# Metaheuristic linear modeling technique for estimating the excitation current of a synchronous motor

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**Abstract:** The subject of modeling and estimating of synchronous motor (SM) parameters is a challenge mathematically. Although effective solutions have been developed for nonlinear systems in artificial intelligence (AI)-based models, problems are faced with the application of these models in power circuits in real-time. One of these problems is the delay time resulting from a complex calculation process and thus the difficulties faced in the design of real-time motor driving circuits. Another important problem regards the difficulty in the realization of a complex AI-based model in microprocessor-based real-time systems. In this study, a new hybrid technique is developed to solve the problems in AI-based nonlinear modeling approaches. Through this method, the relationships among the motor parameters can be described in a linear/quadratic SM form. The most effective and modern metaheuristic methods are utilized in the creation of SM forms. The SM forms developed in this study lead to an easy design and application of the SM driver software. Therefore, a model that is faster, more effective, and more easily applicable than AI-based popular methods is developed for SMs. The proposed techniques can also be applied to many other industrial modeling problems that have nonlinear features.

**Key words:** Synchronous motor, metaheuristic modeling, gravitational search optimization, linear and quadratic SM forms, parameter estimation

## 1. Introduction

Synchronous motors (SMs) are AC motors with constant speed [1]. The rotation of the shaft is synchronized with the frequency of the AC supply current. They have high operating efficiency and reliability, controllability of the power factor, and relatively low sensitivity to voltage dips. Thus, they have been commonly used in the power factor correction task [1–3]. The wide variety of applications of SMs as reactive power compensators makes it necessary to achieve a fast and reliable parameter modeling system design [4–7]. The usage of SMs in industrial applications leads to a poor power factor. It is an important problem in terms of cost, efficiency, electrical overload, and capacity. This configuration in the power line also requires the increasing of the capacities of power breakers, transformers, relays, and isolations [2–5,8–11]. There are a number of methods used in the power factor correction task in order to reduce cost and improve efficiency. A detailed review about the usage of various capacitor groups for power factor correction task can be found in [10]. If a SM is used as a reactive power compensator, it works in a transmission line as a leading operation condition. A SM can be used to increase the quality of power factor and the voltage stability of the line by adjusting the amount of excitation current [2,5]. There are no clear relationships among the SM parameters [5,12]. Thus, modeling of SM parameters, such as

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excitation current, power factor, load current when the SM is operating at lagging, and the leading and unity condition for reactive power compensation, is a difficult task. The relationships among the SM parameters are mostly complex and nonlinear [5,12–15]. Researchers have suggested artificial intelligence (AI)-based nonlinear modeling techniques, such as proportional plus integral plus derivative [16], pulse width modulation [17–20], fuzzy logic [2,3], Kalman filter-based methods [7,15,21], artificial neural networks (ANNs) [22,23], particle swarm optimization (in real-time applications) [24], intuitive k-nearest neighbor (k-NN) estimator and genetic algorithm (GA) [5,25], and adaptive ANNs [4] for modeling the parameters and/or predicting the excitation current of SMs and permanent magnet synchronous machines. The modeling of SM parameters using modern AI-based methods for excitation current estimation was realized in recently published studies [4,5,17]. Although effective solutions were developed by means of AI-based models, significant problems arose in the real-time environments of these models. There were important differences between the results of the simulations and experimental works. The response time in the simulation environments was faster than in the real-time environments. This was also determined by the operational characteristics of the microprocessor or digital signal processor and switching frequency of the motor drivers. These factors limit the response time of real-time applications [26,27]. Additionally, AI-based models also affect the response time of real-time applications and simulation environments negatively. The purpose of this study is to facilitate the complex calculation process in the AI-based methods, simplify the representation of the SM parameters, and decrease the workload of the control unit in real-time applications. For this purpose, linear and quadratic form-based new heuristic hybrid methods are developed to solve the problems in AI-based nonlinear modeling techniques. Through this method, the parameters of SMs are converted into linear and quadratic equations and modeled. The most effective and modern metaheuristic methods, such as the GA, artificial bee colony (ABC), and gravitational search algorithm (GSA), are utilized in the development of AI-based exploring units and the creation of the linear/quadratic SM forms. After a linear/quadratic SM form is created in an offline training process, it can be easily applied in a microprocessor or microcontroller-based real-time application environment. The linear/quadratic SM form developed in this study leads to an easy design and realization of the SM driver software. Therefore, a model that is faster, more effective, and more easily applicable than AI-based popular methods is developed in this study. It is expected that the proposed hybrid approach might be effectively and easily applicable for many other industrial modeling problems that cannot be mathematically modeled and have complex modeling parameters.

The proposed metaheuristic AI methods are used to explore the best parameter coefficients of SM forms and create the best linear/quadratic equation in an offline training process. The methods have the advantages of the heuristic searching strategy, linear modeling technique, and hybrid modeling approach. These properties provide several benefits, such as the elimination of local optima, simplicity and high speed in real-time decision making, and easy realization.

In this study, simple linear or quadratic SM forms can be successfully created, the parameter modeling system can be easily realized in a microprocessor unit, and stable estimations can be generated by the decision-making unit. An experimental set for SMs and representation of the SM parameters will be given in the following sections. The proposed hybrid approach will be explained in more detail. The testing of linear and quadratic SM forms and details of experimental studies will be expressed and demonstrated in Section 4.

## 2. General knowledge of SMs

A SM has important advantages, such as ability to operate at leading, lagging, and a unity power factor over a wide range, which can be readily adjusted by changing its excitation current. The operating conditions and properties of the SM are given in Table 1.

**Table 1.** Operating conditions and properties of the SM [2,4,5,28].

| Operating condition | Property |
|---|---|
| • Overexcited SM<br>• At leading current | • It behaves like a condenser<br>• Improves the power factor of the system (reactive power compensator) |
| • Unity power factor<br>• At constant source voltage and frequency<br>• No load ($\cos\phi = 1.0$) | • Efficiency of SM is maximum<br>• Stator current of SM is minimum<br>• Adjust its excitation current |
| • If the excitation current is reduced<br>• ($\cos\phi < 1.0$) in unity power factor condition and the SM is operated with an underexcited field | • It is run in lagging condition<br>• The lagging current may be sufficient to compensate the condensing effect of the transmission line |
| • If the excitation current is increased | • The stator current of SM is reduced and its lagging condition reduces and approaches the unity power factor |
| • If the excitation current is increased more than the unity point ($-\cos\phi < 1.0$) | • Operation condition of SM is changed from unity power factor to leading current |

The scheme of work for the experiment with a SM is shown in Figure 1 [2,4,5]. The excitation current estimation and parameter modeling for a SM in the power factor correction task are realized under operating conditions of $\Upsilon/\Delta$ 400 / 231 V, 5.8 / 10 A, $\cos\phi = 0.8$, 4 kVA, 1000 rpm. These parameters are used to prepare the datasets for the AI-based heuristic exploring unit and create the linear and quadratic SM forms.
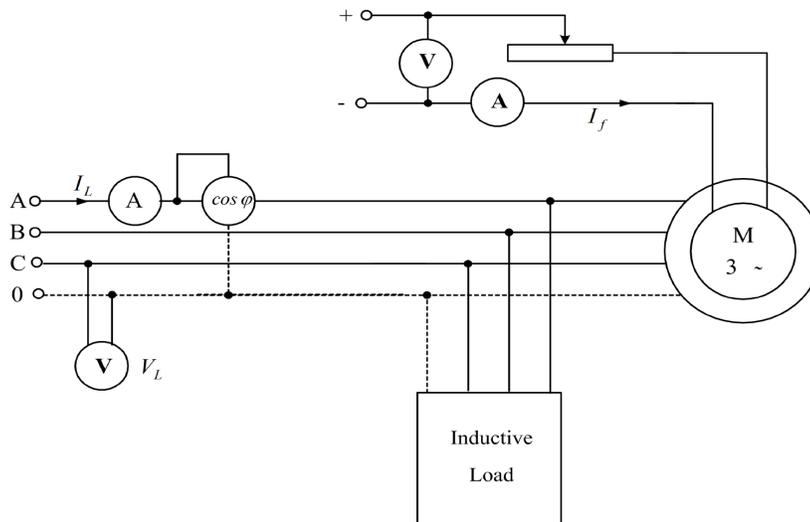


**Figure 1.** The scheme of work for the experiment with a SM [2–5].

The experimental study procedures are given below:

i) An auxiliary motor is used to drive the SM in the test rig. For this purpose, a serial rheostat is used to obtain a variable DC supply in the field circuit manually.

ii) An AC voltage is applied to the stator windings of the SM until the speed of the motor is very close to the synchronous speed.

iii) A DC voltage is applied to the field winding of the SM and so synchronous operation is started.

iv) After synchronous speed is realized, the field current of the SM is adjusted to its minimum value by means of a serial rheostat connected in series to the field circuit.

After step 4, the motor draws minimum current from the supply, the efficiency is maximum, and the power factor of the SM is at unity. To choose this point as a reference operation condition, the field current is adjusted by the serial rheostat. Thus, the load and voltage are kept constant. If the field current is increased, the motor shifts from a unity power factor to leading power factor operation conditions. The experimental tests are repeated several times under different load conditions. The input and output parameters of the SM are measured and recorded from the test rig [2–5]. Finally, these parameters are used to create linear and quadratic SM forms in the heuristic exploring unit.

Five parameters are used to represent and model the SM as in the literature [2–5]: the load current ($I_y$), power factor (pf), power factor error (e), variation in excitation current ($d_{if}$), and excitation current ($I_f$). $< I_f >$ is the output and $< I_y$, pf, e, $d_{if} >$ are the input parameters of the SM in the power factor correction task. A recent study [5] was executed to explore the numerical weights or effects of input parameters $< I_y$, pf, e, $d_{if} >$ on the changing of output $< I_f >$ individually. $F_{SM}$ represents an array of input parameters and $T_{SM}$ represents an array of output parameters for a SM dataset, as given in Table 2 [4–5].

**Table 2.** Representation of the SM parameters in the AI-based model [4].

| $\mathrm{F}_{SM}$ (input parameters) | | | | $\mathrm{T}_{SM}$ (target) |
|---|---|---|---|---|
| Load | Power | Power factor | Changing of excitation | Excitation |
| current | factor | error | current | current |
| $I_y$ | pf | e | $d_{if}$ | $I_f$ |

## 3. Development of the heuristic modeling technique for creating linear and quadratic SM forms

A detailed description of the proposed heuristic modeling technique is given in this section.

The processing steps are shown in Figure 2. Depending on the input and output parameters in Table 2, a SM dataset can be represented in $\mathrm{D}_{SM}$ matrix form, as given in Eq. (1). Here, $<f_{Iy}$, $f_{pf}$, $f_e$, $f_{dif} >$ represents the numerical values of sample cases belonging to the input parameters in the $\mathrm{F}_{SM}$ dataset and $<\mathrm{t}_{If} >$ represents the numerical values of sample cases belonging to the output parameters in the $\mathrm{T}_{SM}$ dataset.

The $\mathrm{D}_{SM}$ dataset is used to explore the best candidate solution and finally test the performance of the created linear and quadratic SM forms in the heuristic modeling unit.

$$D_{SM\,[j,4]} = \begin{bmatrix} f_{I_{y[0,0]}} & f_{pf[0,1]} & f_{e[0,2]} & f_{dif_{[0,3]}} & t_{I_{f[0,4]}} \\ \vdots & & & & \\ f_{I_{y[j,0]}} & f_{pf[j,1]} & f_{e[j,2]} & f_{dif_{[j,3]}} & t_{I_{f[j,4]}} \end{bmatrix} \tag{1}$$

In this study, estimation of the excitation current of the SM based on the input parameters $<I_y$, pf, e, $d_{if} >$ is modeled using linear and quadratic forms. The linear form can be expressed as below.

$$E_{linear} = w_1 * x_1 + w_2 * x_2 + w_3 * x_3 + w_4 * x_4 + w_5 \tag{2}$$
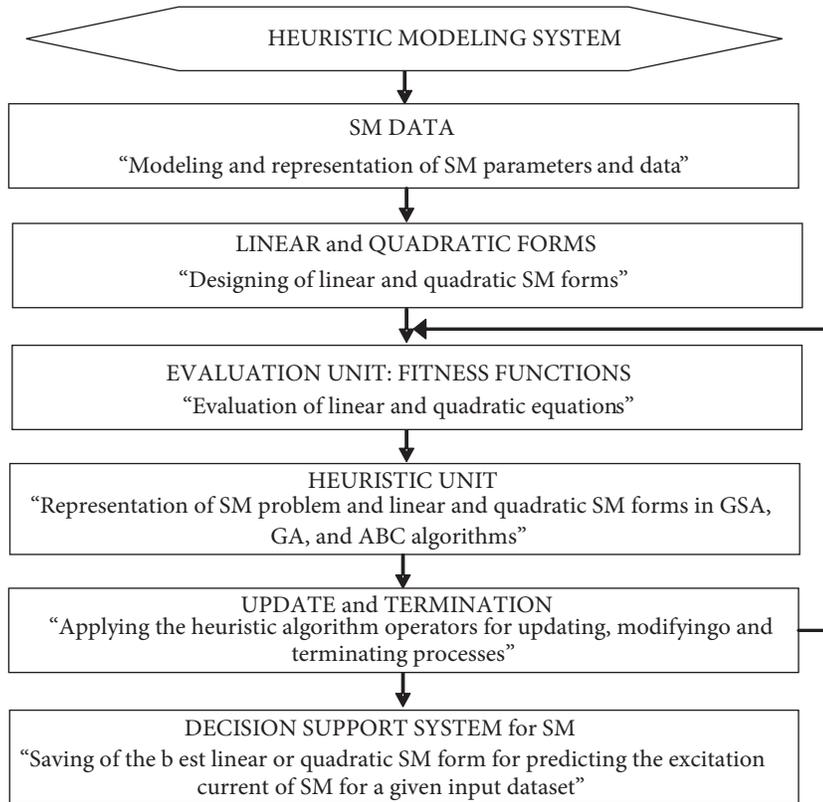
**Figure 2.** Processing steps of the developed heuristic modeling system.

Here, the optimization coefficients are represented by $w_1$, $w_2$, . . .,$w_5$ and the design parameters are represented by $x_1$, $x_2$, . . ., $x_4$. We can rewrite the above expression in Eq. (2) to produce the linear SM form and estimate the excitation current.

$$E_{linear(SM)} = I_f^{Predicted} = w_1*i_y + w_2*pf + w_3*e + w_4*d_{if} + w_5 \tag{3}$$

The fitness function for the linear SM form can be written as below [Eq. (4)]. Eq. (4) can be used to determine the fitness values of the candidate solutions, which are created by the metaheuristic modeling unit.

$$Min\, f\,(v) = \sum_{k=1}^{j} (I_f^{Predicted} - I_f^{observed})^2 \tag{4}$$

The expression of quadratic form is given in Eq. (5).

$$
\begin{aligned}
E_{linear(SM)} \quad &\equiv \quad I_f^{predicted} = w_1*x_1 + w_2*x_2 + w_3*x_3 + w_4*x_4 + w_5*x_1*x_2 + w_6*x_1*x_3 + w_7*x_1*x_4 \\
&+ w_8*x_2*x_3 + w_9*x_2*x_4 + w_{10}*x_3*x_4 + w_{11}*x_1^2 + w_{12}*x_2^2 + w_{13}*x_3^2 + w_{14}*x_4^2 + w_{15}
\end{aligned}
\tag{5}
$$

Note that the optimization coefficients ($w_1$, $w_2$, . . ., $w_{15}$) and design parameters ($x_1$, $x_2$, . . ., $x_4$) in Eq. (5) are similar to those in Eq. (3).

### 3.1. Metaheuristic modeling unit

The task of the metaheuristic modeling unit is to create and modify linear and quadratic SM forms using Eq. (3) and a rewritten version of Eq. (5) to explore the best candidate. The fitness function [Eq. (4)] is used to evaluate the fitness value of the candidates and to determine the best solution. Finally, the unit predicts the value of the excitation current of the SM for arbitrary values of input parameters $<I_y$, pf, e, $d_{if}>$ based on the best SM form.

The GSA is based on the law of Newtonian gravity and mass interactions [29]. The gravitational force might be stated as a communication and interaction form among the masses. The gravitational force $F_{ij}$ between the particles or masses $i$ and $j$, is defined as follows.

$$F_{ij} = \frac{M_{aj} \, x \, M_{pi}}{R^2} \tag{6}$$

Here, $M_{aj}$ represents the active gravitational mass of particle $i$, $M_{pi}$ represents the passive gravitational mass of particle $j$, and $R^2$ is the square distance between the particles. The acceleration of particle $i$ is calculated as follows (Eq. 7).

$$a_i \frac{F_{ij}}{M_{ii}} \tag{7}$$

Here, $M_{ii}$ represents the inertia mass of particle $i$. In the GSA, agents are considered as particles in nature. The performance of the agents is measured by their masses. The agents attract each other by the gravitational force, as given in Eq. (6). Each agent represents a solution for a problem. The agents, which have heavy masses, present good solutions and move more slowly than lighter ones. An agent is defined by 4 parameters ($X_{ij}$, $M_{ii}$, $M_{aj}$, and $M_{pi}$).

The position $X_{ij}$ of the $i$th agent is equal to the solution of the problem and its gravitational masses, such as active, passive, and inertial ($M_{aj}$, $M_{pi}$, $M_{ii}$), are specified using a fitness function [29–31]. The principle of the GSA is shown in Figure 3. The formulation of the GSA is detailed depending on its flow chart in the following lines.

i) *Generate initial population:* First, a population is created with $N$ masses or agents. Each agent has 4 specifications: position, inertial mass, active gravitational mass, and passive gravitational mass. For a system with $N$ agents, the position of the $i$th agent is defined as follows:

$$X_i = \left(x_i^l, \ldots, x_i^d, \ldots, x_i^n\right) for = 1, 2, \ldots, N \tag{8}$$

where $x_i^d$ represents the position of the $i$th agent in the $d$th dimension. Positions of the agents represent the optimization coefficients [in Eq. (3)] for creating a linear/quadratic SM form in the GSA-based metaheuristic unit specifically.

ii) *Evaluate fitness for each agent:* Fitness functions are used to evaluate the gravitational and inertia masses of the agents. A specific fitness function for each problem is formulated by the user [see Eq. (4)]. Depending on the fitness function, the agents that have heavier masses are more efficient than the other agents.

iii) *Update the G best and worst of the population:* The gravitational and inertial masses are updated depending on Eqs. (9)–(11), as follows:
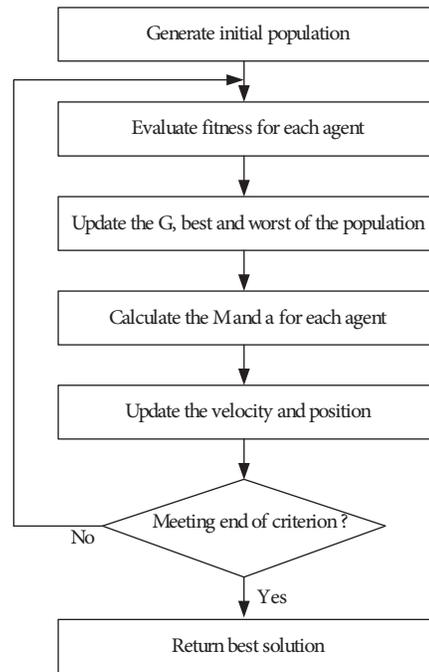
**Figure 3.** Flow chart of the GSA [29].

The gravitational constant G is calculated using Eq. (9). G is initialized at the start randomly and then is decreased depending on time $t$ to control the search accuracy. According to Eq. (9), $G$ is a function of the initial value $(G_0)$ and time $(t)$:

$$G(t) = G(G_0, t).$$ (9)

Eq. (4) could be rewritten as in Eq. (10), as follows:

$$G(t) = G_0 e^{-\alpha \frac{t}{T}},$$ (10)

where $\alpha$ is a specific constant determined by the user, and $t$ and $T$ are the number of current iterations and the number of total iterations, respectively. For a minimization problem, the $best(t)$ and $worst(t)$ are defined in Eqs. (11) and (12), as follows:

$$best(t) = \min_{j \in \{1,...,N\}} fit_j(t),$$ (11)

$$worst(t) = \max_{j \in \{1,...,N\}} fit_j(t).$$ (12)

For a maximization problem, the $best(t)$ and $worst(t)$ are defined in Eqs. (13) and (14), as follows:

$$best(t) = \max_{j \in \{1,...,N\}} fit_j(t),$$ (13)

$$worst(t) = \min_{j \in \{1,...,N\}} fit_j(t).$$ (14)

where $fit_j(t)$ is the fitness value of agent $I$.

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iv) *Calculate M and a for each agent:*

$$M_{ai} = M_{pi} = M_{ii} = M_i, i = 1, 2, \ldots N \tag{15}$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{16}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{17}$$

Here, $fit_i(t)$ is the fitness value, $m_i(t)$ is the inertial mass, and $M_i(t)$ is the gravitational mass of agent $i$ at time $t$. The gravitational force $F_{ij}$ between agents $i$ and $j$ at a specific time $t$ is defined in Eq. (18), as follows.

$$F_{ij}^d(t) = G(t) \frac{M_{pi}(t) x M_{aj}(t)}{R_{ij}(t) + \varepsilon} \left( x_j^d(t) - x_i^d(t) \right) \tag{18}$$

Here, $G(t)$ is the gravitational constant at time $t$, ? is a small constant, and $Rij$ is the distance between the $i$th and $j$th agents. Depending on the experimental results, Rashedi et al. [29] reported that $R_{ij}$ provides better results than $Rij^2$ in all of the experimental cases. The Euclidean metric is used to measure the distances between $i$ and $j$ objects/agents. It is defined as follows:

$$R_{ij}(t) = \|X_i(t), X_j(t)\|_2. \tag{19}$$

The total force for agent $i$ in dimension $d$ can be a randomly weighted sum of the $d$th components of the forces sourced from other agents and is calculated as in Eq. (20).

$$F_i^d(t) = \sum_{j=1, j \neq i}^{N} rand_j F_{ij}^d(t) \tag{20}$$

Here, $rand_j$ is randomly generated and the interval of the $j$-values is in the range of [0,1]. $k_{best}$ is the set of $K$ agents that have the best fitness value and biggest mass. According to the law of motion, the total force $F_i^d(t)$ and the inertial mass $M_{ii}$ are used to calculate the acceleration of agent $i$ at time $t$ in the $d$th dimension directly. The $a_i^d(t)$ value is given in Eq. (21), as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)}. \tag{21}$$

The next velocity of agent $i$ is calculated depending on the acceleration. The acceleration of the agent is added to its current velocity. The next velocity and next position of agent $i$ can be calculated with Eqs. (22) and (23), as follows:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t), \tag{22}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1), \tag{23}$$

where $v_i^d(t+1)$ is the next velocity, $rand_i$ is a random number in the interval [0,1], $v_i^d(t)$ is the current velocity, $a_i^d(t)$ is the acceleration, $x_i^d(t+1)$ is the next position, and $x_i^d(t)$ is the current position of agent

$i$ at time $t$ in dimension $d$. Rashedi et al. [29] proposed reducing the number of agents and using only a set of agents with a bigger mass to apply their force to the other agents. They also used only the best agents $K_{best}$ for attraction to the others. Based on this strategy, Eq. (20) can be rewritten as follows:

$$F_i^d(t) = \sum_{j \in Kbest, j \neq i}^{N} rand_j F_{ij}^d(t). \tag{24}$$

$K_{best}$ is defined as a function of time, with the initial value $K_0$ at the beginning and decreasing with time. Based on this strategy, all of the agents can apply a force to each other in the initialization process. As time passes, $K_{best}$ is linearly decreased, and at the end of the process, there will be just one agent applying force to the others.

## 4. Experimental study: testing of linear and quadratic SM forms

In this study, the steps of the proposed method are implemented according to Figure 2. The linear and quadratic SM forms are created by the heuristic unit in the experimental study. Test studies are conducted to explore the best linear or quadratic equation and investigate the performances of GSA-, ABC-, and GA-based methods according to the conditions given in Table 3. Each of the experiments is repeated 20 times with different random seeds.

**Table 3.** Parameters of the GA-, ABC-, and GSA-based exploring methods.

| GSA parameters | | | | |
|---|---|---|---|---|
| Population size (linear/quadratic) | Iteration number | α constant | | Gravitational constant |
| 100/200 | 20,000 | 0.01 | | 10 |
| ABC parameters | | | | |
| Population size | Iteration number | Onlooker bees | Employed bees | Neighborhood coefficient |
| 100/200 | 20,000 | 50/100 | 50/100 | [0.001; 0.01] |
| GA parameters | | | | |
| Population size | Iteration number | Parent selection method | Crossover method | Mutation coefficient | Mutation method |
| 100/200 | 20,000 | *Roulette wheel | *Flip bit, *Boundary *Nonuniform,*Uniform | Interval [0.001; 0.01] | *Single point *2 points *Inversion |

A SM dataset is obtained from a real experimental set. For the experimental study, 594 data samples are used for the training and testing processes of the linear/quadratic SM forms [4,5,22,23] and 394 test samples (training data) from the dataset are chosen randomly. The rest of the dataset (200 sample cases) is used in the test process. The SM forms are created by metaheuristic exploring methods in the forms of Eqs. (3) and (5). The fitness function [Eq. (4)] is used to evaluate the performance of the created forms. The task is to create the best linear or quadratic form to estimate the excitation current of SM. The estimated excitation current is compared with the real value in the test dataset of SM.

*Test case 1*: *Creating and testing the linear SM forms and identification of the optimization coefficients:* First, linear SM forms are created in the form of Eq. (3). The forms have 5 optimization parameters. The best parameter values are explored by a metaheuristic searching unit. The accuracy of the SM forms is validated by experimental tests. The best optimization values of the other experimental parameters are given in Table 4.

**Table 4.** Application of the proposed methods on the SM dataset and experimental test results for linear SM forms.

| Method | Optimization coefficients | | | | | Fitness Value (Training) | Error % (Test) | Standard Deviation (Test) |
|--------|-------|-------|-------|-------|-------|-----|-----|-----|
| | $w_1$ | $w_2$ | $w_3$ | $w_4$ | $w_5$ | | | |
| GSA | 0.069097 | 0.135676 | 0.815564 | 0.575546 | 0.824279 | 0.007626 | 3.48 | 3.58 |
| ABC | 0.010779 | 0.637809 | 0.637809 | 0.946734 | 0.533464 | 0.010840 | 4.16 | 2.78 |
| GA | 0.117146 | 0.286163 | 0.999948 | 0.304766 | 0.557133 | 0.005586 | 5.16 | 3.01 |

The best linear SM form [Eq. (25)] can be achieved for each heuristic method by substituting the optimization ratios given in Table 4 in Eq. (3).

$$E_{linear(SM)} = I_f^{Predicted} = 0.069097 * i_y + 0.135676 * pf + 0.815564 * e + 0.575546 * d_{if} + 0.824279 \qquad (25)$$

The accuracy of the developed method is tested using the linear SM form swiftly and simply. This feature proves the measurability, testability, and verifiability of the developed method in comparison with the available AI-based black-box methods. The excitation currents can be estimated for each sample in the set of test data using the design ratios in the set of test data (parameter rates related to each test sample) and linear SM forms achieved using each metaheuristic method.
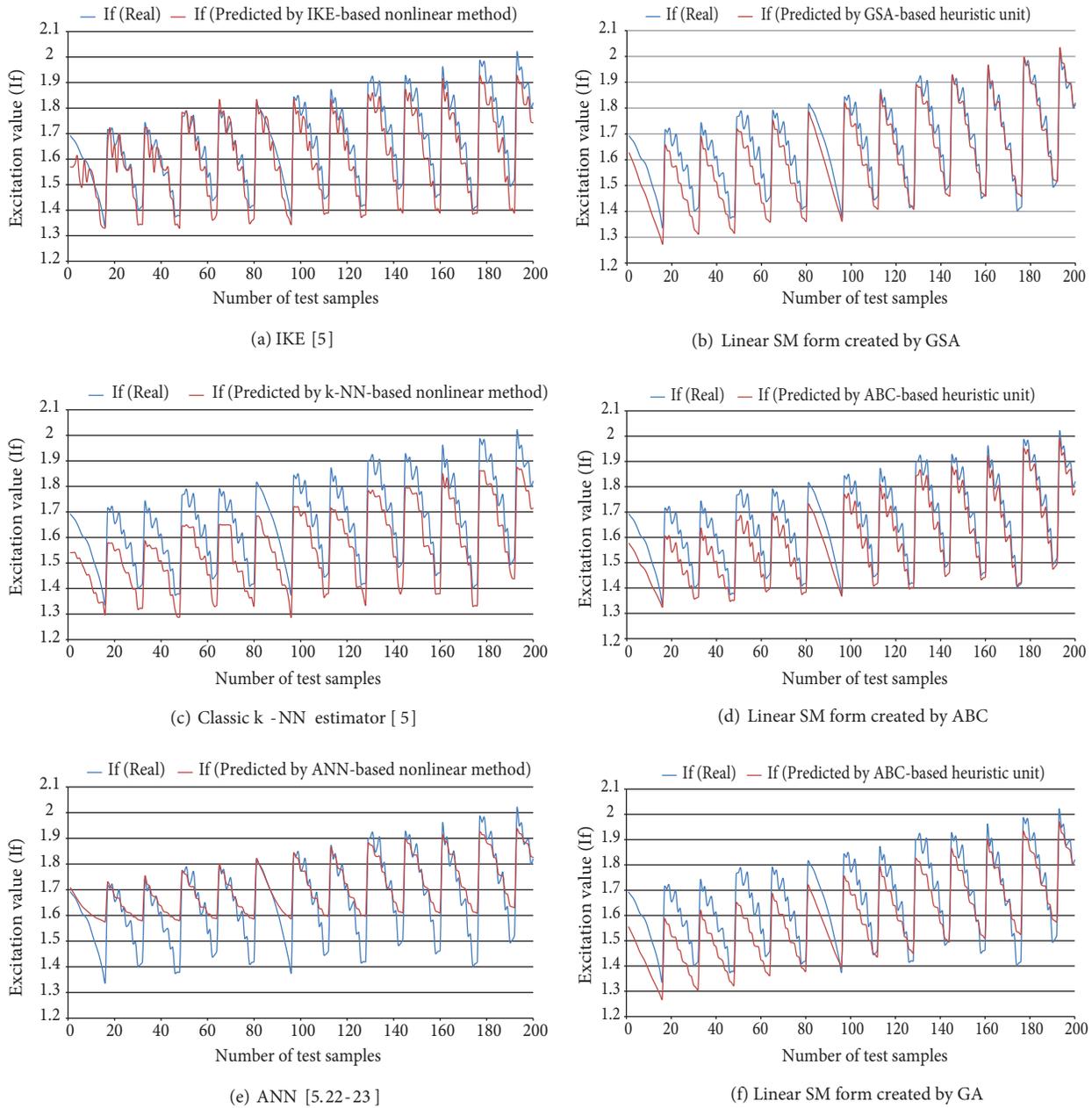
Estimation charts created by the AI-based nonlinear methods such as the IKE [5], k-NN estimator [5], ANN [4,22,23], and proposed methods are given in Figure 4. The excitation currents can be estimated with high accuracy and sensitively using the developed linear SM forms, as seen in Figure 4. When compared with the estimation results produced by the linear and nonlinear techniques, it is seen that despite the simplicity, the proposed technique is at least as successful as AI-based nonlinear methods.

The percentages of error rates that occurred in the excitation current estimation for each heuristic technique are given in Figure 5. Figure 5a shows the error rates that occurred in the nonlinear techniques based on the IKE [5], k-NN estimator [5], and ANN [5,22,23], whereas the error rates that occurred in the proposed techniques are given in Figure 5b.

*Test case 2*: *Creating and testing quadratic SM forms and identification of the optimization coefficients:* Quadratic SM forms are created in the form of Eq. (6) by the metaheuristic exploring unit. The forms have 15 optimization parameters. The accuracy of these forms is validated by the experimental tests. The best optimization values, which are explored by the GSA-, ABC-, and GA-based metaheuristic techniques, and the other experimental parameters are given in Table 5.

To achieve the best quadratic SM form, one can replace in Eq. (5) the optimization ratios related to the GSA given in Table 5. Similarly, other SM forms can be also achieved by replacing in Eq. (5) the optimization ratios that are discovered with the ABC- and GA-based heuristic methods. The excitation currents for each sample in the set of test data can be estimated using the design ratios in the set of test data (parameter rates related to each test sample) and quadratic SM forms.

It is seen that a more sensitive modeling system for SM forms is developed compared to recent works in literature, based on the error percentages and standard deviation rates that occurred in the excitation current estimation given in Table 5 [4,5,22,23]. It has the most advantages. For example, the proposed model is realized easier than the AI-based nonlinear models. It does not have complex functions. The quadratic SM forms represented in simple formula form can be easily implemented to microprocessor-based systems. Hence, it has the ability to produce faster responses. In addition to these advantages, the error rates and standard deviation values in the estimation of the excitation current in the proposed model are quite low.

**Figure 4.** Comparison of the estimation results of AI-based nonlinear methods and proposed linear SM forms: a) intuitive k-NN estimator (IKE) [5], b) linear SM form created by the GSA, c) classic k-NN estimator [5], d) linear SM form created by the ABC, e) ANN [5,22,23], f) linear SM form created by the GA.

In Figures 6a–6c, the excitation current estimations for GSA-, ABC-, and GA-based quadratic SM forms are given, and the percentages of the error rates are given in Figure 6d.

*Test case 3*: *Comparing the response time of the proposed linear/quadratic SM forms and the AI-based nonlinear methods:* In this case, the response time of the algorithms is compared. The algorithms are realized in the MS Visual Studio .NET software development environment [32].
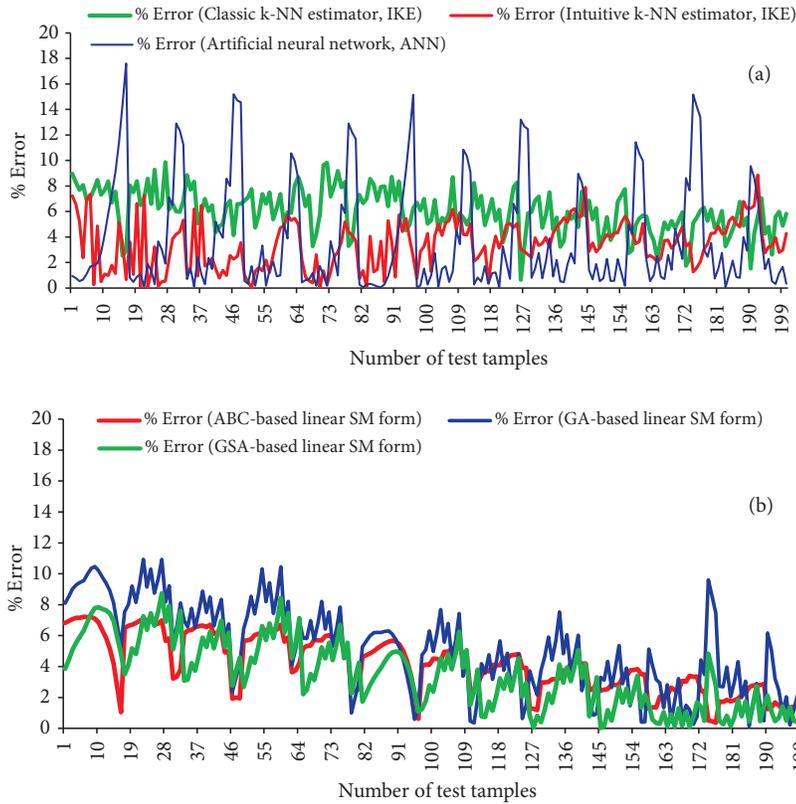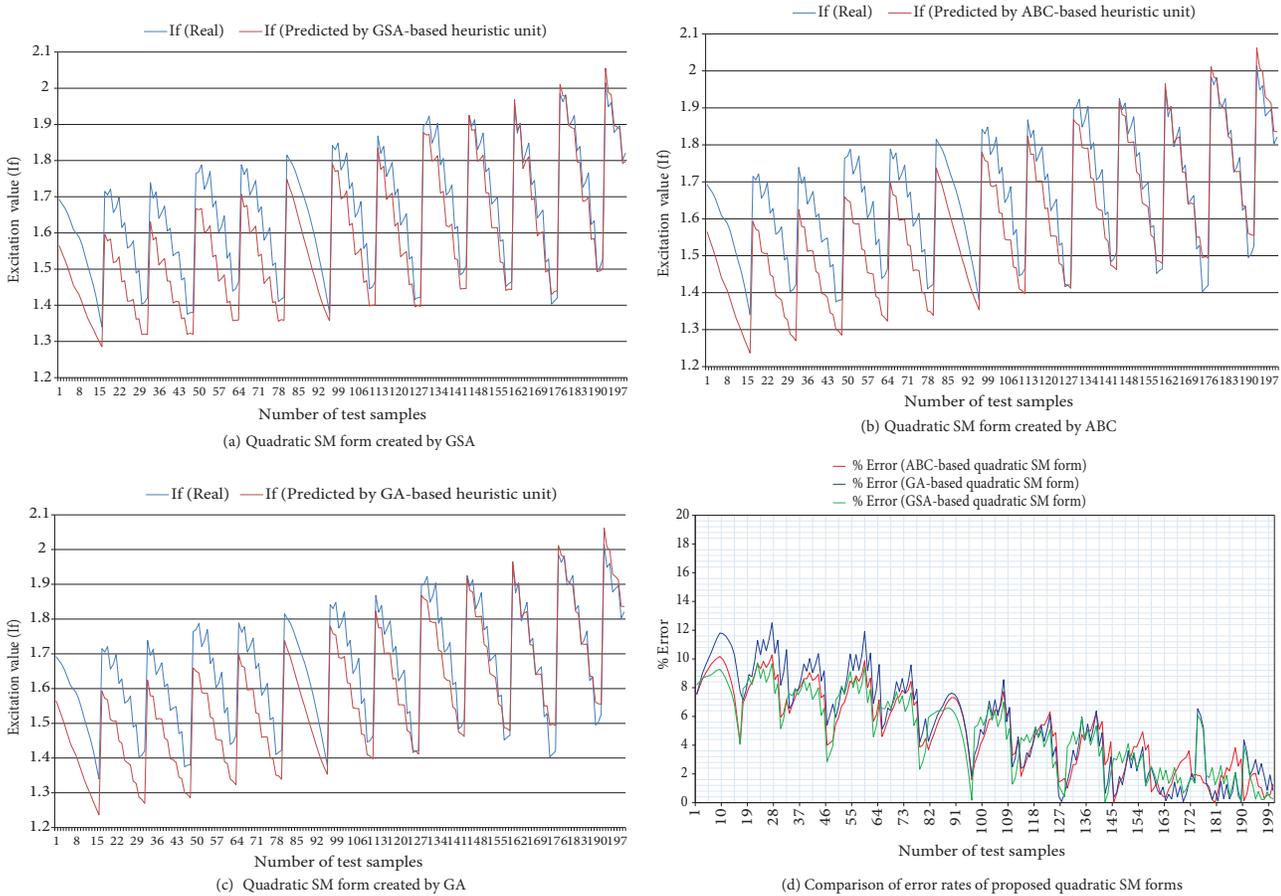
**Figure 5.** Comparison of the error rates of the AI-based nonlinear methods (a) and proposed linear method (b).

**Table 5.** Application of proposed methods to the SM dataset and experimental test results for the quadratic SM forms.

| Method | Optimization coefficients W $(w_1, w_2, w_3, \ldots, w_{15})$ | Fitness value (training) | Error % (test) | Standard deviation (test) |
|--------|---------------------------------------------------------------|--------------------------|----------------|---------------------------|
| GSA | (0.003976, 0.563066, 0.878701, 0.116363, 0.016562, 0.019134, 0.016564, 0.890887, 0.264445, 0.185232, 0.007866, 0.220562, 0.185250, 0.044121, 0.277656) | 0.006101 | 4.91 | 3.03 |
| ABC | (0.001967, 0.673275, 0.689621, 0.190243, 0.033631, 0.174685, 0.001971, 0.691692, 0.311157, 0.309606, 0.001967, 0.372069, 0.674622, 0.052454, 0.030473) | 0.006670 | 5.05 | 3.06 |
| GA | (0.007219, 0.589528, 0.981977, 0.046613, 0.046613, 0.046613, 0.046613, 0.981977, 0.046613, 0.046613, 0.007219, 0.231306, 0.832696, 0.046613, 0.114425) | 0.005083 | 5.50 | 3.50 |

The mean response time of the proposed and classic methods for the test dataset is measured as shown in Figure 7. In the linear SM model, the mean response time is 247 times faster than with the IKE and 11 times faster than with the ANN method. The calculation of the distances among the observations and an increment in the k-value (nearest neighbor count) and the number of sample observations negatively affect the workload of the processor and response time of the IKE. Thus, the algorithm response time is delayed in the

**Figure 6.** The estimation and error results of the proposed quadratic SM forms: a) quadratic SM form created by the GSA, b) quadratic SM form created by the ABC, c) quadratic SM form created by the GA, d) comparison of the error rates of the proposed quadratic SM forms.

IKE. Detailed information about the application of the IKE method to the SM problem can be found in [5]. The number of nodes and the hidden layers, types of activation functions in the nodes, and input/output numbers of the ANN-based model negatively affects its response time [4]. Detailed information about applying the ANN method to the SM problem can be found in [4,5,22,23]. Maiti et al. [33] reported that AI-based methods require large memory support and include computational complexity. Consequently, the decision-making process and input/output operations in AI-based nonlinear methods are more complex than in the proposed method.
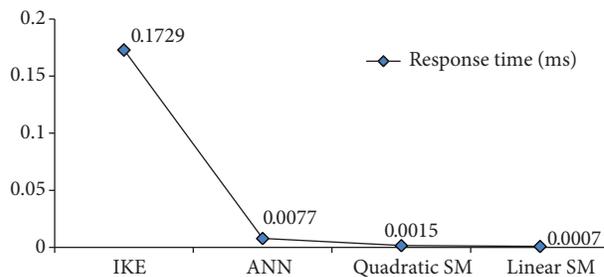


**Figure 7.** Mean response time of the proposed and classic methods for the test dataset.

(a) IKE-based method [5]



(b) ANN-based method [5. 22 -23]



(c) Quadratic SM form
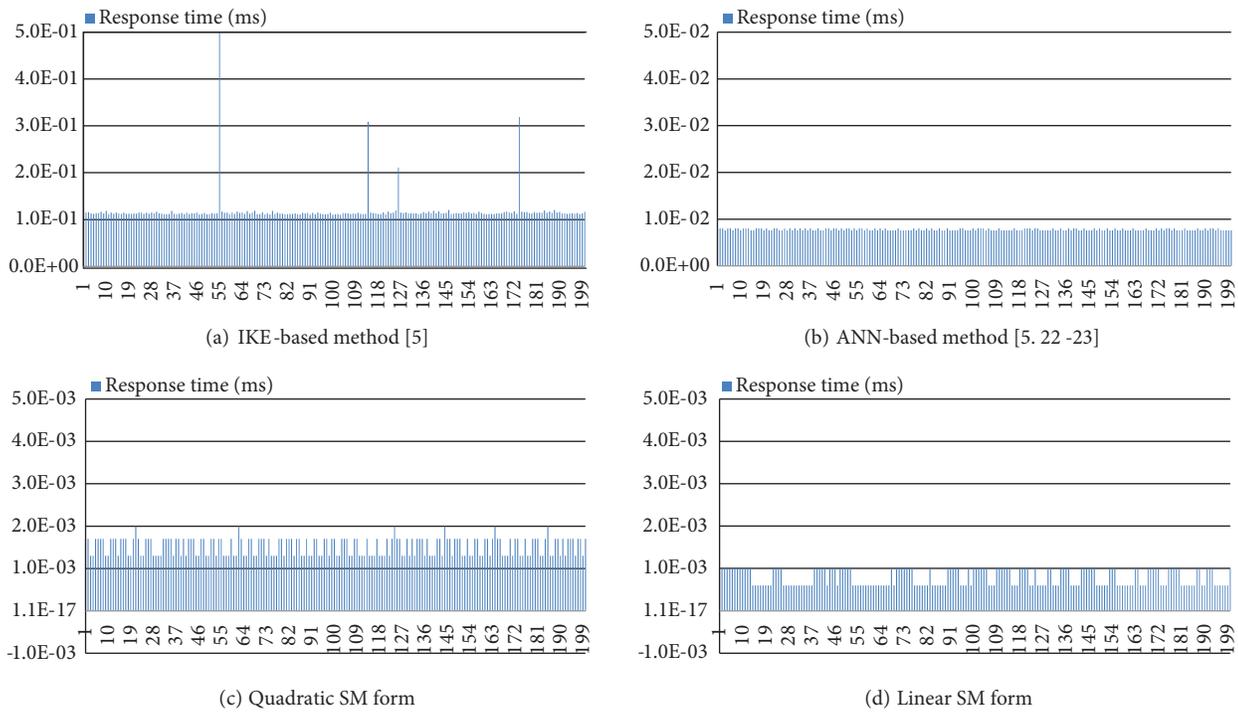


(d) Linear SM form

**Figure 8.** A comparison of the AI-based nonlinear methods (a and b) and proposed quadratic/linear methods (c and d) for the response times: a) IKE-based method [5], b) ANN-based method [5,22,23], c) quadratic SM form, d) linear SM form.

The response times of the proposed and classic methods for each observation in the test dataset are measured as shown in Figure 8. The proposed methods improve the response time through the simple linear/quadratic SM forms significantly.

## 5. Conclusions

A hybrid estimation method for the excitation current of a SM using a metaheuristic exploring technique and linear/quadratic SM forms is proposed for the design of a parameter modeling system. Based on a hybrid estimation method of the excitation current, 3 metaheuristic methods, including the proposed technique, are implemented for the performance comparison. Next, as an effective way of estimating the excitation current of a SM in a simple manner, the motor parameters are modeled using the best linear or quadratic SM forms. Since only a simple equation of the linear and/or quadratic SM form is used for the motor parameter modeling, the driver software designs are considerably simpler and the computational load of the microprocessor for estimation of the excitation current is smaller than in the existing AI-based popular and actual techniques. Through the various comparative experimental studies, it is verified that the proposed modeling technique yields a robust, stable, and fast estimation performance and creates simple linear and quadratic SM forms. As a result of this, improved complexity versus nonlinear modeling techniques can be obtained without requiring an AI-based black-box modeling approach, such as in ANNs. With the proposed approach, the relationships among the SM parameters can be represented with a simple linear/quadratic form. As a result of this study, the complexity problem of the popular AI-based nonlinear modeling techniques is solved, the convergence problem in the ANN-based methods is overcome, and the estimation results from the well-known popular solutions are better achieved. The proposed technique can be considered as a powerful alternative to AI-based black-box modeling.

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