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# Performance of support vector regression machines on determining the magnetic characteristics of the E-core transverse flux machine

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**Abstract:** The E-core transverse flux machine (ETFM) has major advantages with its different and unique structure in conventional electrical machines. It is a combination of transverse flux and reluctance principle. In this work, support vector regression machines (SVRMs) are used to obtain the magnetic characteristic parameters of the ETFM for the first time and it is compared with its artificial neural network model. The data for the training and testing of the SVRMs are obtained from experimental measurements. It is proven that SVRMs can conveniently be used in the modeling of the magnetic behaviors of highly nonlinear ETFM with better accuracy and efficiency.

**Key words:** E-core transverse flux machine, magnetic characteristics, artificial neural network, support vector regression machines

## 1. Introduction

Transverse flux machines (TFMs) have recently become attractive and popular in electrical machine areas due to their favorable characteristics, specific torque, high force density, and high efficiency. Nevertheless, TFMs have quite an old history, like that of the classical radial machines. In 1971, Laitwaite et al. presented a significant paper that shaped future research by using the transverse flux principle in linear electrical machines [1]. Compared with the more usual kind of linear motor, the new machine has flux paths lying transversely to the direction of motion in running phases. First Weh and May introduced a new rotating machine by combining the permanent magnet excited structure and the TFM concept [2,3]. After the 1990s, alternative shapes of stator and rotor poles were also tried for improvement of TFMs. Henneberger and Bork presented a new concept of a TFM that has a U-shaped inner stator with three ring windings and the outer rotor carries permanent magnets [4,5]. Liu and Kuo adapted the transverse flux of E-shaped stator and rotor poles to investigate a linear reluctance machine design [6]. A special reluctance motor with a transverse flux path that is free of expensive permanent magnets was presented by Kruse et al. in [7]. As in the literature [4,8–10], TFMs can be categorized according to different concepts, such as those with an active rotor where the exciting permanent magnets are placed on the rotor or those with a passive rotor where the permanent magnets are located on the stator parts.

The E-core transverse flux machine (ETFM) is another concept uniting the transverse flux principle and an electrically excited reluctance motor without any permanent magnets. It was initially patented by Rasmussen [11] in 2007. A segmental stator design is used to improve the torque per weight ratio with a lower cost. With

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short flux paths, closed magnetic systems without common yokes, and many advantages such as high torque density, reliability, and high load ability, it differs from classical electrical machines.

Magnetic characteristics of ETFMs such as flux linkage, phase inductance, and electromagnetic torque are highly nonlinear functions of the rotor position and phase current, which causes difficulties in the model. There are several methods proposed in the literature on obtaining and describing the magnetic characteristics of similar electrical machines. Analytical approaches are used to characterize the flux linkage and torque with respect to the current magnitude and rotor position, but most lack accuracy and complexity. Finite element analysis (FEA) is the most commonly used method for machine design and performance predictions. Getting better approximations, 3D FEA is applied to deal with the end magnetic field effects. Direct or indirect experimental measurements take a long time to be implemented and the magnetic data obtained are stored in look-up tables. Nevertheless, the interpolation methods are not compatible or accurate enough for nonlinear characteristics due to high magnetic saturation. On the other hand, artificial intelligence approximation and learning techniques based on artificial neural networks (ANNs), fuzzy logic, genetic algorithms, and support vector machines (SVMs) are successfully used to solve complex problems and are well suited to obtaining the nonlinear functions of magnetic fields.

ANNs are a favorable and powerful technique for nonlinear real-time control and system identification problems in engineering applications. An ANN has the ability of detecting complex nonlinear relationships and all possible interactions between dependent and independent variables with a simple architecture. With the attractive advantages, ANNs have become an unconventional alternative method for modeling and design problems in the field of electrical machines.

SVMs are a group of supervised learning methods that can be applied to classification or regression. In the last decade, there have been very significant developments in the theoretical understanding of SVMs as well as algorithmic strategies to implement them and applications of approaches to practical problems. It is a system for efficiently training linear learning machines in the kernel-induced feature spaces while respecting the insights provided by the generalization theory and exploiting the optimization theory. The model depends only on a subset of the training data [12].

In contrast to well-known ANNs, SVMs use the principle of structural risk minimization that aims to minimize an upper bound of the generalization error instead of the empirical risk minimization that minimizes the training error used in ANNs. It solves a convex constrained quadratic optimization problem, and its error surface is free of local minima and has a unique global optimum. Therefore, SVMs can be implemented simply and reliably in regression, classification applications, and system identification [13–15].

In the literature, it can be seen that support vector regression machines (SVRMs) are used in the control and modeling of electrical machines. A control method based on a least square SVM algorithm was introduced for switched reluctance machine (SRMs) in [16]. Moreover, a novel approach proposed position estimation for SRMs based on SVRMs [17]. A nonlinear model of SRMs based on least square SVMs and the genetic algorithm was presented in [18].

This paper proposes the use of SVRMs to determine the nonlinear magnetic characteristics of an ETFM for the first time in the literature. Data required in the training and testing of the SVRM are directly obtained from experimental measurements. To reveal the performance of the SVRM for this application, ANN models are generated with the same training data. The effectiveness of two popular ANN and SVRM methods for obtaining the nonlinear magnetic characteristics of the ETFM is discussed in this paper. The paper is structured as follows: the ETFM is introduced in the next section. The third section is devoted to the fundamentals of the SVRM method. Essentials of modeling of the magnetic characteristics of the ETFM will be given in the fourth section for the practiced methods. The conclusions finally end the paper.

## 2. E-core transverse flux machine

The typical feature of TFMs is that the flux linkage is perpendicular to the direction of motion and current flow. Thus, the magnetic circuit is independent from the design of the electrical circuit. This decoupling in structure simplifies the control method. The torque can be increased only by increasing the pole number while the machine size is kept the same, whereas the winding space is a significant limitation for conventional machines. Since the TFM allows the pole number to be increased without reducing the magneto motive force per pole, it enables much higher power densities than a conventional machine [19–21].

Figure 1 shows the stator and rotor views. It is based on general E-shaped cores traditionally used for single-phase transformers. Each E-core has a coil around the centered leg and is assembled parallel to the rotor axis. This placement of the stator E-cores generates the transverse flux principle. The ETFM has steel laminations on the rotor and stator. There are no windings or permanent magnets on the rotor. Due to the fact that the stator poles and the phases are separate, no steel is shared. Thus, the mutual couplings between phases can be ignored for the analysis. The frame of the ETFM is shown in Figure 2 [22].

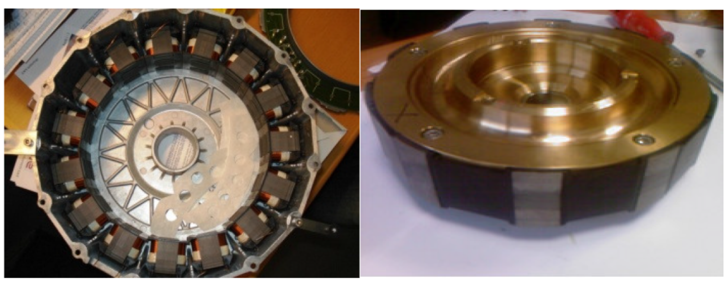


**Figure 1.** Stator and rotor structure of the ETFM.

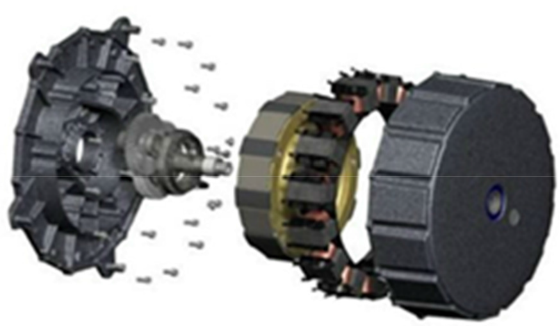


**Figure 2.** Frame of the ETFM.

In Table 1, the parameters of the ETFM are given. The cross-section and the axial view of the ETFM that has 15/10 stator/rotor pole numbers are illustrated in Figure 3.

The flux generated by one winding of a phase does not link with the other winding of the same phase on the other side of the E-core stator segment. Therefore, the ETFM has short flux paths. Each stator pole has closed magnetic systems without common yokes. Figure 4, derived from FEA, shows the axial flux path of the

ETFM for one stator pole and one rotor pole in an aligned position. As can be seen, the flux linkage pattern is distributed from stator pole legs to yoke and then from middle legs to air gap through to the rotor pole. The magnetic field flux linkage is dependent on stator winding currents and rotor replacement angle.

**Table 1.** The parameters of the ETFM.

| | |
|---|---|
| Ns (stator pole number) | 15 |
| Nr (rotor pole number) | 10 |
| Phase number | 3 |
| R (one-phase winding resistance) | 0.09 ohm |
| In (nominal current) | 40 A |

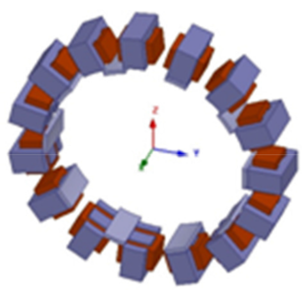


**Figure 3.** The cross-section and axial side view of the ETFM.

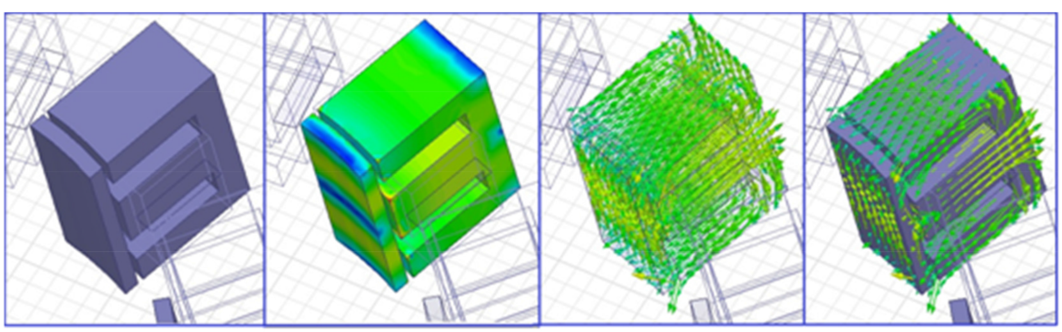


**Figure 4.** The axial flux paths of the ETFM for one stator pole and one rotor pole in an aligned position.

The machine is controlled by switching the phase currents in synchronism with the regions showing increasing inductance or decreasing inductance of the stator windings of the motor. As the rotor pole moves from aligned position to unaligned position with a stator pole, the inductance of that stator winding decreases from a maximum value to a minimum value. If each phase is excited in this region, the ETFM operates in generating mode.

## 3. Support vector regression machines

The regression problem related to the estimation of the flux linkage ($F_\ell$) and torque ($T_\ell$) characteristics can be stated as follows: first, let us consider $F_\ell$. In the training phase, a set of $L$ training pairs $\{(\boldsymbol{x}^o, F_\ell^o), (\boldsymbol{x}^1, F_\ell^1), \ldots, (\boldsymbol{x}^{L-1}, F_\ell^{L-1})\}$ is constructed by considering ($\boldsymbol{x}$) as the input variable vector and ($F_\ell$) as the output. Starting from these samples consisting of input/output values of $F_\ell$, the goal is to find a function $\tilde{F}_\ell$ that approximates the unknown function, $F_\ell(x)$. By using the support vector regression, $\tilde{F}_\ell$ is defined as:

$$\tilde{F}_\ell(x) = \langle w, \varphi(x) \rangle + b, \tag{1}$$

where $\langle .,. \rangle$ denotes the inner product between $w$ and $b$. $\varphi$ is a nonlinear mapping vector that performs a transformation of the input vector to a high-dimensional space. $w$ and $b$are the weighting vector and bias, respectively which are obtained by the minimization of the primal convex objective function:

$$R_{reg} = \frac{1}{2} \|w\|^2 + C \sum_{i=0}^{L-1} L^\varepsilon(x, F_\ell, \tilde{F}_\ell), \tag{2}$$

where $C$ is the regularization constant and $L^\varepsilon(x, F_\ell)$ is a general loss function. The objective function given in Eq. (2) has no local minima and it guarantees the global minimum. This is one of the superiorities of SVMs over other pattern recognition methods, particularly neural networks. In this work, the so-called $\varepsilon$-insensitive loss function developed by Vapnik [23] is used:

$$L^\varepsilon(x, F_\ell, \tilde{F}_\ell) = \begin{cases} 0, if \left| F_\ell^i - \tilde{F}_\ell(x^i) \right| \leq \varepsilon \\ \left| F_\ell^i - \tilde{F}_\ell(x^i) \right| - \varepsilon, else \end{cases}. \tag{3}$$

This equation defines an $\varepsilon$ tube. If the predicted value is within the tube, the loss is zero, and if the predicted point is outside the tube, the loss is the magnitude of the difference between the predicted value and radius $\varepsilon$ of the tube. It is possible to rebuild the minimization of the regression risk as a dual optimization problem. In the dual optimization problem, the $\boldsymbol{w}$ vector can be written in terms of $\boldsymbol{x}$ as follows:

$$w = \sum_{i=0}^{L-1} (\alpha_i - \alpha_i^{'}) \varphi(x^i), \tag{4}$$

where $\alpha_i$ and $\alpha_i^{'}$ are the unknown Lagrange coefficients. By substituting Eq. (4) into Eq. (1), $\tilde{F}_\ell$ can be rewritten as follows.

$$\begin{aligned} \tilde{F}_\ell(x) &= \sum_{i=0}^{L-1} (\alpha_i - \alpha_i^{'}) \left\langle \varphi(x^i), \varphi(x) \right\rangle + b \\ &= \sum_{i=0}^{L-1} (\alpha_i - \alpha_i^{'}) \mathbf{K}(x^i, x) + b \end{aligned} \tag{5}$$

Here the coefficients $\alpha_i, \alpha_i^{'}$, and $b$must be selected in order to minimize the regression risk. In Eq. (5), $K(x^i, x) = \left\langle \varphi(x^i), \varphi(x) \right\rangle$is the kernel function that works on the original space. After applying the standard Lagrange multiplier technique, equivalent maximization of the dual space objective function is obtained:

$$W(\alpha,\alpha^{'}) = -\varepsilon \sum_{i=0}^{L-1} (\alpha_i^{'} + \alpha_i) + \sum_{i=0}^{L-1} F_\ell^i (\alpha_i^{'} - \alpha_i) - \frac{1}{2} \sum_{i,j=0}^{L-1} (\alpha_i^{'} - \alpha_i)(\alpha_i^{'} + \alpha_i) K(\mathbf{x}^i, \mathbf{x}). \tag{6}$$

The constraints of this function are as follows:

$$0 \leq \alpha_i^{'}, \alpha_i \leq C, \tag{7a}$$

$$\sum_{i=0}^{L-1} (\alpha_i' - \alpha_i) = 0. \tag{7b}$$

Using Karush–Kuhn–Tucker conditions to maximize Eq. (6) subject to the constraints given by Eqs. (7a) and (7b), $\alpha_i, \alpha_i'$ (dual variables) and $b$ are computed. From Karush–Kuhn–Tucker conditions, it can be observed that only for $\left|\tilde{F}_\ell(x^i) - F_\ell^i\right| \geq \varepsilon$ may the Lagrange coefficients be nonzero. For all data samples inside the $\varepsilon$-tube, the coefficients disappear. Consequently, a sparse expansion of $w$ in terms of $x^i$ is obtained. The samples that come with nonvanishing coefficients are called support vectors. The reduced number of training data also has enormous computational advantages in the training phase. This property together with the guaranteed global minimum is the superiority of SVMs over the alternative methods. A detailed theoretical background can be found in [24–26].

The regularization parameter C is a parameter to represent the capability of the approach in estimating the flux linkage using training and test sets. In order to correctly approximate the $F_\ell$ function, $L$ data pairs in the form of $\{(\boldsymbol{x}^o,\ F_\ell^o),\ (\boldsymbol{x}^1, F_\ell^1), \ldots, (\boldsymbol{x}^{L-1},\ F_\ell^{L-1})\}$ obtained from the measurement setup for the TFM are used in the training phase. At the end of the training phase, in the so-called test phase, $F_\ell$ values are estimated for the new current values that are not included in the training set. Similarly, support vector regression can be applied to the regression of the magnetic torque characteristic, $T_\ell$. Numerical details of the support vector regression analysis for $F_\ell$ and $T_\ell$ of the ETFM will be given in the next section.

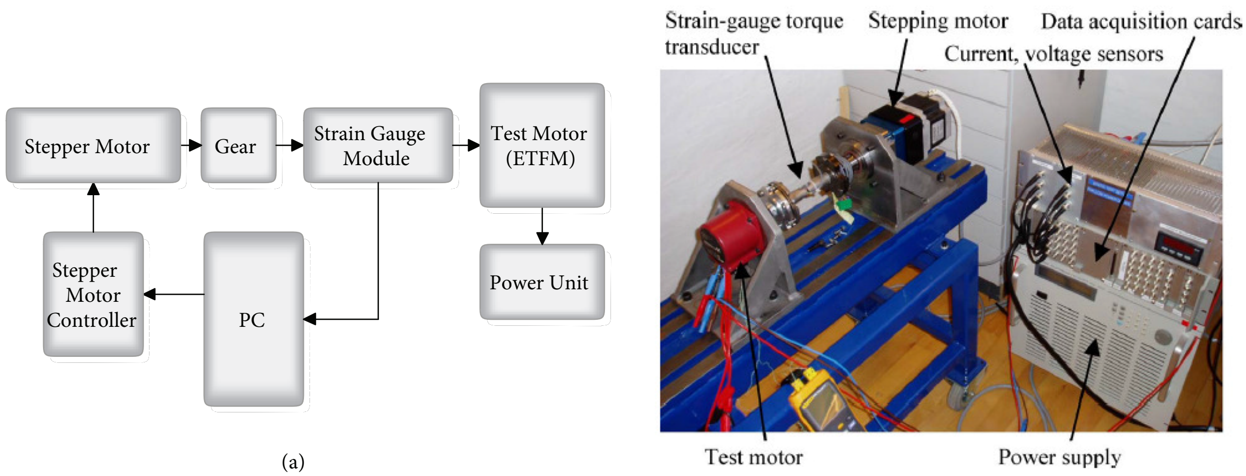
## 4. Determination of the magnetic characteristics of the ETFM with SVRM

The magnetic characteristics such as flux linkage, phase inductance, and electromagnetic torque of the ETFM are highly nonlinear functions of the rotor position and phase current. It will thus be very difficult to model the ETFM due to its special structure. Intelligent approximation and learning algorithms such as SVRMs and ANNs offer an option to obtain the nonlinear characteristics of the ETFM successfully. However, these methods are only based on the experimental data.

### 4.1. Data acquisition with experimental measurements

Training and test data for the SVRM and ANN models are obtained by an experimental test system on the machine. The test system is shown in Figure 5a with a block diagram. A photo of the actual measurement setup is given in Figure 5b [27]. The computer controls a stepping motor that changes the rotor's position of the testing machine to the desired position and locks it. Between the stepping motor and the test machine, a gear and a strain-gauge torque transducer are placed. The applied voltage is adjusted by a programmable power supply.

For the measurement procedure of the torque characteristics, first the rotor is locked at the desired position and a DC pulse is applied to the one-stator phase winding. The static torque values, which are measured by the strain-gauge module, are recorded for several rotor position values according to different current values. The effects of friction and mechanical misalignment can be ignored in static torque measurement for ETFMs. Each phase has a periodicity of $2\pi/N_r$ that is equal to $36°$ for the 15/10 pole ETFM. Rotor position is changed from an unaligned position ($0°$) to an aligned position ($18°$). Torque characteristic curves are interchanged from an aligned position to an unaligned position ($36°$).



(a)

**Figure 5.** (a) Block diagram, (b) photo of the test system used to determine the ETFM characteristics.

The resistance of the phase winding is first measured temperature-dependently for the measurement procedure of flux linkage curves. The phase winding is supplied with a required AC voltage at a fixed rotor position mechanically while the other phases are open-circuit. Afterwards, the instantaneous terminal winding voltage and line current values are recorded simultaneously. For each rotor position, the measurement is repeated at the desired current values. The flux linkage is calculated numerically based on an equation that is the integral of the difference between the terminal voltage and the stator resistive voltage drop:

$$\lambda = \int_0^t [u(t) - Ri(t)]dt + \lambda(0), \tag{8}$$

where $\lambda(0)$ is the value of the flux linkage at t $= 0$, $R$ is the phase armature resistance, $u(t)$ is terminal voltage, and $i(t)$ is the line current. The flux linkage characteristic is obtained according to the currents for different rotor positions from unaligned to aligned positions. An overview of the existing measurement methods and their advantages or limitations can be found in [27].

### 4.2. SVRM model for the characteristics of the ETFM

In this paper, the SVRM is proposed for determining the flux and torque characteristics of the ETFM. For the training and testing of the SVRM, the experimental data obtained by the experimental setup defined in the previous subsection are used.

In SVRM training, the radial basis function is chosen as the kernel type:

$$K(x^*, x) = \exp(-\gamma \left\| x - x^i \right\|^2). \tag{9}$$

Suitable parameters are chosen with several trials to enhance the ability of the generalization. In the SVRM model for torque characteristic, width parameter $\gamma$ is set to 5. The regularization parameter $C$ is set to 100 and $\varepsilon$ is chosen as 0.001 for the optimal performance. Out of 323 sampling data, 134 are chosen as SVs for determination of the flux characteristics. In the SVRM model for torque characteristics, $\gamma = 50$ and $C = 1000$ give the highest accuracy, and 320 data out of a total of 627 data are chosen as SVs by the SVRM. The scatter plots of target and predicted values of the magnetic characteristics are given in Figure 6.

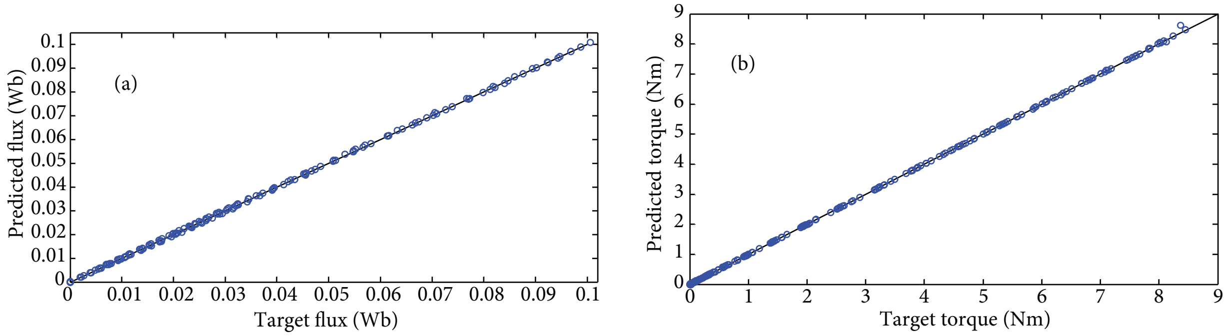



**Figure 6.** Scatter plots of target and predicted values for (a) flux and (b) torque characteristic with SVRM.

To compare the performance and reliability of the SVRM in determination of the magnetic characteristics of the ETFM, an ANN model for the magnetic characteristics of the ETFM is constructed and compared with the SVRM model. In ANN models, the Levenberg–Marquardt backpropagation method is utilized to train the network built with two inputs, two outputs, and two hidden layers. There are ten and eight neurons in the two hidden layers, respectively. The tangent sigmoid transfer function is used in the hidden and output layers as the activation function [28].

In Figure 7, the flux linkage characteristic is given with respect to current values for different rotor positions from the aligned position (0°) to the unaligned position (18°). Here the comparison between the performance of the SVRM and ANN models with experimental test data is shown for flux characteristics. The comparison for torque characteristics versus angle (aligned to unaligned positions) for different current values is given in Figure 8.

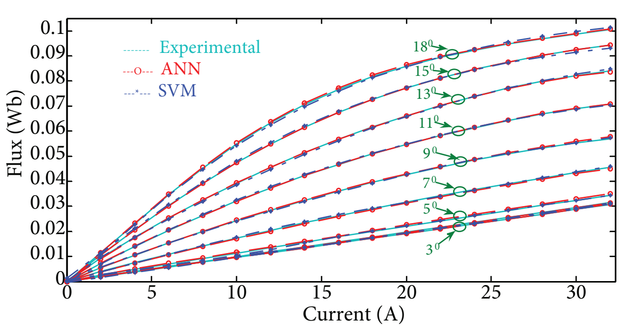



**Figure 7.** The comparison of the ANN and SVRM with experimental results for the flux linkage characteristic of the ETFM.

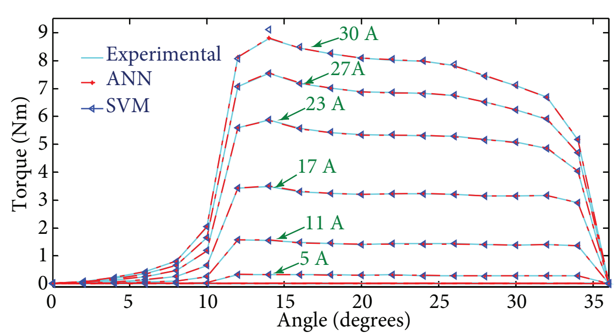



**Figure 8.** The comparison of the ANN and SVRM with experimental results for torque characteristic of the ETFM.

In Figures 7 and 8, the curves for SVRM and ANN show impressive similarity with the measurement results. This proves the performance of the methods in the regression problem. To define the performance of the SVRM and ANN more precisely, an error term is defined. To evaluate the quality of the conformity to target data and to make comparisons between the SVRM and ANN models, the following error analysis is convenient:

$$E_k = \frac{1}{N} \sum_{i=1}^{n} \frac{\left|x_i^k - \hat{x}_i^k\right|}{x_i^k}, \tag{10}$$

where $x_i^k$, $\hat{x}_i^k$ are the target and predicted flux values, respectively, of the $i$th data sample depending on the angle value of the flux characteristics.

$$Accuracy = 1 - \frac{1}{k}\sum\nolimits_{j=1}^{k} E_j \tag{11}$$

Accuracy for the flux and torque curves is found by the accuracy definition given in Eq. (11). In Table 2, the error analysis of the SVRM and ANN for the flux characteristic is given for $N = 17$ sampled data and $K = 9$ angles. Similarly, the error and accuracy analyses for the torque characteristics are given in the Table 3. It is observed that the best results with respect to accuracy and error analysis are achieved by the SVRM function approximation using the structural risk minimization principle. It can be seen that 99.092% accuracy in SVRM modeling of flux characteristics and 99.066% accuracy in SVRM modeling of torque characteristics are achieved.

**Table 2.** Error analysis of the SVRM and ANN for flux characteristics.

| | ANN | SVRM |
|---|---|---|
| Angle (degrees) | Error | |
| 1 | 0.011457562 | 0.005414622 |
| 3 | 0.013033656 | 0.002518011 |
| 5 | 0.008921297 | 0.003757087 |
| 7 | 0.009356167 | 0.002419386 |
| 9 | 0.007726156 | 0.006528174 |
| 11 | 0.012239434 | 0.013477708 |
| 13 | 0.024245817 | 0.020152875 |
| 15 | 0.028661428 | 0.027484747 |
| 17 | 0.02422929 | 0.02138142 |
| Total error | 0.012849057 | 0.009083623 |
| Accuracy (%) | 98.715 | 99.092 |

**Table 3.** Error analysis of the SVRM and ANN for the torque characteristics.

| | ANN | SVRM |
|---|---|---|
| Current (A) | Error | |
| 3 | 0.13429 | 0.08205 |
| 5 | 0.02601 | 0.01439 |
| 7 | 0.01709 | 0.00806 |
| 9 | 0.01093 | 0.00529 |
| 11 | 0.00580 | 0.00462 |
| 13 | 0.00371 | 0.00331 |
| 15 | 0.00487 | 0.00245 |
| 17 | 0.00290 | 0.00242 |
| 19 | 0.00300 | 0.00157 |
| 21 | 0.00257 | 0.00124 |
| 23 | 0.00268 | 0.00117 |
| 25 | 0.00172 | 0.00149 |
| 27 | 0.00197 | 0.00096 |
| 29 | 0.00250 | 0.00386 |
| 31 | 0.00136 | 0.00725 |
| Total error | 0.01476 | 0.00934 |
| Accuracy (%) | 98.524 | 99.066 |

## 5. Conclusion

ETFMs have a unique structure and major advantages in electrical machines. Determination of the very nonlinear magnetization characteristics (flux linkage and torque) of ETFMs is quite important for accurate performance prediction, modeling, and design verification.

The contributions of this work can mainly be considered as the adaptation of the support vector regression to the area of electrical machines. It is a novel technique based on rigorous mathematical fundamentals and the most competitive technique as compared to the popular ANNs. The problem was defined and mathematically formulated, and then the support vector regression was adapted accurately and the performance of the SVRM was investigated.

For the first time, the SVRM was implemented for estimating the nonlinear characteristics of the ETFM. It was also clearly shown that the SVRM is accomplished as a competitive machine against the ANN method. Moreover, fewer training data due to SVRM theory results in reduced CPU time for training by resulting in a faster model development process. The nonlinear regression ability of the SVRM has been demonstrated by forming the SVRM models of the torque and flux characteristics of the ETFM. Therefore, it can be concluded that ANNs can be replaced by SVRMs in modeling and future control applications due to their higher accuracy.

This modeling approach is significant in the reliability and accurate generalization of the finite discrete data obtained from either simulators or measurements. It is expected to be implemented for the optimal performance of ETFMs in various application areas such as vehicle motors, wheelchairs, exercise bikes, or servo motors.

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