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Driving training-based optimization technique for estimating synchronous motor excitation current

Karthikeyan Murugesan[1], Rengaraj Ramasubbu[2]
[1]Department of Electrical and Electronics Engineering, Faculty of Engineering and Technology, SRM Institute of Science and Technology Ramapuram, Chennai, India
[2]Department of Electrical and Electronics Engineering, Sri Sivasubramaniya Nadar College of Engineering, Kalavakkam, India

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ABSTRACT

This paper introduces an innovative application of the driving training-based optimization (DTBO) technique to optimize a multiple linear regression (MLR) model for estimating synchronous motor (SM) excitation current. Inspired by structured learning in driving training, DTBO is utilized to accurately determine regression coefficients with fast convergence. The DTBO-based MLR model is compared with other optimization techniques, such as gravitational search algorithm (GSA), artificial bee colony (ABC), genetic algorithm (GA), symbiotic organisms search (SOS), and various machine learning algorithms. Using a dataset of 557 samples (390 for training, 167 for testing), the DTBO-based model achieves the lowest objective function value, demonstrating superior performance in minimizing estimation errors. Key metrics like maximum error, error percentage, standard deviation, and root mean square error (RMSE) validate the results. The DTBO-based approach not only outperforms other methods but also provides a clear mathematical relationship between excitation current and input features, enabling easier hardware implementation and faster computation. This study establishes the DTBO-based MLR model as a robust and efficient alternative to complex machine learning algorithms for estimating SM excitation current, offering significant contributions to power systems engineering and smart grid applications.

Corresponding Author:

Karthikeyan Murugesan
Department of Electrical and Electronics Engineering, Faculty of Engineering and Technology
SRM Institute of Science and Technology Ramapuram
Bharathi Salai, Chennai–600 089, Tamil Nadu, India
Email: karthikm14@srmist.edu.in

1. INTRODUCTION

Synchronous motors (SMs) are known for their efficiency, dependability, good power factor control and less warmth to power quality issues. SMs operate at synchronous speed with applications mainly to drive pumps, fans and to support in power factor correction [1]. SMs require both AC and DC power unlike other motors requiring any one power [1]. Hence, SMs need special arrangement as the motor starts as an induction motor (IM) and when the rotor reaches synchronous speed, the rotor of SMs is interlocked with the stator using excitation current [1], [2]. When the SM is running at synchronous speed, it is possible to change the power factor of the motor by adjusting the field current [3], [4]. Capacitors can also be employed to recover power factor in the power system but it requires frequent switching. Also, when SM is not driving any load, it can provide improved voltage regulation by continuously absorbing or generating reactive power [5], [6]. Reactive power management plays a dynamic role in refining the stability of today's smart grid. An overexcited SM famously known as synchronous condenser improves the stability of transmission lines in smart grid. Inertia of SM improves short-circuit strength and frequency stability [7], [8].

SMs possess the capability to operate at three different power factors for reactive power management, making the accurate determination of SM parameters under these conditions a challenging task due to the complex and nonlinear relationships involved [9]. To address this, researchers have explored various artificial intelligence-based modeling techniques, including proportional integral derivative (PID) control [10], pulse width modulation (PWM) [11], [12], Kalman filter-based methods [13]-[15], and artificial neural networks (ANNs) [16]-[19]. Various optimization techniques have been suggested to address this estimation challenge, including gravitational search algorithms (GSA) [16], artificial bee colony (ABC) methods [18], particle swarm optimization (PSO) [20], k-nearest neighbor (k-NN) estimators enhanced by genetic algorithms (GA) [21], adaptive ANN [22], and symbiotic organisms search (SOS) [23]. Furthermore, machine learning algorithms such as support vector machines (SVM), decision trees (DT), and extreme gradient boosting regressors (XGBoost) [24] have been utilized to forecast excitation current. However, these machine learning techniques are often criticized for being "black boxes," where the relationship between input and output is not easily expressed in linear terms. Moreover, the real-time implementation of ANN-based systems is computationally intensive, resulting in delays due to complex calculations and difficulties in finding suitable hardware [25].

A significant research gap exists in developing a model that not only accurately predicts the excitation current of SMs but also offers a more transparent and computationally efficient approach. To address this gap, a multiple linear regression (MLR) model has been proposed, which conveniently represents excitation current in terms of four input parameters: load current, power factor, power factor error, and change in excitation current [25]. Estimating the excitation current is of great importance to regulating the output voltage of synchronous machinery [26]-[28]. Previous studies have employed GA, ABC, GSA, and SOS algorithms to estimate the regression coefficients of the MLR model, with the quality of these coefficients directly influencing the model's estimation performance. However, the application of the driving training-based optimization (DTBO) technique, known for its quick convergence characteristics and superior performance compared to 11 other optimization algorithms [29], has not been explored in this context.

In this work, we introduce the DTBO technique to enhance the MLR model for estimating SM excitation current. The DTBO algorithm, which has demonstrated success in solving power system problems such as optimal power flow with stochastic wind and solar power generators [30] and optimal maximum power point tracking of wind turbine doubly fed induction generators [31], offers a computationally efficient alternative to existing methods. By leveraging the DTBO's high exploitation and exploration capabilities, the proposed MLR model achieves better regression coefficients than those reported in the literature, thereby reducing estimation errors and addressing the identified research gap.

2. MULTIPLE LINEAR REGRESSION MODEL FOR ESTIMATING EXCITATION CURRENT

Today's smart grid provides self-balanced real and reactive power to ensure quality and reliability of power to consumers. Grid power factor is reduced due to IM loads resulting in higher reactive power. Power factor correction helps in improving the efficiency of the power system. SM through its wide operating characteristics is utilized to adapt the changing power factor of the power system. SM operating at leading power factor can deliver reactive power to the system as shown in Figure 1. The power factor of the SM depends on the excitation current. An accurate and quick estimation of excitation current helps to ensure desired power factor. Hence there is a need for a regression model to estimate the excitation current. The input features for the regression model are load current, power factor, power factor error and change in excitation current as shown in Table 1. The output parameter is the excitation current which is given as (1):

$$I_f^{estimated} = \hat{f}\left(I_L, pf, e, \Delta I_f\right) = c_1 . I_L + c_2 . pf + c_3 . e + c_4 . \Delta I_f + c_5 \quad (1)$$

where c_1, c_2, c_3, c_4, and c_5 are the regression coefficients of the estimated excitation current.
The power factor error is:

$$e = cos\varphi_{ref} - cos\varphi_{system} \quad (2)$$

The change in excitation current is calculated by subtracting the previous sample of excitation current with the current sample as (3):

$$\Delta I_f = I_{f(i)} - I_{f(i-1)} \quad (3)$$

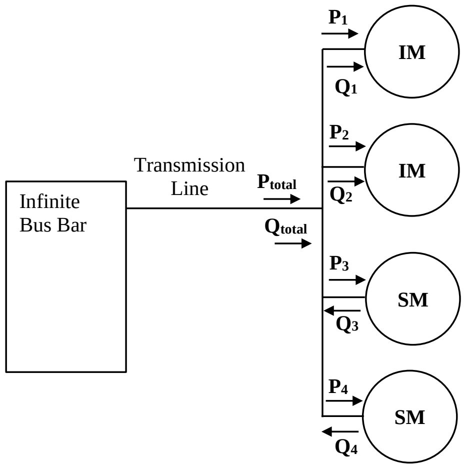

Figure 1. Reactive power injection using SM

Table 1. Input and output parameters considered for MLR model of SM

Input features				Output (target)
Load current	Power factor	Power factor error	Change in excitation current	Excitation current
I_L	pf	e	ΔI_f	I_f

Accurately estimating the regression coefficients is crucial for precisely estimating the excitation current in SM. In this work, we applied the DTBO technique, known for its fast convergence and accuracy, to determine these coefficients. These coefficients reveal the influence of each input feature on the output excitation current, making them essential for understanding and improving the model's performance. Table 1 outlines the input features and the resulting output used in our model. By employing a MLR model with inputs such as load current, power factor, power factor error, and change in excitation current, we aim to create a model that is not only accurate but also straightforward, offering a clear and reliable method for estimating excitation current.

3. DRIVING TRAINING-BASED OPTIMIZATION ALGORITHM IN ESTIMATING EXCITATION CURRENT OF SYNCHRONOUS MOTOR

3.1. Overview of driving training-based optimization algorithm

For the first time, the DTBO technique is applied to determine the regression coefficients of a mathematical model for estimating excitation current. Inspired by the human process of learning to drive, DTBO is designed to mimic the structured training provided in driving schools, with a particular focus on the guidance offered by instructors [29]. The DTBO method is modeled in three distinct phases: i) instruction by the driving teacher, ii) students emulating the instructor's skills, and iii) practice by the learner [29].

As shown in (1), the mathematical model for excitation current requires five regression coefficients to achieve accurate predictions. These coefficients must account for various operating conditions of the SM, making the optimization process crucial. To ensure robustness, the experimental dataset includes diverse operating conditions, as represented in (4). DTBO then optimizes the regression coefficients by considering all the training data, aiming to minimize the objective function (error) in (5) and deliver precise estimates of the excitation current across different scenarios. The excitation current for N samples are related to:

$$\begin{bmatrix} I_{f1} \\ I_{f2} \\ \vdots \\ I_{fN} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} & c_{15} \\ c_{21} & c_{22} & c_{23} & c_{24} & c_{25} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ c_{N1} & c_{N2} & c_{N3} & c_{N4} & c_{N5} \end{bmatrix}_{N\times 5} \cdot \begin{bmatrix} I_{L1} & I_{L2} & \cdots & I_{LN} \\ pf_1 & pf_2 & \cdots & pf_N \\ e_1 & e_2 & \cdots & e_N \\ \Delta I_{f1} & \Delta I_{f2} & \cdots & \Delta I_{fN} \\ 1 & 1 & \cdots & 1 \end{bmatrix}_{5\times N} \tag{4}$$

$$F_n(O_n) = \sum_{i=1}^{N} \left(I_{fi}^{estimated} - I_{fi}^{actual}\right)^2 \tag{5}$$

In (6) shows the population matrix of DTBO. The initial value of this matrix is randomly assigned using (7).

$$C=\begin{bmatrix}C_1\\C_2\\\vdots\\C_N\end{bmatrix}_{N\times5}=\begin{bmatrix}c_{11}&c_{12}&c_{13}&c_{14}&c_{15}\\c_{21}&c_{22}&c_{23}&c_{24}&c_{25}\\\vdots&\vdots&\vdots&\vdots&\vdots\\c_{N1}&c_{N2}&c_{N3}&c_{N4}&c_{N5}\end{bmatrix}_{N\times5} \quad (6)$$

$$c_{ij}=lb_j+r.\left(ub_j-lb_j\right) \quad (7)$$

where $i=1,2,3,\dots,N$ and $j=1,2,3,4,5$ (number of variables/regression coefficient). c_{ij} is the value of the jth variable determined by the ith candidate solution. N is the size of the population of DTBO. r is a random number from the interval $[0\ ,1]$. lb_j and ub_j are the lower and upper bounds of the jth problem variable.

To begin the estimation process, the initialized regression coefficients are substituted into (4) to calculate the excitation current. These estimated values are then compared to the actual excitation currents from the training data using (5). The objective functions, derived from these initial regression coefficients, are presented in (8). This comparison and adjustment process is key to refining the model for more accurate predictions.

$$F=\begin{bmatrix}F_1\\F_2\\\vdots\\F_N\end{bmatrix}_{N\times1}=\begin{bmatrix}F(C_1)\\F(C_2)\\\vdots\\F(C_N)\end{bmatrix}_{N\times1} \quad (8)$$

where F is the vector of the objective functions.

Based on the objective function values, the top-performing regression coefficients from the initial population matrix are selected to serve as the "driving instructors," while the remaining coefficients are designated as "learner drivers." This distinction allows the model to focus on refining and improving the performance of the learner coefficients by emulating the successful patterns of the instructors.

– Phase 1: training by the driving instructor (exploration)

In each iteration, the matrix representing the driving instructors, as shown in (9), is updated with the best regression coefficients from the previous iteration. This continuous refinement ensures that the model evolves by incorporating the most effective strategies, ultimately leading to more accurate predictions.

$$DI=\begin{bmatrix}DI_{11}&DI_{12}&DI_{13}&DI_{14}&DI_{15}\\\vdots&\vdots&\vdots&\vdots&\vdots\\DI_{i1}&DI_{i2}&DI_{i3}&DI_{i4}&DI_{i5}\\\vdots&\vdots&\vdots&\vdots&\vdots\\DI_{N_{D1}}&DI_{N_{D2}}&DI_{N_{D3}}&DI_{N_{D4}}&DI_{N_{D5}}\end{bmatrix}_{N_{DI}\times\mathbf{5}} \quad (9)$$

Where DI is the matrix of driving instructors. The number of driving instructors:

$$N_{DI}=\left[0.1\cdot N\ \cdot\ \left(1-\frac{t}{T}\right)\right] \quad (10)$$

t is the current iteration, T is the maximum number of iterations.

During the first phase, the regression coefficients are initially calculated using (11). These coefficients are then updated only if they lead to an improvement in the objective function by lowering its value. If no improvement is achieved, the regression coefficients remain unchanged, as outlined in (12). This selective updating process ensures that only beneficial adjustments are made, enhancing the model's accuracy.

$$c_{ij}^{P1}=\begin{cases}c_{ij}+r\cdot\left(DI_{k_{ij}}-I\cdot c_{ij}\right),F_{DI_{k_i}}<\ F_i\\ c_{ij}+r\cdot\left(c_{ij}-\ DI_{k_{ij}}\right)\text{ , Otherwise}\end{cases} \quad (11)$$

$$C_i=\begin{cases}C_i^{P1}\ \ F_i^{P1}<\ F_i\\ C_i\ otherwise\end{cases} \quad (12)$$

C_i^{P1} is the new calculated status for the ith candidate solution based on the first phase of DTBO. c_{ij}^{P1} is its jth dimension. F_i^{P1} is the objective function value. I is a number randomly selected from the set $\{1,2\}$. r is a random number in the interval $[0,1]$. DI_{k_i} represents a randomly selected driving instructor to train the ith member (k_i is randomly selected $\{1,2,\ldots,N_{DI}\}$. $DI_{k_{ij}}$ is its jth dimension with its objective function value $F_{DI_{k_i}}$.

– Phase 2: patterning of the instructor skills of the student driver (exploration)

In this phase of DTBO, the learner driver emulates the driving instructor's techniques. Mathematically, this is implemented by calculating new regression coefficient values for the learner using (13). These coefficients are only updated if they lead to an improvement in the objective function, as indicated in (14). This process ensures that the learner driver continually enhances performance by adopting the most effective strategies.

$$c_{ij}^{P2}=P \cdot c_{ij} + (1-P) \cdot DI_{k_{ij}} \tag{13}$$

$$C_i = \begin{cases} C_i^{P2} & F_i^{P2} < F_i \\ C_i & otherwise \end{cases} \tag{14}$$

C_i^{P2} is the new calculated status for the ith candidate solution based on the second phase of DTBO. c_{ij}^{P2} is its jth dimension. F_i^{P2} is the objective function value. P is the patterning index.

$$P = 0.01 + 0.9\left(1-\frac{t}{T}\right) \cdot c_{ij} \tag{15}$$

– Phase 3: training by the driving instructor

In the final phase of DTBO, the learner driver refines their driving skills through personal practice. This is mathematically represented by calculating new regression coefficient values for the learner using (16). These coefficients are updated only if they result in an improvement in the objective function, as detailed in (17). This phase focuses on individual enhancement, allowing the learner to achieve better performance through self-directed improvement.

$$c_{ij}^{P3}=c_{ij} + (1-2r) \cdot R \cdot \left(1-\frac{t}{T}\right) \cdot c_{ij} \tag{16}$$

$$C_i = \begin{cases} C_i^{P3} & F_i^{P3} < F_i \\ C_i & otherwise \end{cases} \tag{17}$$

C_i^{P3} is the new calculated status for the ith candidate solution based on the third phase of DTBO. c_{ij}^{P3} is its jth dimension. F_i^{P3} is the objective function value. r is a random number in the interval $[0,1]$. R=0.05 (constant). t=counter of iterations, T=maximum number of iterations.

After updating the regression coefficients through phases 1 to 3, one iteration of DTBO is considered complete. These three phases are then repeated in subsequent iterations. The update process continues, guided by (9) through (17), until the maximum number of iterations is reached. The DTBO technique excels in determining the optimal regression coefficients by effectively balancing exploration and exploitation within the solution search space. At the end of the maximum iterations, the best regression coefficients are identified, representing the most effective solution for the objective function.

4. RESULTS AND DISCUSSION

This section delves into the performance of the DTBO-based MLR model employed in this study. We benchmark its effectiveness against several other techniques, including GSA [25], ABC [25], GA [25], SOS [23], and various machine learning algorithms [24] reported in the literature. The evaluation utilizes 390 training samples randomly selected from an experimental dataset [21], with the remaining 167 samples reserved for testing. The sample distribution follows a 70% training and 30% testing ratio. For reference, Table 2 displays ten examples from the experimental data, while Figures 2(a) and (b) illustrates the actual excitation current values for both training and test samples.

Table 2. Samples of the training and test data set

Type of sample	Sample index	I_L (A)	pf	e	ΔI_f	I_f (A)
Training	5	3	0.74	0.26	0.317	1.497
Training	79	3.4	0.78	0.22	0.306	1.486
Training	185	4	0.74	0.26	0.406	1.586
Training	274	4.5	0.72	0.28	0.442	1.622
Training	313	4.7	0.79	0.21	0.49	1.67
Training	403	5.2	0.79	0.21	0.536	1.716
Training	540	6	0.65	0.35	0.769	1.949
Testing	22	3.1	0.72	0.28	0.369	1.549
Testing	205	4.1	0.78	0.22	0.436	1.616
Testing	553	6	0.91	0.09	0.142	1.322

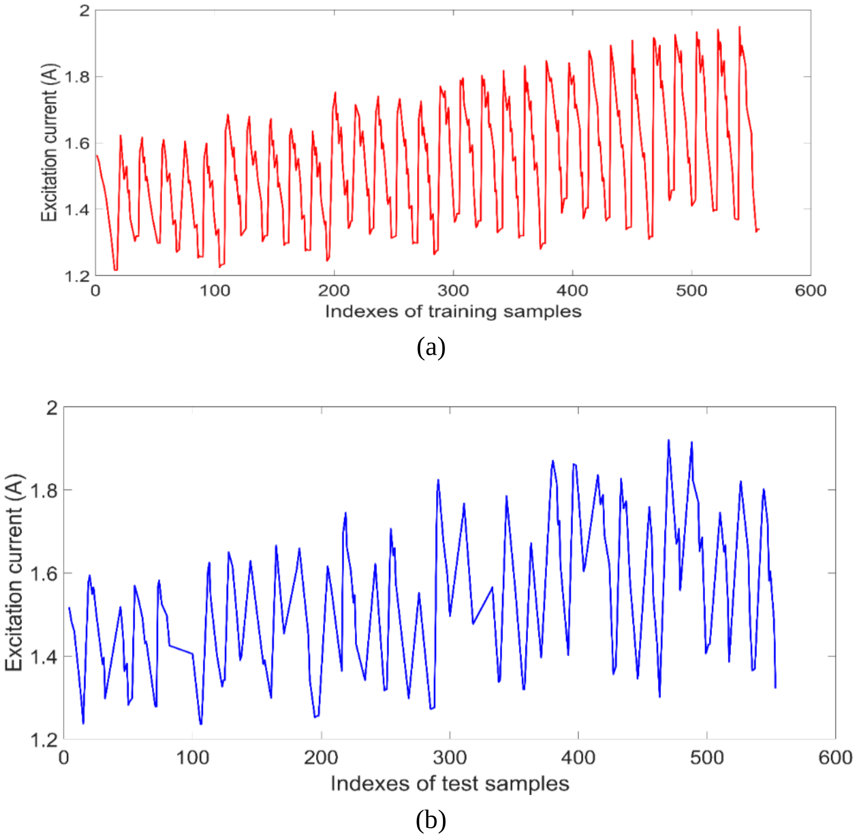

Figure 2. Excitation current; (a) training samples and (b) test samples

Table 3 outlines the parameters needed for various optimization algorithms. Notably, DTBO simplifies the process by requiring no additional tuning beyond specifying the number of agents and the maximum number of iterations. Figure 3 illustrates the convergence behavior of the DTBO algorithm for the objective function defined in (5). The algorithm achieves its optimal solution by the 20th iteration, demonstrating its rapid convergence and efficiency.

Table 3. Parameters required by algorithms compared

Algorithm	Tuning parameters
GA [25]	number of chromosomes=100/200, number of generations=20000, parent selection method, crossover method, mutation coefficient=[0.001;0.01], mutation method.
ABC [25]	number of ants=100/200, maximum iteration number=20000, onlooker bees=50/100, employed bees=50/100, neighborhood coefficient=[0.001;0.01].
GSA [25]	population size=100/200, number of iterations=20000, gravitational constant=0.01.
SOS [23]	number of organisms=30, maximum number of iterations=40.
DTBO	number of agents=30, maximum number of iterations=1000.

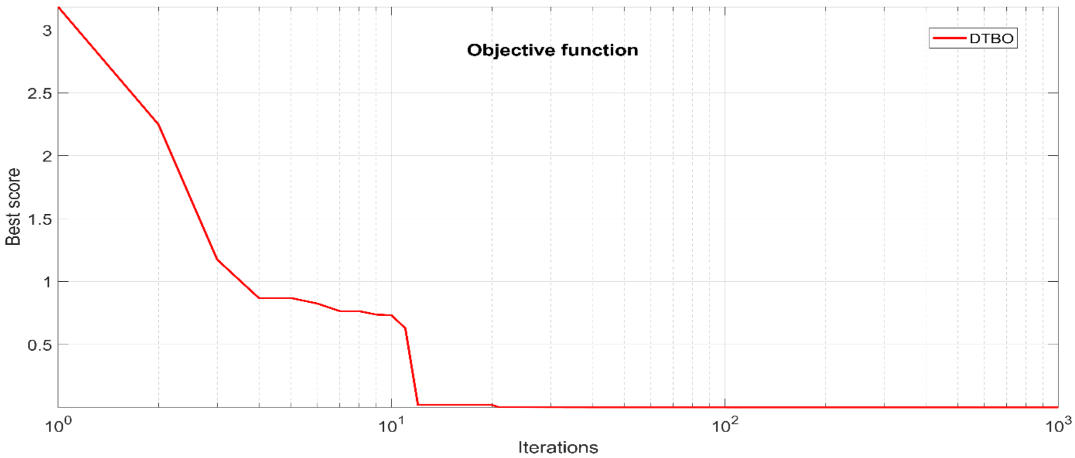

Figure 3. Convergence characteristics of DTBO algorithm for four features

Table 4 presents the regression coefficients and objective function values achieved using the DTBO algorithm for the experimental dataset. For comparison, these results are contrasted with those obtained using GA based simulated annealing GASA [32], SOS [23], GSA [25], ABC [25], and GA [25] algorithms reported in the literature. As highlighted in Table 4, the DTBO-based regression coefficients deliver the most optimal outcome, achieving minimum objective function value of F_1=2.832×10^{-7}. This is significantly lower than the values obtained with SOS (F_1=2.66×10^{-4}), GSA (F_1=76.26×10^{-4}), GA (F_1=55.86×10^{-4}) and GASA (F_1=1.16×10^{-4}). Using the regression coefficients obtained from DTBO, a linear expression that relates the selected features to the excitation current can be formulated as (18):

$$I_f^{estimated} = 0.0000487 * I_L + 0.78398 * pf + 0.78453 * e + 0.99963 * \Delta I_f + 0.39584 \quad (18)$$

Using (18), we calculated the excitation current for the 167 test samples, and the results are illustrated in Figure 4. Table 5 presents a comparison of the maximum error in estimating excitation current, along with the percentage error, standard deviation, and root mean square error (RMSE) for the DTBO-based MLR model and other algorithms reported in the literature. The DTBO-based MLR model demonstrates superior performance compared to other machine learning algorithms.

Table 4. Regression coefficients of optimization algorithms and objective function values

Method	Regression coefficients					Objective function value
	c_1	c_2	c_3	c_4	c_5	F_1
SOS [23]	0.000246	0.595301	0.611129	0.989786	0.584195	2.66×10^{-4}
GSA [25]	0.069097	0.135676	0.815564	0.575546	0.824279	76.26×10^{-4}
ABC [25]	0.010779	0.637809	0.637809	0.946734	0.533464	108.4×10^{-4}
GA [25]	0.117146	0.286163	0.999948	0.304766	0.557133	55.86×10^{-4}
GASA [32]	0.000763	0.619446	0.628955	0.992026	0.558231	1.16×10^{-4}
DTBO (proposed)	0.0000487	0.78398	0.78453	0.99963	0.39584	2.832×10^{-7}

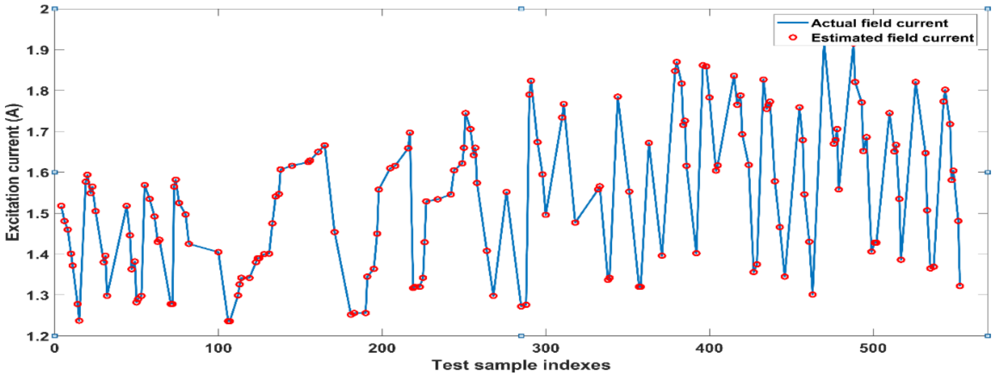

Figure 4. Excitation current estimation of test samples

Table 5. Performance metrics of test data with different algorithms

Algorithm	Maximum error (A)	Error (%)	Standard deviation	RMSE
IKE [21]	-	3.4	1.9	-
KNN [21]	-	6.0	1.7	-
SOS [23]	0.018	0.0398	0.0278	6.956×10^{-7}
GA [25]	0.2906	5.16	3.01	0.111
ABC [25]	0.0474	4.16	2.78	5.3292×10^{-4}
GSA [25]	0.1703	3.48	3.58	0.0056
SVM	0.005	0.0083	0.0112	0.0052
ELA	0.0085	0.1192	0.1024	0.0021
DT	0.0176	0.2224	0.1937	0.0048
DTBO (proposed)	0.00011	2.9×10^{-4}	0.0021	9.48×10^{-10}

To enhance the performance of SVM, ensemble learning algorithms (ELA), and DT, hyperparameter tuning was conducted using Bayesian optimization. Additionally, five-fold cross-validation was applied during the training of these algorithms [33]-[35]. This advanced hyperparameter tuning significantly improved the performance of these machine learning algorithms beyond what was previously reported [24]. However, machine learning algorithms are often considered "black boxes" because the relationship between input features and output variables is not explicitly mathematically defined [35]. This complexity can increase computation time during testing. The DTBO-based MLR model's (18) distinctly illustrates the connection between excitation current and input features, thereby facilitating straightforward hardware implementation through a basic arithmetic logic unit.

5. CONCLUSION

In this paper, we introduced and evaluated a DTBO technique applied to a MLR model for estimating SM excitation current. Our approach leverages DTBO's rapid convergence and optimization capabilities to determine the regression coefficients with high precision. The DTBO-based MLR model demonstrated superior performance in comparison to several established optimization algorithms, including GSA, SOS, ABC, and GA, as well as various machine learning algorithms. The results presented show that the DTBO-based MLR model achieved the lowest objective function value, indicating its effectiveness in minimizing estimation error. The model's simplicity, compared to more complex machine learning algorithms that are often treated as "black boxes," offers a clear mathematical relationship between excitation current and input features. This transparency facilitates easier hardware implementation and faster computation. Additionally, hyperparameter tuning for SVM, ELA, and DT algorithms, performed through Bayesian optimization and five-fold cross-validation, improved their performance but did not surpass the accuracy and efficiency of the DTBO-based MLR model. The comprehensive evaluation of performance metrics maximum error, error percentage, standard deviation, and RMSE further confirms the robustness of our proposed model.

Overall, the DTBO-based MLR model presents a promising and efficient solution for estimating SM excitation current, combining accuracy with ease of implementation and computation. This approach could serve as a valuable tool in power systems engineering, enhancing both theoretical research and practical applications in smart grids. Future work could explore nonlinear models, such as polynomial regression or neural networks, to capture more complex relationships between excitation current and input features. Implementing the DTBO-based MLR model in real-time systems, such as smart grid platforms, would assess its practical performance.

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BIOGRAPHIES OF AUTHORS

Karthikeyan Murugesan received his B.E Electrical and Electronics Engineering degree from Madurai Kamaraj University, M.E. Applied Electronics from Bharathiar University and Ph.D. from Anna University, Chennai. He is an assistant professor in SRM Institute of Science and Technology Ramapuram. His research interests include signal processing, machine learning, and deep learning applications to power system engineering. He can be contacted at email: karthikm14@srmist.edu.in.

Rengaraj Ramasubbu received his B.E. Electrical and Electronics Engineering degree first class with distinction from ManonmaniamSundaranar University, M.E. Power Systems Engineering degree first class with distinction and secured University Third Rank from the Anna University, Chennai and Ph.D. from the Anna University, Chennai. Currently He is an associate professor in the Department of Electrical and Electronics, Sri Sivasubramaniya Nadar College of Engineering. His research interests include artificial intelligence, machine learning, and speciality cables. He has published over 70 research publications in refereed national and international journals and in proceedings of international conferences. He had Co-authored 3 books published by Pearson Education and Tata McGraw Hill. He has also received TATA Rao Gold Medal from Institution of Engineers (India) for the publication of best paper in electrical engineering division. He can be contacted at email: rengarajr@ssn.edu.in.