

Electric Voltage Control as an Implementation of Neural Network Applications

¹Ahmad A. Al-Rababah and ²Usamah A. Al-Rababah

¹Department of Software Engineering, Applied Science University, Jordan

²Department of Computer Science, Al-Zahra' College for women, Oman

Abstract: Present study was proposed the monitoring of mathematical model of electric voltage source with using neural network for application in control systems as sensor and command signal. The monitoring system, consist of toroidal choke or transformer with high saturated ferromagnetic cores. The input information we receive from current periodic curves. The current was distributed into Fourier or walsh series. The combination of these harmonics and their amplitude values determine monitoring voltage value directly. For increase of this system precision, the mathematical model was constructed on basis of partial differential quasi-stationary electromagnetic field equations and ordinary differential electromagnetic circuit equations combination.

Key words: Artificial neural network, differential equations, computer science, electric control, information monitoring

INTRODUCTION

Artificial neural networks are simplified models of the central nervous system. They are networks of highly interconnected neural computing elements that have the ability to respond to input stimuli and to learn to adapt to the environment. It is believed by many researchers in the field that neural network models offer the most promising unified approach to building truly intelligent computer systems and that the use of distributed, parallel computations as performed in ANNs is the best way to overcome the combinatorial explosion associated with symbolic serial computations when using Von Neuman computer architectures.

Neural networks neurocomputing is based on the wistful hope that we can reproduce at least some of the flexibility and power of the human brain by artificial means. Neural networks consists of many simple computing elements connected together by connections of varying strength, a gross abstraction of the brain, which consists of very large numbers of far more complex neurons connected together with fare more complex and far more structured couplings^[1,5].

Artificial neural networks are viable computational models for a wide variety of problems, including pattern classification, speech synthesis and recognition, adaptive interfaces between humans a complex physical systems, function approximation, image data compression, associative memory, clustering, forecasting and predication, combinatorial optimization, nonlinear system modeling and control. The using of

computers in monitoring of electric voltage in different Systems particular in high voltage Systems is very encouraging idea. It may be realized by connection precise mathematical model of saturated choke or transformer, artificial neural network and computer. We propose in the study such, solving which was realized successful. For guarantee preciseness of the monitoring system we propose original semi field mathematical model of choke.

MATERIALS AND METHODS

Differantial equations: Differential equations is an equation which contains derivatives or differential terms. Differential equations are used to describe the behavior of dynamic systems including dynamic neural networks. Ordinary Differential Equations (ODE) involve derivatives of a function of one independent variable, such as time. The order of a differential equation is the highest-order derivative appearing in the equation^[2]. The degree of a differential equation is the power of the highest-order derivative in the equation. To solve a differential equation, anti derivatives must be found for all derivative terms in the equation. An example of a system of ODE's used to model a dynamic neural network are as follows:

$$\frac{dy}{dy} = \sum_i w_{,j} x_i + \sum_{kes, j} v_{kj} y_k - h(y_j) \quad (1)$$

Corresponding Author: Ahmad A. Al-Rababah, Department of Software Engineering, Applied Science University, Amman, Jordan 11931

$$\frac{dw_{ij}}{dt} = \alpha(\chi_i - w_{ij}) \quad (2)$$

The Eq. 1 show the time rate of change of the output y of a unit as a function of external inputs x_i and internal inputs y_j weighted by the connection synaptic weights, w_{ij} and v_{kj} , respectively.

The equation defines the learning dynamics of the network where the time rates of change of the weights are a function of the inputs and weights^[4,5,8].

Control system applications: Control system problems typically require nonlinear time dependent mappings of the input signals. The complete dynamics of these systems are often unknown. Therefore, it would seem that an Recurrent Neural Networks (RNN) might be a likely candidate for controller tasks if input/output training data is available for the system. Indeed, the potential applications for RNNs in the area of control appear to be numerous.

The general control problem can be stated as follows: Given a system with unknown dynamics, in order to construct a suitable controller for the system a model is often required. A model is any device that can imitate the behavior of the system. The process of constructing a model when only the relationship between the inputs of the system and the outputs from the system are available is known as identification. The model itself is called an identifier^[3]. Once a model is available, an inverse model can be constructed to serve as a controller of the real system or plant. This type of problem accrues in many control settings including robotic systems, drive motors for various systems, automatic weld control, truck backer upper and so on. Examples of two such systems are described below. The nation of using an adaptive ANN as a model is shown in Fig. 1, where the weights of the ANN, which is receiving the same input signal as the unknown system, are adaptively modified until its output closely matches the output of the system.

Once the ANN has learned to model the system, an inverse of the model can be constructed. The inverse model is then capable of acting as a controller for the system^[2,9].

A typical system with its ANN controller is shown in Fig. 2, where a unit time delay has been added to account for the signal delay through the system/controller loop. Noise has also been added in the system loop to depict a more realistic system. Note that the ANN is a tempting to drive the system to produce an output, which matches the delayed input to produce a zero error. In doing so, it must learn the inverse of the system dynamics.

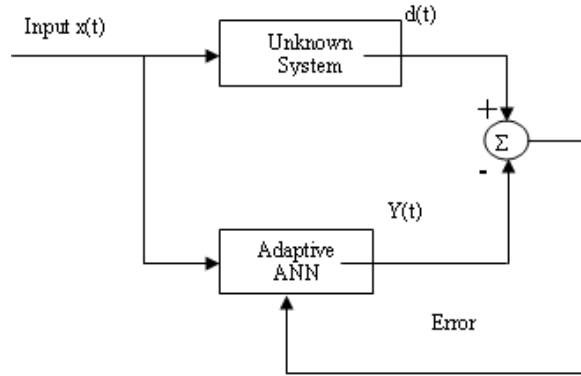


Fig. 1: Adaptive ANN learning to model unknown system

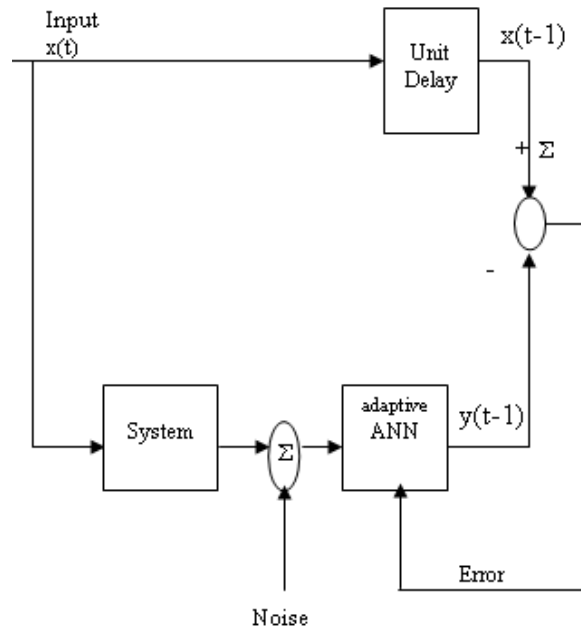


Fig. 2: Adaptive ANN controller for a dynamic system

RESULTS AND DISCUSSION

The mathematical based model. The toroidal saturated choke is one of widely used electric devices. It influences visible on proceed of electromagnetic process in system, where it works in whole^[4,7]. So, his device must be circumscribed with high precision, especially, when it works main functions in system, for example, in measurement the practice of mathematical modeling shows that precision models must be built on the basis of electromagnetic field theory. The toroidal core of saturated choke is produced from laminated magnetic conductor to prevent eddy currents, must

equivalent by solid anisotropy medium, because the computation will be very complicated^[5,6,9]. The cross-section of toroidal core is shown on Fig. 3.

In cylindrical coordinates vectors of magnetic field intensity H magnetic induction B and electric field intensity E we orient as:

$$\mathbf{H} = \alpha_0 \mathbf{H}; \mathbf{B} = \alpha_0 \mathbf{B}; \mathbf{E} = r_0 \mathbf{E}_r + Z_0 \mathbf{E}_z \quad (3)$$

where, r_0, z_0, α_0 are spatial orts.

The exchange of laminated ferromagnetic in axis r, z, α is made by summing up electric and magnetic conductivities of ferromagnetic and non-magnetic layers, in axis r by summing up corresponding resistances:

$$\begin{aligned} \gamma_r = 0; \gamma_\alpha = \gamma_z = \frac{d_f \gamma_f}{d_f + d_0} \\ v_\alpha = \frac{(d_f + d_0) v_f}{d_f + d_0 v_f / v_0} \end{aligned} \quad (4)$$

where, v_f, γ_f , are static relativity and conductivity of ferromagnetic, d_f, d_0 are widths of ferromagnetic and nonmagnetic gap.

The static relativity of ferromagnetic we find from general magnetization curve.

The first Maxwell's equation in quasistationary approach with conditions (I) obtain a form:

$$\frac{\partial \mathbf{H}}{\partial z} = \gamma_r \mathbf{E}_r; \frac{\partial \mathbf{H}}{\partial r} + \frac{\mathbf{H}}{r} = \mathbf{E}_z \quad (5)$$

Let us write the second Maxwell's equation:

$$\frac{\partial \mathbf{B}}{\partial t} = \frac{\partial \mathbf{E}}{\partial z} \quad (6)$$

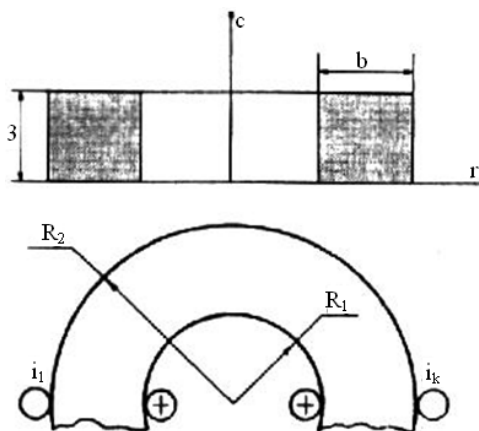


Fig. 3: The cross-section of toroidal core

The calculation equation of electromagnetic field we obtain from solving (5) with (6) taking into consideration that according to (3) $\gamma_r = 0$:

$$\frac{\partial \mathbf{B}}{\partial t} = \frac{1}{\gamma_\alpha} \left(\frac{\partial^2 \mathbf{H}}{\partial r^2} + \frac{1}{r} \frac{\partial \mathbf{H}}{\partial r} - \frac{\mathbf{H}}{r^2} \right) \quad (7)$$

The connection between components of vectors H and B, follow to (4) will be:

$$\mathbf{H} = v_\alpha(\mathbf{B}). \mathbf{B} \quad (8)$$

where, v_α is static relativity of equivalent media, which we calculate by magnetization curve of ferromagnetic.

The integration area (7) $R_1 \leq r \leq R_2$ where R_1 is internal radius of toroid; R_2 is external radius of toroid. The axial dimension of toroid we mark as α .

The boundary conditions are defined from Ampere's Law:

$$\mathbf{H}(R_1) = \frac{wi}{2\pi R_1}; \mathbf{H}(R_2) = \frac{wi}{2\pi R_2} \quad (9)$$

Where:

w_i = Magneto-motive force of magnetization) winding

I = Current

w = Number of turns

The toroidal saturated choke ordinary work in regime of given electric voltage for instance of current, so the latest is related to unknown values. its calculation needs including of addition equations.

This equation has form:

$$\frac{di}{dt} = \alpha \left(U - Ri - w \frac{d\Phi}{dt} \right) \quad (10)$$

There u is electric voltage, which we consider as given value, i is current; Φ is main magnetic flux; R is winding resistance; α is inverse inductively of dissipation, which we consider as constant, because on the ways of dissipation fluxes the definition is air resistance w number of turns of magnetization winding; The unknown flux we obtain from spatial time distribution of magnetic induction:

$$\Phi = \int_s \mathbf{B} ds = a \int_{R_1}^{R_2} \mathbf{B} dr \quad (11)$$

The calculation of induction on the border of integration zone needs solving of two independent

systems of nonlinear algebraic Eq. 8, 10 on every time step. Here easy way is using of method of dividing by half^[9].

Relatively Eq. 11 the Simpson's rule may be used:

$$\Phi = \frac{a\Delta r}{3.2m} \sum_{k=1}^n q_k B_k \quad (12)$$

Where:

Δr = Step of spatial discretization in radius dimension
 $2m$ = Number of steps of discretization of integration zone

B_k = Value of induction in k-th node of spatial mesh

q_k = Constant coefficients: 1, 2, 4

The Eq. 12 after its differentiation by time give the following form:

$$w \frac{d\Phi}{dt} = \xi (P + Q) \quad (13)$$

Where:

$$p = \lambda \frac{di}{dt}; Q = \sum_{k=2}^{n-1} q_k \frac{\partial B_k}{\partial t}; \xi = \frac{wa\Delta r}{6m} \quad (14)$$

There:

$$\lambda = \frac{w}{2\pi} \left(\frac{1}{v_\alpha^2(R_1)R_1} + \frac{1}{v_\alpha^2(R_2)R_2} \right) \quad (15)$$

where, v_α^2 is differential reluctivity. It we finding likewise (5) by main magnetization curve of ferromagnetic $H_f = H_f(B)$.

Substituting (14),(15) into (13), the next obtaining result in (10), we obtain:

$$\frac{di}{dt} = \chi(u - Ri - \xi Q) \quad (16)$$

where, χ is coefficient:

$$\chi = \frac{\alpha}{1 + \xi\alpha\lambda} \quad (17)$$

Now the system of mixed nonlinear differential Eq. 7, 16 undergo common integration.

Let us create the column of unknown:

$$X = (B_\Delta, i)_t \quad (18)$$

where, $B_\Delta = (B_2, B_3, \dots, B_{n-1})_t$ is sub column of discrete values of induction in spatial mesh nodes with the exception of border nodes.

With condition (18) to system (7), (16) we give canonical form

$$\frac{dX}{dt} = f(X, t) \quad (19)$$

where, $f(X, t)$ is T - periodical.

The integration (19) from initial condition X_0 is initial-boundary (Cauchy) problem for ordinary differential equations. The result of such problem determines the transient process of device. For obtaining steady - state process it needs to put on (19) additional condition of T-periodicity:

$$X(0) - X(T) = (0) \quad (20)$$

The common solution (19), (20) constitutes the two-point boundary problem for ordinary differential equations. The solution with absence of constant component in periodical result can be obtained by easy way by naive algorithm.

$$X(0)^{k+1} = X(T)^k - 0.5(X_{\max}^k + X_{\min}^k) \quad (21)$$

Where X_{\max}^k, X_{\min}^k are columns of maximum and minimum values $X(t)$ on interval of time $[0, T]$.

As we can see the iteration equation is connected with integration (19) on interval of one Period. On Fig. 3-5 are shown the computation result of steady-state some regime of choke.

The voltage monitoring system: The system consists from saturated choke working in certain regime of electric voltage and artificial neural network. the goal of neural network is to indicate the supplied voltage of choke. As the input signal, for the network was used the periodical electric current in magnetizing winding.

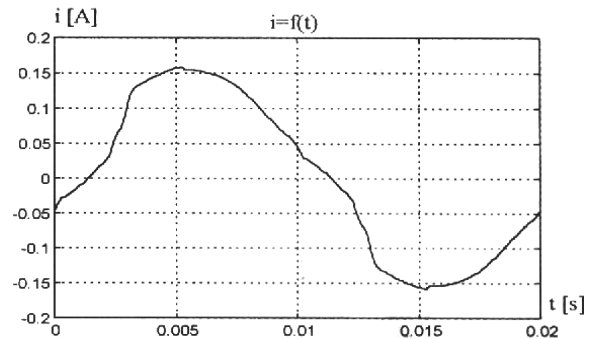


Fig. 4: The curve of steady-state current of choke in period

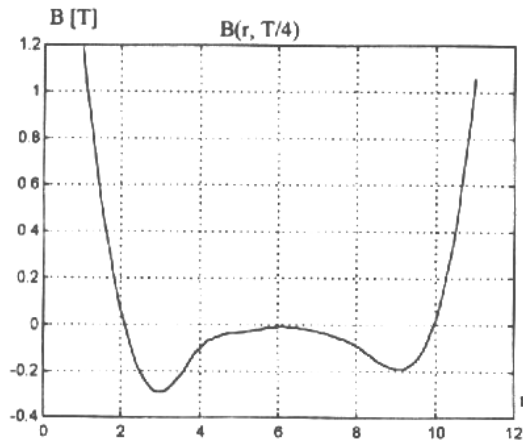


Fig. 5: The spatial distribution of B in steady-state regime of choke in fixed time T/4

In order to decrease neural network architecture was necessary pre-processing of input data. In our case number of input neurons depends on preciseness of Fourier series distribution^[1,3,8].

The neural network consists of one hidden layer. In output layer there is one neuron indicating measured voltage value. In our numerical experiments we tested neural network with neuron linear transfer function in hidden layer and tan sigmoid and sigmoid transfer function in hidden layer. We tested the following neural network architectures: 3, 4, 5, 6, 7 and 10 neurons in the hidden layer and 4, 5, 6, 7, 8, 9 and 10 receptors what is equal to number of current harmonics in the Fourier distribution. As the training algorithm we used well-known back-propagation rule with momentum technique. In order to obtain proper input signal interpolation we tested various network architectures. Neural Network efficiency strongly depends on neural network architecture and number of learning vector presentation simultaneously, but increasing number of receptors up to 9 doesn't give effect. For fixed neural network architectures we assumed different input vectors lengths (number of presentation). In Table 1 we present some results obtained for different neural network parameters. For the neural network learning process we used learning vector from regime voltage 5: IOV. Characteristic positions in Tables show on values in input vector, which were used in learning process.

In our presentation we selected only some values from small range of voltage.

As we can show in Table 1 network gives results with preciseness 1V but with architecture Table 2 preciseness reaches 0.1V in this same voltage regime.

Table: 1 H = 3. ΔU = 0.5V

Up [V]	Ux [V]	δ [%]
7.64	7.63	0.13
7.80	7.80	0.00
7.90	7.91	0.13
8.00	8.00	0.00
8.10	8.13	0.37
8.11	8.14	0.37
8.12	8.15	0.37
8.13	8.16	0.37
8.14	8.17	0.37
8.15	8.18	0.37
8.16	8.19	0.37
8.17	8.21	0.49
8.18	8.21	0.37
8.19	8.22	0.36
8.20	8.24	0.49
8.30	8.35	0.60
8.50	8.56	0.70

Table : 2 H = 4, ΔU = 0.25V

AUp [V]	Ux [V]	δ [%]
7.64	7.62	0.26
7.80	7.81	0.13
7.90	7.91	0.13
8.00	8.00	0.00
8.10	8.10	0.00
8.11	8.11	0.00
8.12	8.12	0.00
8.13	8.12	0.12
8.14	8.13	0.12
8.15	8.14	0.12
8.16	8.14	0.25
8.17	8.16	0.12
8.18	8.17	0.12
8.19	8.19	0.00
8.20	8.21	0.12
8.25	8.25	0.00
8.50	8.56	0.00

Result of numerical experiments for two network architectures.

CONCLUSION

Such mathematical model is constructed on base of electric circuit theory and quasistationary electromagnetic field theory. It has high precision and high usefulness of computer realization simultaneously. Especially very important is that the mathematical model gives possibility to receive periodical solution, which in our research we receive directly the input information for Artificial Neural Network from. Efficiency of proposed measure system confirm by computation results convincible.

AKNOWLEDGMENT

I would like to owe thanks to Applied Science University (ASU)-Jordan for supporting this research.

REFERENCES

1. Dan Paterson, W., 1996. Artificial Neural Networks: Theory and Applications. 1st Edn., Prentice Hall PTR, Upper Saddle River, New Jersey, USA., ISBN: 0132953536, pp: 400.
2. Mohammad H. Hassoun, 1995. Fundamentals of Artificial Neural Networks. 1st Edn., The MIT Press, USA., ISBN: 10: 026208239X.
3. Bart, Kosko, 1991. Neural Networks and Fuzzy Systems. A Dynamical Systems Approach to machine Intelligence. Har/Dis Edn., Prentice Hall, USA., ISBN: 10: 0136114350, pp: 224.
4. Bart Kosko, 1991. Neural Networks for Signal Processing. 4th Edn., Prentice Hall, Englewood Cliffs, New Jersey, USA., ISBN: 10: 013617390X, pp: 800.
5. Cardot, H., M. Reven4, B. Victorri and J. Revillet, 1993. An artificial networks architecture for handwritten signature authentication. Proceeding of the SPIE Applications of Artificial Neural Networks II, Apr. 13-13, Orlando, FL., pp: 633. <http://dx.doi.org/10.1117/12.152564>
6. Carpenter, G. and S. Grossberg, 1987. A massively parallel architecture for a self-organizing neural pattern recognition machine. *Comput. Vision Graph. Image Process.*, 37: 54-115. <http://profusion.bu.edu/techlab/Docs/CarpenterGrossberg1987.pdf>
7. Widrow, B. and R. Winter, 1988. Neural nets for adaptive filtering and adaptive pattern recognition. *IEEE Comput.*, 21: 25-39. DOI: 10.1109/2.29
8. Kong S.G. and B.Kosko, 1991. Differential competitive learning for centroid estimation and phoneme recognition. *IEEE Trans. Neural Network*, 2: 118-124. DOI: 10.1109/72.80297
9. Kosko, B., 1990. Unsupervised learning in noise. *IEEE Trans. Neural Networks*, 1: 44-57. DOI: 10.1109/72.80204