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ESTIMATION OF SYNCHRONOUS MOTOR EXCITATION CURRENT USING MULTIPLE LINEAR REGRESSION MODEL OPTIMIZED BY SYMBIOTIC ORGANISMS SEARCH ALGORITHM

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Abstract

In this paper, an effective and simple means of estimating the excitation current of a synchronous motor (SM) is presented for power factor correction task. First, a multiple linear regression model with four predictor variables such as motor load current, actual power factor, power factor error and excitation current change is formed to estimate the SM excitation current. Then, recently introduced symbiotic organisms search (SOS) algorithm is benefitted in the hope of searching better values of regression coefficients in that model using the data collected from the prepared experimental setup. The supremacy of SOS over some recently published algorithms such as genetic algorithm, artificial bee colony and gravitational search algorithm is widely attested through comparative computer simulations for the similar compensation system. The results exhibited in this article show that the presented technique outperforms the other reported popular algorithms from the aspects of simplicity, robustness and accuracy. In view of this, the suggested tuning of regression coefficients of the multiple linear regression model yields a better estimating performance of SM excitation current than the earlier studies.

Keywords: Synchronous motor, power factor correction, multiple linear regression model, symbiotic organisms search algorithm, optimization

SİMBİYOTİK ORGANİZMALAR ARAMA ALGORİTMASI İLE OPTİMİZE EDİLMİŞ ÇOKLU DOĞRUSAL REGRESYON MODELİ KULLANILARAK SENKRON MOTOR UYARTIM AKIMININ TAHMİNİ

Öz

Bu belgede güç faktörü düzeltme işlemi için senkron motor (SM) uyartım akımının tahminine yönelik etkili ve basit bir yol sunulmuştur. Bu işlem için ilk olarak motor yük akımı, gerçek güç faktörü, güç faktörü hatası ve uyartım akımının değişimi karar değişkenleri olarak ele alınarak çoklu doğrusal regresyon modeli oluşturulmuştur. Ardından hazırlanan deneysel düzenekten toplanan veriler kullanılarak bu modeldeki regresyon katsayılarının iyileştirilmesi amacıyla yeni ortaya konulan simbiyotik organizmalar arama algoritmasından faydalanılmıştır. Bu algoritmanın benzer kompanzasyon işlemi için genetik algoritma, yapay arı kolonisi ve yerçekimi algoritması gibi yakın zamanda yayınlanan algoritmalara olan üstünlüğü karşılaştırmalı bilgisayar simülasyonları ile gösterilmiştir. Bu makalede sergilenen sonuçlar, sunulan tekniğin bahsi geçen literatürdeki algoritmalara göre basitlik, gürbüzlük ve doğruluk açılarından daha iyi performans verdiğini göstermiştir. Bu bağlamda çoklu doğrusal regresyon model katsayıların önerilen şekilde ayarı önceki çalışmalardan daha iyi SM uyartım akımı tahmin performansı sağlamıştır.

Anahtar Kelimeler: Senkron motor, güç faktörü düzeltme, çoklu doğrusal regresyon modeli, simbiyotik organizmalar arama algoritması, optimizasyon

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1. Introduction

Synchronous motors (SMs) are the class of doubly-excited, constant speed alternating current (AC) motors used in electrical power utilities to convert electrical energy to mechanical energy [1]. As its name intimates, they spins at a synchronous speed equal to that of rotating stator magnetic field regardless of the perturbation in load torque until the break torque is achieved. Such motors have the benefits and advantages of high efficiency, reliable operation and favorably high insensitivity to voltage dips [2]. Moreover, it shows SMs exhibits two important advantages: one is the controllable field current which makes the driver more flexible, and the latter is that there are no expensive rare earth magnets on the rotor surface [3]. Since the excitation current can be controlled independently of the stator current, synchronous motors can either supply or absorb reactive power, which makes them beneficial for power factor correction of industrial loads [4-6]. The drawback of such motors is the dependence on brushes to inject the field current, which requires periodic maintenance, and is specifically a challenge in inflammable environments and electric vehicle applications where the brushes must be sealed from the coolant oil. There are works in the state-of-the-art literature overcoming the aforementioned phenomenon (see [7], for instance).

Reactive power compensation (RPC) is a significant task for electric power network, as lack of reactive power in power grids leads them to instability, which causes voltage drop and oscillation [8]. The topic has also received considerable attention in the literature since it is related to electric energy savings, which is an important issue present in our today's world. The role of RPC is to provide system with the required amount of reactive power by several techniques, some of which are optimally fixed capacitors (FCs), thyristor controlled reactor-fixed capacitors (TCR-FCs), thyristor switched capacitors (TSCs), thyristor controlled reactors with thyristor switched capacitors (TCRs+TSCs), and SMs [9]. Of these, the approaches based on static capacitor banks suffer from a number of deficiencies such as slow response, under or over compensation and harmonic content in current and voltage resulting from switching on/off capacitor groups in certain steps. On the other hand, smooth and faster reactive power compensation can be realized with TCRs and TSCs without leading to step changes and mechanical problems, whereas they exhibit voltage and current with harmonic content as well as instability in the system [9]. The aforementioned problems can be solved by using a SM as a dynamic power factor compensator, which has countless merits over its counterparts. When equipped with advanced controls, these machines can prove very efficient in allowing the system to settle to a desired power factor with ease.

The underlying idea of how a SM can be used as a reactive power compensator is that the phase of armature current varies by altering the excitation voltage fed to the motor field winding and so does the power factor accordingly. When under-excited, the motor does operate with lagging power factor requiring reactive power from the grid and when over-excited with leading power factor supplying reactive power to the grid, which is associated with the role of SMs as reactive power compensators. In this sense, supplying some of the reactive power necessary for inductive elements from SMs installed near the load rather than the remote power station itself will improve the plant power factor and reduce the amount of reactive current circulating in transmission lines. As a result, active power capacity of the power network will be increased [10]. Between the two operating regions, there is an excitation current value that allows operation with unity power factor ($\cos\varphi = 1.0$) and minimum armature current.

By feeding motor load current (I_L) and power factor error (e) to a designed fuzzy logic controller (FLC), the change of excitation current (ΔI_f) is obtained from the output of FLC in [10]. Experimental results show that the FLC estimates the excitation current properly based on the value of load current and power factor error without knowing the mathematical model amongst the concerned variables. An application of artificial neural network (ANN) is made in [11] to estimate the SM excitation current based on the input motor variables such as $I_L, e, \Delta I_f$ and the actual power factor of the system ($\mathrm{pf} = \cos\varphi_{system}$) while the only output of the ANN controller is the excitation current (I_f). In the study given by [12], a genetic algorithm-based k-nearest neighbor estimator (also termed as intuitive k-NN estimator, IKE) is deployed to search for optimum weighting parameters of $< I_L, \mathrm{pf}, e, \Delta I_f >$ to efficiently estimate the target parameter I_f, which therefore aims at discovering the correlation among those data. The comparative results ANN-based technique, classic k-NN-based estimator and the proposed IKE method affirm the superior performance of IKE method over the others. To model the SM excitation current in an easier way, a simple ANN with one hidden layer and 6 hidden nodes is suggested in [13] where the activation functions of the hidden neurons are determined by using GA. After training the resulting ANN with 394 samples and testing with 200 test data, the estimation accuracies are found to be approximately similar to those reported in [9, 11, 12] despite having less number of hidden layers and neurons. It is stressed in [14] that artificial intelligence (AI)-based models produce good estimation results, but they cause problems in a real-time implementation such as increased computation burden, delay time resulting from a complex calculation process and the difficulty faced in realization of such complex models in real-time. To amend these problems, multiple linear and nonlinear regression models are developed in [14] in order to create the most representative mathematical equation for estimating the SM excitation current I_f with regard to the considered input parameters $< I_L, \mathrm{pf}, e, \Delta I_f >$, where the relationship among the SM parameters are regarded as mostly complex and nonlinear task [15-17]. To optimize the regression coefficients in the proposed models, genetic algorithm (GA), artificial bee colony (ABC) and gravitational search algorithm (GSA) are applied individually. It is shown that the proposed two models are simpler and more effective than other published studies [9, 11, 12], where GSA-tuned quadratic regression model is the pioneer for the estimation of excitation current which is followed by the models based on ABC and GA, respectively. In the study, mean response time comparisons with classical methods are also presented which verify that presented models have improved the response time compared to those using IKE and ANN. To the knowledge of this article's author, there may be a room for making better the estimation performance of the multiple regression model presented in [14]. In this sense, the values of the regression coefficients may even become more appropriate than the ones offered by GSA [14], ABC [14], and GA [14]. SOS algorithm that we use in this article, as the modern and powerful optimization algorithm, can solve this drawback by the ability to search for better regression coefficients, which may yield a decrease in estimation error value, and in turn contribute to the estimation performance.

In the present study, a multiple linear regression model similar to that reported in [14] is assumed with four predictor variables $< I_L, \mathrm{pf}, e, \Delta I_f >$ to represent the SM excitation current I_f. Since the estimation performance of this model is greatly affected by the regression coefficients, we formulated the estimation problem as constrained optimization problem and SOS algorithm is employed for the first time to find out regression coefficients better than the reported ones. Several numerical results are presented which validate the performance of the suggested strategy. Finally, we conclude that comparing to the existing algorithms, such as GSA [14], ABC [14], and GA [14], the proposed SOS method in this paper is simpler, more robust and effective. Its superiority over the indicated evolutionary algorithms is demonstrated by the comparative analysis for the same model scheme with identical predictor variables.

2. SOS-tuned Regression Model for Power Factor Correction

Loads on electrical grids can be resistive, inductive and capacitive or a combination of them. While resistive loads draw active power from the grid, reactive power which maintains the magnetization in electrical devices is required by the inductive components. Since this reactive power alternately flows from source to the load and back from load to source without being transformed into any type of energy, it unnecessarily increases electricity generating costs, reduces the active power carrying capacity of the transmission line, and increases voltage drop when supplied from the power station itself through transmission line [18]. In order to increase the line capacity, reactive power requirement of the inductive elements must be met from a source connected near the load. This source of reactive power is extracted mostly from a synchronous motor dynamically and a group of capacitors statically [19]. By meeting reactive energy demand of inductive circuits in this way instead of from far away from the point the load is connected to power grid, reactive power flow in transmission line is reduced and accordingly active power capacity of the line is increased, which accordingly leads to enhance the power factor and efficiency of the electric power network. However, we herein stress that an adequate amount of reactive power is needed for controlling the voltage in a transmission network to transfer active power which requires the network voltage to be high enough.

In the present study, reactive power compensation is performed by a SM operating at leading power factor condition as depicted in Fig. 1, and it is aimed to model the SM with the help of four predictor variables using multiple linear regression approach, which describes how a response/target variable depends linearly on a number of predictor variables.

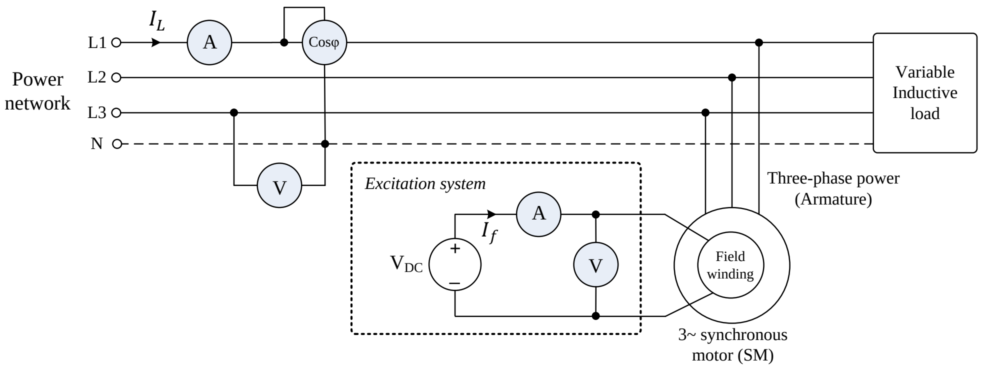


Figure 1. Block diagram of reactive power compensation using a SM.

In the case study, response variable or output/target parameter is excitation current I_f while predictor variables are load current I_L, power factor pf, power factor error e and change of excitation current ΔI_f, which is mathematically given as,

$$I_f^{estimated} = \hat{f}(I_L, \mathrm{pf}, e, \Delta I_f) = w_1.I_L + w_2.pf + w_3.e + w_4.\Delta I_f + w_5 \quad (1)$$

where the power factor error is

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

and the excitation current change is computed by subtracting the previous SM excitation current $I_{f(k-1)}$ from its current value $I_{f(k)}$ as

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

Notice that w_1, w_2, w_3, w_4 and w_5 are regression coefficients which identify the importance of each feature over the value of I_f in Eq. 1. For example, a relatively high value of w_1 means that the corresponding feature I_L affects I_f more importantly than other features, and vice versa. In order to estimate the excitation current value with a high accuracy, it is very crucial to obtain five optimal regression coefficients w_{1-5} jointly for which reason SOS algorithm is mainly utilized in this paper. In other words, by performing an efficient search of the regression coefficients in the range of 0.0-1.0 using SOS, it is expected to model the relationship among the features $< I_L, \mathrm{pf}, e, \Delta I_f >$ and the target parameter I_f in a better way. The SM feature vector $\mathbf{F_{SM}}$ including the corresponding one target parameter $\mathbf{T_{SM}}$ can be represented as in Table 1.

Table 1. Representation of feature/input vector and target parameter of SM.

Feature vector				Target parameter
Load current	Power factor	Power factor error	Change of excitation current	Excitation current
I_L	pf	e	ΔI_f	I_f

3. SOS Algorithm in Estimating Excitation Current of SM

In this section, a brief overview of SOS algorithm is initially given, then how to achieve appropriate values of w_1, w_2, w_3, w_4 and w_5 using the SOS is discussed. To the author's knowledge, it is the first time that SOS is employed to design a multiple linear regression model with its coefficients optimized which offers a better way of predicting excitation current depending upon the considered feature vector.

3.1. Overview of SOS Algorithm

Symbiotic organisms search algorithm is a simple and high-performance metaheuristic algorithm developed recently as an alternative to the existing metaheuristics in literature [20]. The algorithm benefits from the simulated three common symbiotic interaction strategies that organisms living together adopt to maintain their existence in the ecosystem. These strategies in the applied order within algorithm are mutualism, commensalism and parasitism, respectively, which are visualized in Fig. 2.

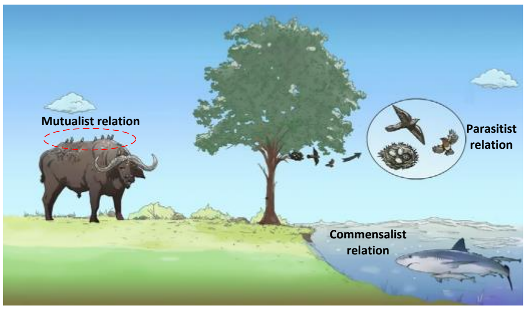


Figure 2. Strategies adopted by symbiotic organisms in the same ecosystem.

Each strategy has its own characteristic serving to guide the algorithm toward a more promising area within specified search space. Considering two organisms, both are benefitted positively in the mutualism phase; one side is benefitted and the other is not affected in the commensalism phase; finally, in the parasitism phase, one side is benefitted while the other is harmed. Each organism interacts with other organisms via all phases in one iteration cycle. SOS algorithm does not require specific tuning parameters which is an important feature in terms of performance robustness over different kind of problems, and thereby makes it one step ahead comparing to most other algorithms that deal with a number of algorithmic parameters hard to be set. The superior performance of SOS over well-known optimization techniques are affirmed in the original paper using some unconstrained mathematical problems and structural engineering design problems [20]. Besides, the SOS algorithm and its modified versions have been successfully employed in the optimization of various benchmarks and real life engineering problems, such as load frequency control of multi-area power system [21, 22], load dispatch problem with valve-point effect [23], off-line optimization of PI parameters for DSP-based DC motor drives [24], optimization of pin-jointed structures [25], economic dispatch problem [26], design of planar concentric circular antenna arrays [27], efficient PID based automatic voltage regulator design [28, 29], static optimal power flow problem [30], and optimal placement and sizing of distributed generators [31]. Nonetheless, in the light of our literature review, SOS has not been yet applied to optimal design of multiple linear regression model in attempting to estimate synchronous motor excitation current for power factor correction task. With this motivation, this research work may be recognized as the first contribution of SOS concerning the design of an estimation model among the SM input and output features. In order to avoid increasing the manuscript page number unnecessarily, interested readers are referred to [20] for detailed algorithm operations.

3.2. Preparation of SOS Algorithm for the Concerned Optimization Task

As shown in Eq. 1, the multiple linear regression model has five parameters which are given focus to determine the values of them optimally. As such, these parameters are suitably encoded into an organism in SOS using real numbers by $O = [w_1, w_2, w_3, w_4, w_5]$. Thus, each organism includes five members. If the ecosystem is composed of NO organisms, then its size becomes $NO \times 5$. In order to obtain a quantitative measure regarding how well each organism solves the given problem, the following simple equation based on the difference between the actual excitation current and the one estimated by Eq. 1 is chosen as fitness function to be minimized.

$$F_n(O_n) = \sum_{i=1}^{N} \left(I_{f\,i}^{estimated} - I_{f\,i}^{actual} \right)^2 \tag{4}$$

It should be highlighted that the introduced regression model is not expected to predict excitation current value under only one operating condition, but under a large number of different operational scenarios. It is therefore a dataset, or maybe termed as training/exemplar data, is required during optimization. Assuming i is an integer indicating each sample in training data of SM and N is the total number of collected training data. $I_{f_i}^{estimated}$ and $I_{f_i}^{actual}$ are, respectively, estimated and actual excitation current of the ith training data, and F is fitness value regarding the organism O. The aim of SOS technique is to tune the regression coefficients simultaneously considering all the training data in a way Eq. 4 is minimized so that the developed model could perform a promising prediction for an unseen feature vector within the domain covered by the training dataset. The whole dataset D_{SM} corresponding to selected SM feature variables and the associated target variable to be estimated can be represented in matrix form in Eq. 5.

$$D_{SM\,j\times 4} = \begin{bmatrix} f_{I_L[0,0]} & f_{pf[0,1]} & f_{e[0,2]} & f_{\Delta I_f[0,3]} & t_{I_f[0,4]} \\ & & \vdots & & \\ f_{I_L[j,0]} & f_{pf[j,1]} & f_{e[j,2]} & f_{\Delta I_f[j,3]} & t_{I_f[j,4]} \end{bmatrix} \quad (5)$$

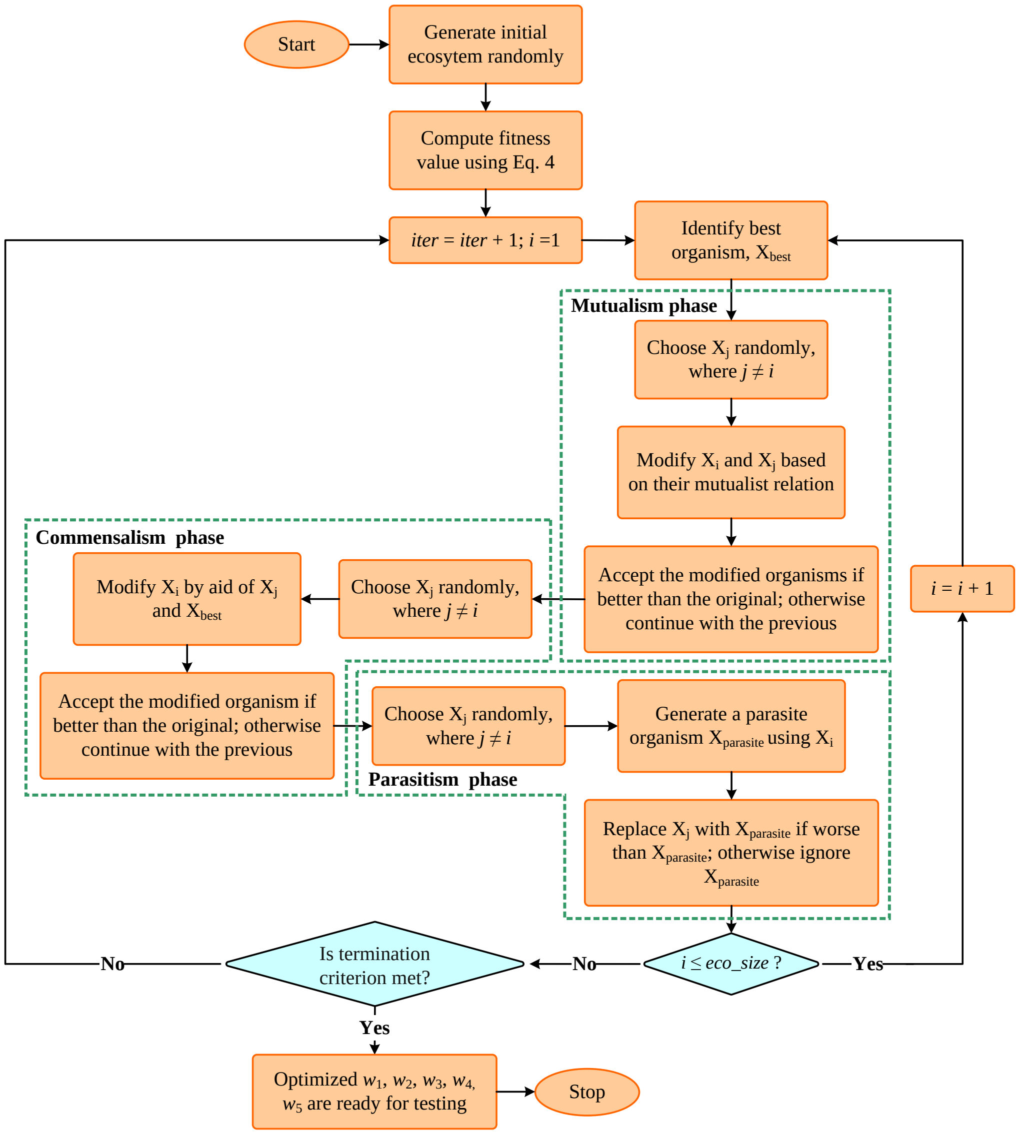


Figure 3. Implemented SOS flowchart.

In this way, 557 data samples are carefully collected from the experimental test bench whose block diagram is depicted in Fig. 1, then the samples are saved into *.xls file*. Briefly, the data collection scheme is described as follows: the excitation current value of SM is firstly set to a value so that the SM can run at unity power factor under a slight load torque on the motor shaft. Then, while keeping the load torque constant, the value of excitation current is gradually increased until the leading power factor of 0.66 is accessed. In each step, the values of I_L, pf, e, and ΔI_f are recorded. Afterwards, the load torque is increased, and then the entire process is repeated until reaching the nominal torque value of the concerned synchronous motor available in our laboratory. A more detailed description of the data collection procedure can be found in [11, 14]. 70% of the collected experimental data is utilized as training data during the optimization of regression coefficients and the remaining portion is assumed as test data to check the prediction capability of the proposed model in presence of different values of SM predictor variables which are not presented to the model during optimization. We adopt the experimental results used in [14] in order to consider it as a benchmark method for comparison purpose.

In the presented technique, the optimization algorithm of SOS is written in Matlab R2017b/m-file script and the experimental data preserved in excel document is imported into that environment. At the beginning of the algorithm, a number of organisms are generated randomly; each organism has the members of w_1, w_2, w_3, w_4 and w_5 in the range of [0, 1]. Then, these organisms are used in Eq. 1 to compute the excitation current value and to evaluate the fitness value using Eq. 4 in the event. As the number of training samples is N, we arrive at N different costs. So the final cost regarding each organism is the sum of these N costs. Eq. 4 shows this process mathematically. As expected, organisms in the ecosystem will have different fitness values. As our problem is a minimization problem, the less the fitness value is, the better the organism is. Next, organisms are updated for the next generation using the SOS operations through mutualism, commensalism and parasitism phases. In this sense, the algorithm is repeated until the squared error between $I_f^{estimated}$ and I_f^{actual} for the entire training set falls below a specified error value. After the optimization progress, SOS optimized regression coefficients of the selected SM features are expected to be more optimal than the existing ones and accordingly achieve the desired efficiency in estimating the excitation current with regard to both training data and testing data. SOS flowchart for optimizing the regression coefficients are depicted in Fig. 3.

4. Numerical Results

This section evaluates the estimation performance of regression model introduced in this paper. A comparison study is also conducted, when the regression coefficients are replaced with those obtained with GSA [14], ABC [14] and GA [14]. The number of the training samples used during optimization is 390 which are picked up homogenously from the whole experimental data set, and the remaining 167 samples are designated as the test data set. Four of the collected experimental data are reported in Table 2.

Table 2. Representation of feature/input vector and target parameter of SM.

No	I_L	pf	e	ΔI_f	I_f
6	3.0	0.76	0.24	0.301	1.481
18	3.0	1.00	0.00	0.037	1.217
359	4.9	0.99	0.01	0.140	1.320
555	6.0	0.95	0.05	0.160	1.340

In addition, excitation current variation for each of the training and test samples is plotted in Fig. 4. It is clear from this figure that average of excitation current gradually increases as sample index raises. This is attributed to the fact that load current is increased gradually during the experiments, which requires a greater excitation current for the synchronous motor to attain the same leading power factor value.

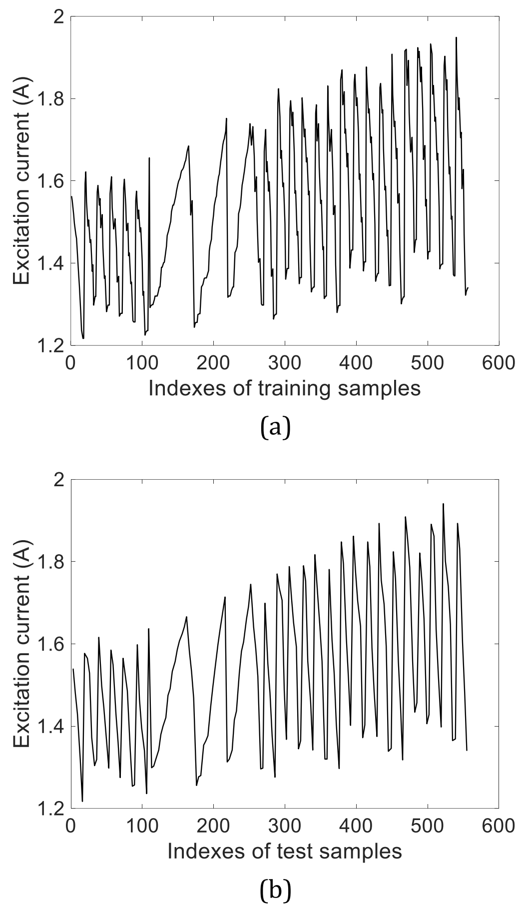


Figure 4. Excitation current value in (a) training set (b) test set.

A comparison of the adjustable parameters required by GA, ABC GSA and SOS are presented in Table 3. As seen, apart from the population size and maximum number of iterations, GA and ABC have four and three additional adjustable parameters, respectively, and two extra parameters must be tuned in GSA. In the case of the proposed SOS algorithm, there is no any other parameter that need to be adjusted depending upon the problem under consideration. Given this context, the presented SOS based regression model for estimating the excitation current of SM can be contemplated to be simpler than GA, ABC and GSA based models in terms of algorithm design. Notice also that since the values of the number of organisms and iteration number are much smaller in SOS, the presented approach is computationally more efficient than other three approaches.

Table 3. A comparison of the adjustable parameters required by GA, ABC GSA and SOS.

Algorithm	Number of parameters	Adjustable parameters
GA [14]	6	number of chromosomes = 100/200, number of generation = 20000, parent selection method, crossover method, mutation coefficient = [0.001; 0.01], mutation method
ABC [14]	5	number of ants = 100/200, maximum iteration number = 20000, onlooker bees = 50/100, employed bees = 50/100, neighborhood coefficient = [0.001; 0.01]
GSA [14]	4	population size = 100/200, number of iteration = 20000, α = 0.01, gravitational constant = 0.01
SOS	2	number of organisms = 30, maximum number of iterations = 40

By implementing the SOS algorithm using the parameter values in Table 3, the optimized regression coefficients and their respective fitness faction value are reported in Table 4, where the corresponding values in the case of employing GSA, ABC, and GA are also given for comparison. It is recognizable in Table 4 that SOS tuned regression coefficients are more optimal than the others as they yield less F value ($F = 2.66 \times 10^{-4}$) as **bolded** compared to GSA ($F = 76.26 \times 10^{-4}$), ABC ($F = 108.4 \times 10^{-4}$) and GA ($F = 55.86 \times 10^{-4}$).

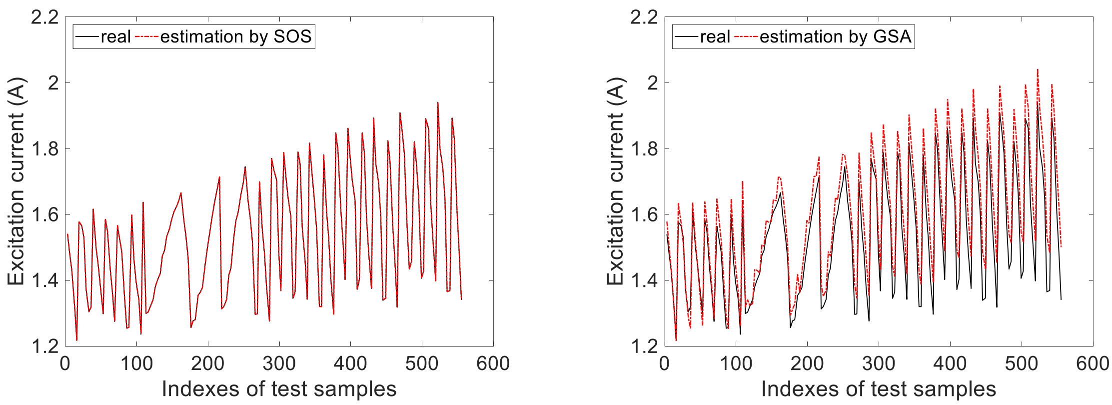
Table 4. Optimized values of regression coefficients and their fitness values using different optimization techniques.

Method	Regression coefficients					Fitness function F
	w_1	w_2	w_3	w_4	w_5	
SOS	0.000246	0.595301	0.611129	0.989786	0.584195	**0.000266**
GSA [14]	0.069097	0.135676	0.815564	0.575546	0.824279	0.007626
ABC [14]	0.010779	0.637809	0.637809	0.946734	0.533464	0.010840
GA [14]	0.117146	0.286163	0.999948	0.304766	0.557133	0.005586

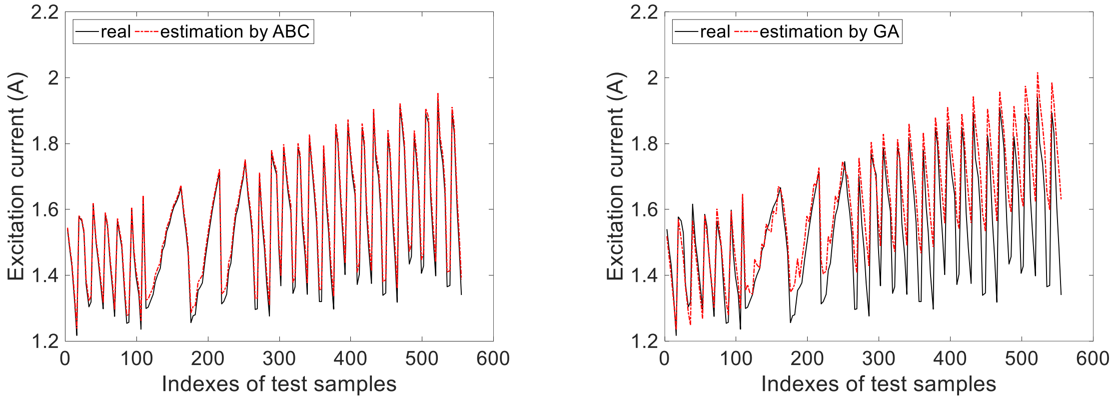
Now that SOS based regression coefficients are available, we can constitute the linear relation equation for estimated SM excitation current with regard to the machine selected features $< I_L, \mathrm{pf}, e, \Delta I_f >$ as follows:

$$I_f^{estimated} = 0.000246 I_L + 0.595301 pf + 0.611129 e + 0.989786 \Delta I_f + 0.584195 \quad (6)$$

It is noticeable in Eq. 6 that the coefficients of pf and e are almost the same which means that both two have similar importance on I_f. It is reasonable as both of them are related to power factor. On the other hand, ΔI_f is the predictor variable that affects I_f with the highest degree while the effect of I_L upon the value of I_f is found to be negligible. Using the regression coefficients in Table 4, the results of real and estimated excitation current values for the 167 test samples are given in Fig. 5. The real and estimated excitation current, I_f, $I_f^{estimated}$, are painted with black and red traces, respectively. It is evident from Fig. 5 that the best estimation performance considering the test samples belongs to our proposal as it is very hard to distinguish the estimation from its actual value in Fig. 5(a). In all other three approaches, deviations from the real excitation current values are clearly viewed in varying amounts. At this point, however, it is difficult to stress that SOS tuned regression coefficients are optimal as their true optimal values for the concerned optimization problem is not known explicitly, but the reality is that they are now closer to the optimality compared to the existing ones.



(a) (b)



(c) (d)

Figure 5. Estimation results of test samples (a) SOS (b) GSA (c) ABC (b) GA.

In Fig. 6, actual error values between the real excitation current and output from the multiple linear regression model are also provided comparatively. As shown, it is the presented technique that responses to each of the test samples with similar error magnitude around zero. Maximum error values in ampere are measured from Fig. 6 as 0.0018A for SOS, 0.1703A for GSA, 0.0474A for ABC and 0.2906A for GA, respectively. As a result, SOS can supersede the other indicated optimization techniques in terms of the issue of tuning a satisfied multiple linear regression model for the estimation of SM excitation current estimation since far less estimation error value is achieved by the SOS algorithm.

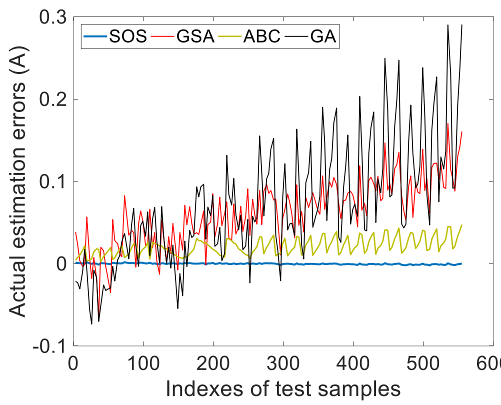


Figure 6. Actual estimation errors of test samples.

5. Conclusion

A new SOS optimized multiple linear regression model is presented for solving the problem of estimating synchronous motor excitation current in a better way for use in an power factor correction system. First, a multiple linear regression model with four predictor variables is assumed and its coefficients are optimized by the SOS algorithm for the first time using the experimental data available. To provide additional value to this work, a recently published study that benefits from GSA, ABC, and GA for the same task is considered as a benchmark method. It has been found that SOS tuned regression model that we propose in this paper can estimate the excitation current value of synchronous motor with remarkably increased accuracy with respect to both training data and test data. Good estimating performance and computational simplicity are significant contributions of this research work, which render it convenient for real-time implementation of SM reactive power compensation system.

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