric fans (i.e., different frame sizes as well as of different ratings). Even at the design stage the model can be applied to estimate the performance of the electric fans and to check whether the performance deviates from the desired one. The developed technique will be very useful to designers and manufacturers.

The work may be extended to improve the results by incorporating system nonlinearities in the model and pre-processing the experimental data for ANN training. Also suitable control system as well as the protection system may be developed based on on-line parameter variations.

REFERENCES

- [1] A. Arredondo, R. Partha, and W. Erin, "Implementing PWM fan speed control within a computer chassis power supply," 20th Annual IEEE Applied Power Electronics Conference and Exposition, pp. 148–151, March 2005.
- [2] I. Takahashi and T. Noguchi, "A new quick-response and high-efficiency control strategy of induction motor," IEEE Transactions on IA, Vol. 22, No. 5, pp. 820–827, September/October 1986.
- [3] S. F. Wang, R. Y. Chen, X. Fang and J. B. Wang, "Research on adjust speed control system of partial fan," IEEE International Conference on Automation and Logistics, pp. 1053–1057, August 2007.
- [4] AMCA Publication 203–90, "Field performance measurement of fan systems," 0203X90A–S Arlington Heights, Ill.: the Air Movement and Control Association International, Inc. AMCA, 1990.
- [5] B. K. Bose, "Expert systems, fuzzy logic, and neural network applications in power electronics and motion control," Proceedings of IEEE, Vol. 82, pp. 1303–1323, August 1994.
- [6] M. Calvo and O. P. Malik, "Machine parameter estimation as a pattern recognition problem," Proceedings of IEEE Power Engineering Society Summer Meeting, Vancouver, BC, Canada, July 15th–19th, 2001.
- [7] D. K. Chaturvedi, "Soft computing techniques and its applications in electrical engineering," Springer, 2008.
- [8] G. Daniel "Principles of artificial neural networks," World Scientific Publishing Co. Pte. Ltd.
- [9] R. D. Fard, M. Karrari, and O. P. Malik, "Synchronous generator model identification for control application using Volterra series," IEEE Transactions on Energy Conversion, Vol. 20, No. 4, pp. 852–858, December 2005.
- [10] K. S. Fu, Ed., "ANN application of pattern recognition," Boca Raton, FL: CRC, 1982.
- [11] H. Tsai, A. Keyhani, J. Demcko, and R. G. Farmer, "On-line synchronous machine parameter estimation from small disturbance operating data," IEEE Transactions on Energy Conversion, Vol. EC–10, pp. 25–36, March 1995.
- [12] H. B. Karayaka, A. Keyhani, G. T. Heydt, B. L. Agraval, and D. A. Selin, "Synchronous generator model identification and parameter estimation from operating data," IEEE Transactions on Energy Conversion, Vol. 18, No. 1, pp. 121–126, March 2003.
- [13] M. Karrari and O. P. Malik, "Identification of physical parameters of a synchronous generator from on-line measurements," IEEE Transactions on Energy Conversion, Vol. 19, No. 2, pp. 407–415, June 2004.

- [14] G. Kenne, T. Ahmed-Ali, L. F. Lagarrigue, and H. Nkwawo, "Nonlinear systems parameters estimation using radial basis function network," *Control Engineering Practice*, Vol. 14, No. 7, pp. 819–832, 2006.
- [15] W. S. Meisel, *Computer-Oriented Approaches to Pattern Recognition*, Academic Press, New York, 1972.
- [16] D. Pitis, "Energy efficient single stage axial fan (ENEF)," *IEEE Canada Electrical Power Conference*, pp. 280–285, October 2007.
- [17] D. K. Chaturvedi, "Modeling and simulation of systems using matlab/simulink[®]," CRC Press, U.K., 2009.