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Modelling dynamic characteristics of synchronous motors via radial basis artificial neural networks

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Abstract

System modelling can be defined as system models that created thanks to the data obtained from applications or mathematical expressions. Modelling helps determine and design dynamic behaviors of a system. Most of industrial applications are not linear. In recent years, artificial neural networks have been widely used in the modelling of complex and non-linear systems. Radial basis artificial neural network is an artificial neural network used in the modelling of non-linear systems. They have increased their popularity in recent years due to their success in curve fitting and classifying non-linear problems. kaTherefore, studies on software and hardware applications related to radial basis artificial neural networks have gained momentum. Synchronous motor is an alternative current motor in which rotor rotational speed is equal to the rotational speed of the stator rotating field and the rotation speed does not vary in loading. These motors are used in industrial applications requiring steady speed. When excitation current of the synchronous motor changes, it is fed by ohmic, inductive and capacitive current. In a synchronous motor operating at a constant load and voltage, the characteristic which yields the relationship between excitation current and stator current is called V current. The change in excitation current is inversely proportional to the change in power coefficient under the same conditions. This study focuses on modelling excitation current-stator current characteristic (V current) and excitation current-power coefficient characteristic based on the data obtained from simulation studies on changes in the excitation current of synchronous motor using radial basis artificial neural networks, which is a special multi-layered and feed-forward form of artificial neural networks.

Key words: Modelling, Synchronous Motor, Radial Basis Artificial Neural Networks.

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1. INTRODUCTION

Artificial neural networks were inspired by the fundamental principles of human mind and simulated by the computers. Early studies focused on creating mathematical models of neurons in the brain. Nowadays, artificial neural networks as a field offer solutions to mathematical problems arising out of functions when various neurons are combined in certain ways [1]. Thanks to their effectiveness in control systems, artificial neural networks can accurately approximate any non-linear function. In recent years, various studies have been conducted on artificial neural network applications in order to model and control non-linear dynamic systems [2]. Artificial neural networks can learn complex mathematical models based on sample input and output data, which is a process called training. They are superior to other modelling techniques because they can model complex and non-linear mathematical expressions without assuming the type of relationship between input and output variables. It can be noted that artificial neural network applications usually benefit from feed-forward and back-propagation algorithms. In addition, general regression artificial neural networks and radial basis artificial neural networks are also used as alternative algorithms [3-5]. Section 2, 3 and 4 describe the general structure of artificial

neural networks, radial basis artificial neural networks and dynamic characteristics of synchronous motor to be modelled, respectively. Section 5 focuses on modelling of dynamic characteristics of synchronous motor via radial basis artificial neural networks. Section 6 discusses the results.

2. GENERAL STRUCTURE OF ARTIFICIAL NEURAL NETWORKS

Artificial neural cell (neurons) is the basic data processing unit of artificial neural networks. A standard neuron is a processing element consisting of a single output and weighted input relations. Artificial neural networks are trained by using the error between system output and model output. Learning is performed by changing the weights of relations between neurons in the network. The basic structure of an artificial neuron is shown in Figure 1.

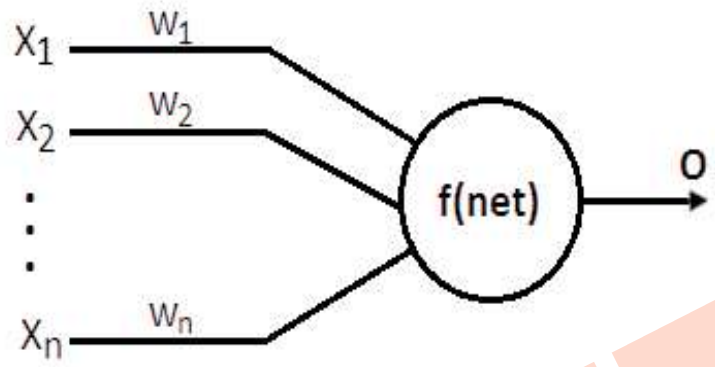


Figure 1: Basic artificial neuron

Neuron output signal is defined as follows:

$$o = f(w^t x) \tag{1}$$

or

$$o = f\left(\sum_{i=1}^{n} w_i . x_i\right) \tag{2}$$

Here, w represents weight vector and x represents input vector.

$$w = [w_1 w_2 \ldots w_n]^t \tag{3}$$

$$x = [x_1 x_2 \ldots x_n]^t \tag{4}$$

In general, a net variable is defined and activation function is used as f(net).

$$net = w^t x \tag{5}$$

3. RADIAL BASIS ARTIFICIAL NEURAL NETWORKS

Developed in 1988, radial basis artificial neural networks were inspired by action-reaction in biological neural cell and applied to filtering problems. The training of radial basis artificial neural network models can be viewed as a curve fitting approach in a multi-dimensional space. Therefore, the training performance of a radial basis artificial neural network model turns into an attempt to find the most suitable surface for data in output vector space, thus being an interpolation problem.

Similar to general artificial neural networks, a radial basis artificial neural network consists of three layers as input, hidden and output layers. However, unlike conventional artificial neural networks, radial basis activation functions and a non-linear clustering analysis are used in the transition from input layer into the hidden layer in radial basis artificial neural networks. The structure between hidden layer

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and output layer, similar to other types of artificial neural networks, continues functioning and actual training is performed here. Radial basis functions have so far been used in the solution of multivariate problems in the numerical analysis, and these functions were also introduced to the modelling of artificial neural networks thanks to the developments in artificial neural networks. Similar to feed-forward artificial neural networks, a radial basis artificial neural network consists of three layers as input, hidden and output layers. However, the transformation from the input layer into the hidden layer, which is performed by radial basis activation functions, is a non-linear constant transformation. On the other hand, a linear transformation occurs from the hidden layer into the output layer. Free parameters which can be adapted in a radial basis artificial neural network are central vectors, width of radial functions and output layer weight. The learning method in this study offers a method based on the non-iterative matrix solution of weights (off-line). Therefore, this network is approached as a definite adaptive radial basis artificial neural network. Such network structure is remarkably successful in learning static graphs and patterns.

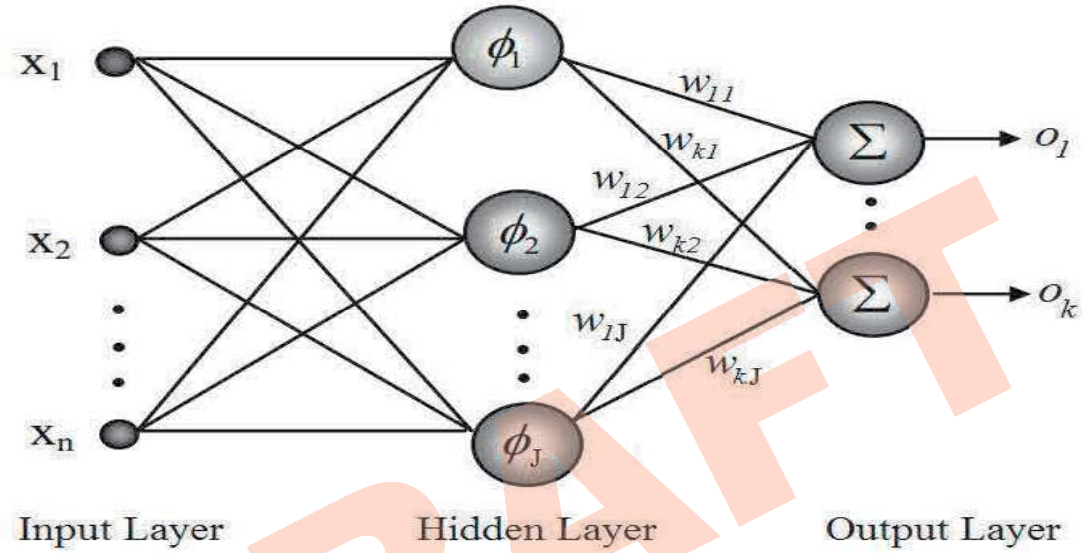


Figure 2: The structure of radial basis artificial neural networks [8].

The basic relation used in learning for radial basis artificial neural networks is given in Equation 1.

$$y_k^p(x) = w_{ko} + \sum_{m=1}^{M} w_{km}\varphi_m(x^p, c_m) \quad (1)$$

w_{k0} is weight coefficient for bias input.

For all p conditions, if $\varphi_0(x^p, c) = 1$, Equation 1 can be defined as in Equation 2.

$$y_k^p(x) = \sum_{m=0}^{M} w_{km}\varphi_m(x^p, c_m) \quad (2)$$

$$y_k^p(x) = \sum_{m=0}^{M} w_{km}\varphi_m(\| x^p - c_m \|^2) \quad (3)$$

i=1,2,...I input number

k=1,2,...,K number of cells in the output layer

N the number of cells in the hidden layer

M central number (M=N)

Here, $x^p \in R^{nx1}$ represents the network input vector,

$\varphi_m(.) \in R^+$ represents radial basis activation function,

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$c_m \in R^{nx1}$ represents radial basis centers selected from a subset of input vector space

$||.||^2$ represents Euclidian norms as a criterion for the distance between input vector and center,

w_{km} represents the weights in the output layer.

The important elements in radial basis artificial neural networks are cell nucleus, weights in the output layer and structure of the activation function used in the network. Various types of functions such as linear, cubic, Gaussian, multiquadratic and inverse multiquadratic functions may be used as an activation function in radial basis artificial neural networks. Gaussian function was used in this study. The mathematic structure of Gauss function is given in Equation 4.

$$\varphi_{pm}(x) = \exp^{-\frac{\sum_{i=1}^{I}(X_{pi}-c_{im})^2}{2\sigma^2_{im}}} \quad (4)$$

Here, X_{pi} represents input vector and c_{im} represents centers.

σ, on the other hand, represents standard deviation value, which is also called dispersion parameter in the field of artificial neural networks and heavily influences the performance of radial basis artificial neural networks.

Radial basis artificial neural networks are trained at two stages: the identification of cell nucleus and optimization of weights in the output layer. Different methods are used to identify cell nucleus and output weights in the literature. K-means and Kohonen clustering methods are widely used to identify cell nucleus. On the other hand, least mean squares (LMS) and Moore-Penrose pseudo-inverse methods are widely used to identify output weights. In general, a constant dispersion parameter is determined for all cells. Although there are approximate equations for dispersion parameter in radial basis artificial neural networks, it can also be determined through trial and error method [6-10].

4. SYNCHRONOUS MOTOR

Synchronous motors consist of a single, two or multiple phases and rotate at a synchronous speed. However, they do not operate when connected to the grid; they can be operated through special starting methods. Stator winding is connected to the alternative current (AA), and rotor winding is connected to the direct current (DA). Therefore, these machines fall into the group of double excited machines. While it is called synchronous alternator if used to convert mechanical energy into electricity, it is also called synchronous motor if used to convert electricity into mechanical energy. The rotor winding of a synchronous motor is fed by a direct current source, and, if an alternative voltage is applied to the stator windings, it can also operate as a synchronous motor. The circuit fed by a direct current source is called excitation circuit. An excitation current is transmitted by the circuit when the voltage is applied to it. At a constant voltage and frequency, V-curves account for the characteristic of varying excitations in a synchronous motor.

These curves are obtained from the phasor diagram of the synchronous motor. In an unloaded state, the motor can be operated at unit power coefficient (cosφ=l) when the excitation current I_E is adjusted. In this case, the stator current I_s is minimized. The input power coefficient of the synchronous motor can be transmitted back and forward when the excitation current is increased or decreased. The changes in I_s current, which corresponds to the excitation current, occurs in the form of V-curve. V curves of a synchronous motor at different load states are shown in Figure 3.

V curves of a synchronous motor varies depending on the different load states. V-curves are at the outermost part when the motor operates at an unloaded state, and they come closer to the ohmic operation curve as the motor is loaded. In case of ohmic operation, the necessary excitation current in the unloaded state increases in a directly proportional way to the load, which is because armature reaction varies depending on the various loads and the saturations increases. The power coefficient characteristic of a synchronous motor depending on changes in excitation current at different loads are shown in Figure 4.

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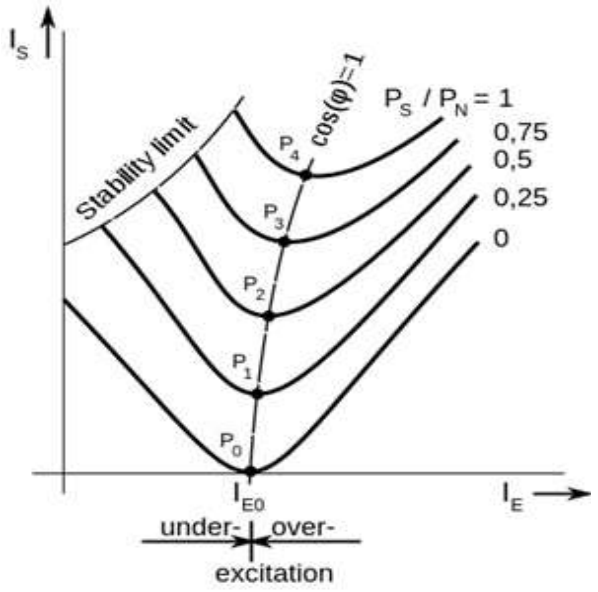


Figure 3: V curves of a synchronous motor at different load states

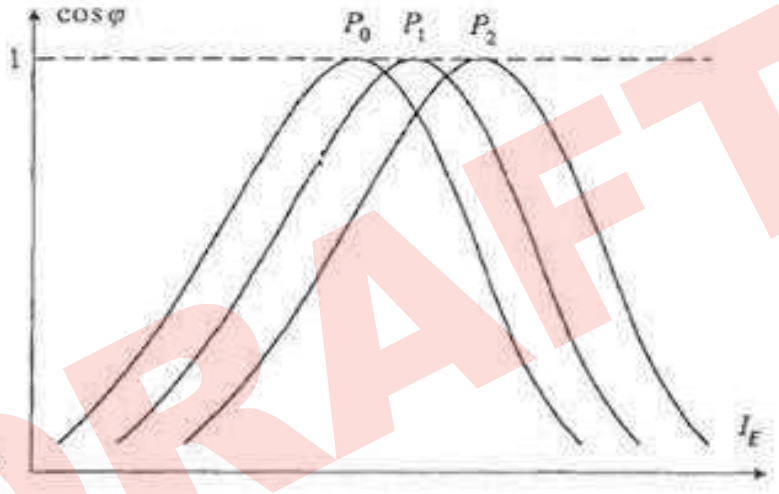


Figure: The excitation current-power coefficient characteristic of a synchronous motor at different loads

As shown in Figure 4, the curve moves from left to the right as the motor is loaded [11]. Parameters of synchronous motor used in this study are given in Table 1.

Table 1. Synchronous *Motor Parameters*

Parameter	Value
Nominal Power(S)	8.1 kVA
Nominal Revolution[n]	1500 rpm
Nominal Voltage(V)	400 V
Nominal Field Current(I)	3 A
Nominal Load Torque(M)	7 Nm
Pole pairs(p)	2
Frequency(f)	50 Hz
Rotor Type	Salient pole
Stator Resistance[R_s]	1.62 ohm
Stator Inductance[L]	4.527 mH
Field Resistance[R_f']	1.208 ohm
Field Inductance[L_f']	0.01132 H
Mechanical Inertia[J]	0.0923 kgm^2
Friction Factor[F]	0.009 N.m.s

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5. MODELLING OF DYNAMIC CHARACTERISTICS OF A SYNCHRONOUS MOTOR VIA RADIAL BASIS ARTIFICIAL NEURAL NETWORKS

As shown in Figure 5, dynamic characteristics of the synchronous motor, which are excitation current-stator current characteristic (V-curve) and excitation current-power coefficient characteristic, were modelled via radial basis artificial neural networks in Matlab M-File.

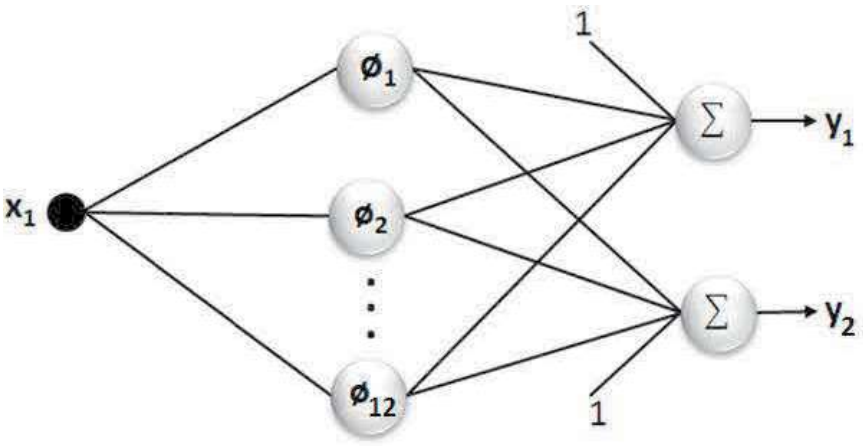


Figure 5: Radial basis artificial neural network used for modelling

i: Input (X) number (I = 1)
m: Number of centers (M = 15)
K: Output (Y) number (K = 2)
Number of neurons=number of centers
p: Number of patterns (Different values for X) (p=80)

$$y_1^p(x) = w_{10} + \sum_{m=1}^{12} w_{1m}\varphi_m(x^p, c) \tag{4}$$

$\varphi_0(x^p, c) = 1$ bias input

$$y_1^p(x) = \sum_{m=0}^{12} w_{1m}\varphi_m(x^p, c) \tag{5}$$

$$\varphi_{pm}(x) = \exp^{\frac{\sum_{i=1}^{1}(X_{pi}-c_{im})^2}{2\sigma^2_{im}}} \tag{6}$$

$Y = G.W$ and $G = \{\varphi_{pm}\}$. It was $\varphi_{p0} = 1$ for bias input.

$$G = \begin{pmatrix} 1 & \cdots & \varphi_{1,12} \\ \vdots & \ddots & \vdots \\ 1 & \cdots & \varphi_{20,12} \end{pmatrix}_{20x13} \quad w = \begin{pmatrix} W_{1,0} \\ . \\ . \\ W_{1,13} \end{pmatrix}_{13x1} \tag{7}$$

Reciprocal of G must be taken in order to find W. Because G is not a square matrix, its reciprocal cannot be taken in a normal way.

$W = (G^T.G)^{-1}.G^T.Y$ helps us find the W weight matrix. The tilt of the curve was taken into consideration when values of weight were calculated. W (values of weight) obtained from the training are given in Table 2.

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C = [0.3 1.0 1.2 1.7 2.4 3.1 3.7 4.0 4.3 4.9 5.6 6.3 7.0 7.6 8.0]

σ = [0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5]

Table 2. W (values of weight) obtained from the training

W_{cosfi}	W_{Is}
0,02362	-1,04317
0,03084	-1,15477
0,07648	-0,57399
0,11925	-2,40932
0,22452	-3,36240
0,26397	-3,67427
0,25415	-2,75255
0,04008	-1,09692
0,24823	-2,63323
0,26690	-3,61751
0,22783	-3,03308
0,15981	-2,38036
0,13307	-1,22487
0,02594	-0,92101
0,10395	0,68809
0,43241	13,12261

V-curve characteristic of the nominally synchronous motor modelled via radial basis artificial neural network is shown in Figure 6.

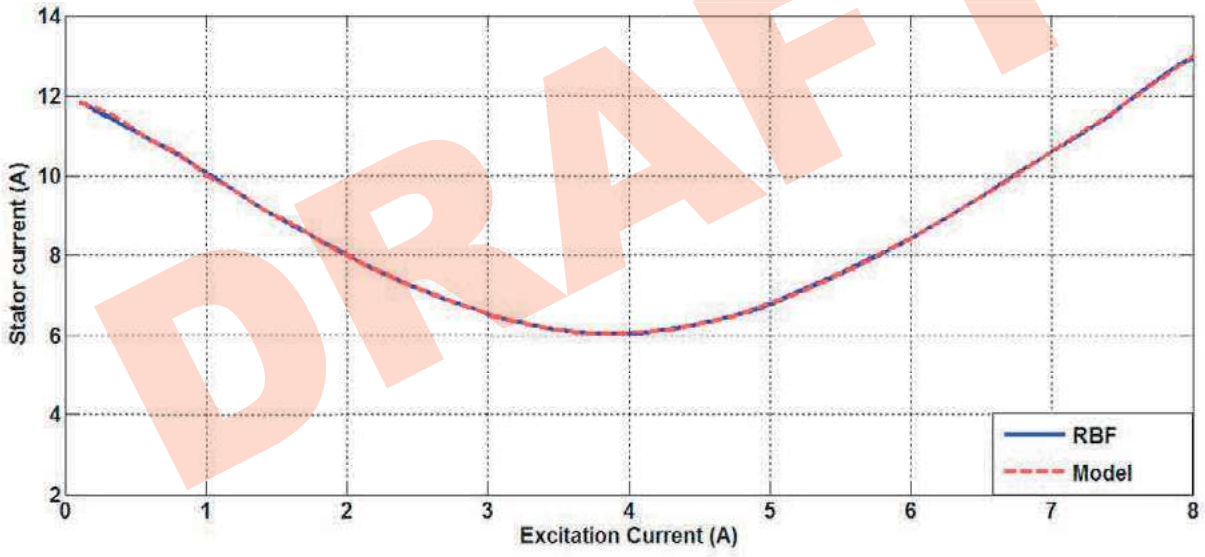


Figure 6: V-curve characteristic of the nominally synchronous motor modelled via radial basis artificial neural network

Excitation current-power coefficient characteristic of the nominally loaded synchronous motor modelled via radial basis artificial neural network is shown in Figure 7.

Weight matrixes of power coefficient and stator current for the motor characteristic were obtained from the modelling via radial basis artificial neural networks on simulation data of nominally loaded synchronous motor. When the actual characteristic and the characteristic obtained from the model are compared, it was observed that the error rate was nearly 0.2-0.3% at maximum, demonstrating fairly low error values.

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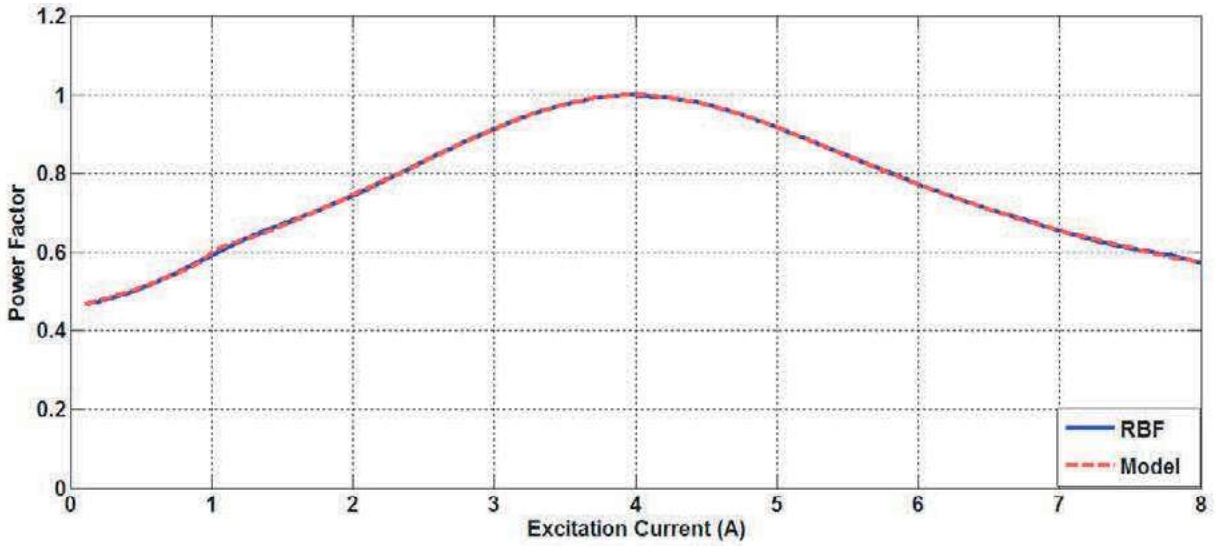


Figure 7: Excitation current-power coefficient characteristic of the nominally loaded synchronous motor modelled via radial basis artificial neural network

6. CONCLUSION

Existing networks used to identify neuron centers can rapidly yield successful results. Radial basis function networks do not lead to a remarkable working load. In addition, radial basis artificial neural networks may eliminate problems encountered in other artificial neural networks such as limited local minimum and the necessity to perform numerous simulations for healthier results. In conclusion, the algorithm proposed in this study may successfully model the characteristics of a synchronous motor when suitable centers are selected and dispersions parameters are identified.

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