Simplified Model and Genetic Algorithm Based Simulated Annealing Approach for Excitation Current Estimation of Synchronous Motor

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***Abstract*—Reactive power demanded by many loads besides active power is one of the important issue in terms of the efficient use of energy. The optimal solution of reactive power demand can be performed by tuning the excitation current of synchronous motor available in power system. This paper presents an effective application of genetic algorithm-based simulated annealing (GASA) algorithm to solve the problem of excitation current estimation of synchronous motors. Firstly, the multiple linear regression model used in a few studies for estimation of excitation current of synchronous motor, is considered and regression coefficients of this model are optimized by GASA algorithm using training data collected from experimental setup performed. The supremacy of GASA over some recently reported algorithms such as gravitational search algorithm, artificial bee colony and genetic algorithm is widely illustrated by comparing the estimation results. Owing to the observation of weak regression coefficient of load current indicating that it is not much beneficial to excitation current, load current is removed from the regression model. Then, the remaining regression coefficients are tuned to accommodate new modification. It is seen from the findings that both training and testing performance of the simplified model are improved further. The major conclusions drawn from this study are that it introduces a new efficient algorithm for the concerned problem as well as the multiple linear regression model, which has the advantages of simplicity and cost-friendliness.**

***Index Terms*—reactive power compensation, power factor, artificial intelligence, genetic algorithms, simulated annealing.**

I. INTRODUCTION

Power quality deals with several problems in power systems to ensure the utilization of the available capacity and substructure efficiently. Because of the widespread of loads consuming reactive power in the industry and daily life, poor power factor is one of the power quality problem [1]. The poor power factor causes overloading of transformers and generators, increase of resistive losses, deterioration of voltage stability, and inadequate use of line transmission capacity [2]. Besides, if consumers exceed the allowable limit of reactive power, they have to pay penalty to electric utility.

The negative effects of poor power factor can be overcome using reactive power compensation. There are several techniques to compensate the reactive power [3]. However, it is difficult to quickly and precisely determine the required reactive power changed depending upon loads in the power system [4]. Due to the low-cost of installation and operation, fixed capacitor groups are the most preferred method to supply reactive power [5]. However, slow response and stepped compensation are important deficiencies of this method [6]. In addition, although the capacitors are not harmonic sources, they may amplify the existing harmonic current components and lead to bigger problems in power system [7]. Another solution to provide the dynamic reactive power is thyristor-based static VAr compensator (SVCs). These systems provide much faster and smoother reactive power to grid compared to capacitor groups [8]. The main drawback of the SVCs is to cause harmonic components with lower order during their operation [9]. Static synchronous compensator (STATCOM) has fastest response time and lowest harmonic component to improve poor power factor among all solution methods [10]. Nevertheless, STATCOM offers a solution approximately 30% more expensive than SVCs for the same VA power rate [11]. Finally, synchronous motor (SM) is a prominent way to compensate reactive power in the literature [6]. If there is a SM in a power system, optimal solution is to provide the dynamic reactive power required by adjusting its excitation current [9]. The greatest advantage of SM is that the desired power factor value can be easily obtained by changing its excitation current without adding or subtracting any component if there is a need for a varying reactive power. In addition, the energy stored in the rotor can help stabilize the system during disturbances [12]. However, the determination of SM excitation current without delay time is main difficulty taking into account the reactive power demand occasionally altering in a power system [9, 13-20].

Various control approaches have been used to detect the excitation current in case of the variable reactive power required [6, 9, 12-21]. The experimental studies show that classical control systems proportional integral (PI) controller and proportional integral derivative (PID) controller can achieve to approximately designate the excitation current of SM under variable reactive power demand, however the artificial intelligence (AI)-based algorithms precisely converge the excitation current value performing the unity power factor [6, 9, 15-17]. I. Colak et al introduced the use of a fuzzy logic controlled SM for reactive power compensation. The obtained results proved that the proposed system can give a very fast response to the reactive power demand of inductive loads [6]. S. Sagiroglu et al suggested the usage of artificial neural networks (ANNs) to forecast the excitation current of SM, and then they investigated the

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compensation performance of the controller for different ANN training methods using the same experimental setup and data set [9, 17]. Reference [18] introduced a genetic algorithm-based k-nearest neighbor estimator (intuitive k-NN estimator, IKE) to detect the optimum weighting of SM associated with the excitation current used for reactive power compensation. The results of the study were compared with the previous study using ANN and it was shown that the proposed IKE algorithm achieved the prediction the excitation current of SM with small prediction errors. ANNs have been traditionally used to forecast the needed quantitative value based on data patterns. Owing to ANN models based on the emulating of human nerve system, they do not need to understand any assumptions unlike traditional regression model. ANN models have some drawbacks that they need the time-consuming training procedures and do not determine global minima on non-convex problem [22]. Especially the required much time for training process makes difficult the implementation using microprocessor based real-time system since such algorithms suffer from heavy computational burden. H.T. Kahraman introduced a multiple linear regression model to simplify the relations between SM variables and thereby estimated the excitation current using a hybrid solution technique [16]. The proposed model includes linear and nonlinear combinations of SM variables such as load current (I_L), power factor (pf), power factor error (e), change of excitation current (dI_f), which are weighted by regression coefficients. These coefficients were then optimized by deploying gravitational search algorithm (GSA), artificial bee colony (ABC) and genetic algorithm (GA), respectively. The findings based on multiple regression model verified that the metaheuristic algorithms produced that more accurate and faster results for estimation of excitation current than other existing approaches. [6, 9, 16-19]. It is also shown that GSA is the pioneer among the algorithms used in the considered study.

There are many solutions for the quantitative forecasting based on regression model and time series model. The regression based models need to many redundant variables. If these variables is eliminated, the co-linearity problem takes place. On the other hand, Time series models is more successful than regression models in some cases, such as in short-term forecasting [23-24]. One of the most known time series models is autoregressive moving integrated moving average (ARIMA) model developed by developed by Box and Jenkins [25]. However, time series models does not predict changes which is not clear in data set. Support vector regression (SVR) model overcomes the shortcomings of ANN models and support vector machines (SVM). SVR models contains the three parameters (C, ε, and σ) and the selection of these parameters influences the forecasting accuracy significantly. However, there is no common opinion among researchers on the determination of parameters. The recent literature have seen a sharp increase in using metaheuristic algorithms for solving various challenging problems in many areas such as engineering, business and economics. To realize optimization, the problem at hand should be formulated as an optimization problem which requires the proper definition of cost function and constraints. As compared to specific heuristics, metaheuristic algorithms are applicable for a wide variety of optimization problems. For instance, genetic algorithms (GAs) are used in extracting the core loss coefficients in [26], which results in a more accurate synthesizing of the core loss coefficients, and accordingly lower errors for the specific core losses than those obtained by the popular magnetic field analysis software. GAs are benefited in [27] to efficiently design a fuzzy logic based speed control system for a permanent magnet synchronous motor drive. It is found that the system performance with the employment of GA is greatly boosted compared to classical trial based design technique. Similarly, in [28], GA is utilized for the design of a fuzzy logic estimator that estimates the commutation angle to reduce commutation current ripple in brushless dc motor drive. In such a case, since there is no available expert knowledge for the design, GA is said to play an important role in achieving the performance objectives. Using of GAs to determine three free parameters in the SVR has outperform the other quantitative forecasting models (ARIMA and ANNs). GAs can lead to a premature convergence to a local optimum in the determining of three parameters in a SVR model. Wei-Chiang Hong et al proposed to maintain the population diversity of GAs in determining the three free parameters of a SVR model based chaotic mapping operator (CMO) and therefore prevented to become trapped in local optima. The authors used the model called SVRCGA for tourist arrivals forecasting. The comparisons with other prediction models proved the integration of chaotic adjustment and the searching capability of GAs into a SVR model [29]. In many control systems the optimal solution can be performed by optimization problem using non-convex objective function. The algorithms inspired by nature with fuzzy control systems problems can work out in solving the optimization problems for complexity of the objective functions and of the possibility to have multiple minima [30]. R.E Precup et al proposed the tuning of a class of fuzzy control systems to ensure a reduced parametric sensitivity on the basis of a new GSA [31]. S. Vrkalovic et al benefited from the swarm intelligence algorithms in order to improve the stability of the Takagi-Sugeno fuzzy controllers for an inverted pendulum system. [32]. Echo State Networks (ESN), which have unique large number neuron and enable the computation of optimal weight with linear regression, have been successfully employed in a broad range of applications. However many implementations require the adaptive learning to adjust the ESN parameters. J. Saadat et al offered harmony search (HS) algorithm for training ESN in an online manner and tested with four different algorithms including Recursive Least Squares (RLS-ESN), Particle Swarm Optimization (PSO-ESN), and their proposed methods (HS-ESN and HSRLS-ESN) [33]. More recently, first attempt to deploy symbiotic organisms search algorithm (SOS) to determine the gains of a windup protected PI scheme for DSP based DC motor speed control system is made in [34]. In [35], PID controller gains are alternatively tuned by stochastic fractal search (SFS) algorithm for the automatic voltage regulator (AVR) system and compared to the reported ones based on six competitive metaheuristic search algorithms. For the same system, a new cost function including minimization of some time-domain and frequency-domain performance indices is presented in [36], and a hybrid algorithm containing SOS and simulated annealing (SA) is suggested to optimize the presented cost function. According to the comparative results on popular studies published in prestigious journals, it is found that the AVR system controlled by the presented control scheme has minimum overshoot and less steady-state error, which has ensured a better stability margin than those using the earlier studies.

SA is one of the most attractive metaheuristic methods formally introduced by Kirkpatrick, Gelatt and Vecchi for solving combinatorial optimization problems [37]. Since then, it has been widely employed in various optimization problems. The algorithm is based upon the annealing process and iteratively applies random perturbations to the evaluation point of the objective function. In the algorithm, good solutions are accepted immediately when detected, while there is even a chance for bad solutions to be accepted depending upon the probability obtained from the Boltzman distribution [38]. The search performance of SA is significantly affected by some factors such as solution representation, neighborhood search strategy and temperature schedule [39]. In recent years, GA has been recognized as an effective and efficient search technique to exhibit good results in many practical problems using three essential operators: natural selection, crossover and mutation [40]. The inspiration for incorporation of GA in the neighborhood search of the SA algorithm in the hope of increasing the SA search performance has been first arose and addressed in [41]. The proposed algorithm, termed as GASA, is a hybrid algorithm based on our preliminary efforts, and its superior performance over the GA and standard SA has been validated for some benchmark functions in the given study. Then, GASA is applied to design a PID controller for an AVR system in [42] in comparison with other reported studies including artificial bee colony (ABC) [43], teaching learning based optimization (TLBO) [44], and biogeography-based optimization (BBO) [45]. It was demonstrated that GASA tuned PID controller performs better than ABC, TLBO and BBO based controller. Nonetheless, the validation of GASA algorithm in optimizing the gains of the regression model of synchronous motor is still an open problem. As a result, it is of interest and necessity to establish such validation with an aim to establish an efficient regression model between the SM parameters.

This study aims to further reduce the complex calculation process brought about by the artificial intelligent-based methods and to determine the excitation current of SM used for reactive power compensation with a higher accuracy. The proposed GASA algorithm has been tried to estimate the excitation current of SM corresponding to the reactive power in power system using with the same experimental set previously used for many times [6, 9, 16-19]. Thus, the obtained results are comparable with the available studies. The results of this comparison indicate that GASA outperforms other estimation methods in terms of the solution accuracy and algorithm convergence. When the results are evaluated, it is explored that the number of predictor variables used in the classical linear regression model can be reduced. This discovery has led to the emergence of a simplified multiple linear regression model. This model has been presented to describe the relation among SM variables for reactive power compensation. The proposed model contains less predictor variables than existing classical form and so the response time, heavy computational load and number of iterations can be minimized for a real-time application. In order to prove this, the developed GASA has been attempted to determine the regression coefficients. From the various computer simulations, it has been demonstrated that less training and test error are successfully achieved, which dictates that the GASA-optimized coefficients are closer to the global optimal solution. Besides, thanks to the simplified linear regression model where the load current is shown to be usefulness, estimator structure is simplified and accordingly its response time is reduced at least by one microcontroller clock cycle. Another significant advantage of our proposal is that it offers cost-reduced solution since it does not any longer require the measurement of load current via an expensive current sensor.

The rest of the work is organized as follow: In Section 2, the general knowledge about SM and experimental design is given. Section 3 contains the experimental validation course, and finally Section 4 presents the conclusions of the study.

II. Improvement of Power Factor Using SM and Experimental Setup

The power factor of SM providing constant speed to the load on the shaft can be adjusted by changing its excitation current. The SM has a distinct excitation current value that provides the unity power factor for each mechanical load. This value is known as normal excitation current. SM draws minimum armature current from grid in case of normal excitation current. If the excitation current is increased from the normal value without changing the load on the shaft, SM begins to draw capacitive reactive current from the grid along with active current.

In this study, a prototype power system consisting of an inductive load and a SM was designed to compensate the reactive power of the system using SM. Authors attempted to determine the excitation current required to provide the unity power factor of the system under different load values on the motor by means of this experimental set. The block diagram of the experimental setup is shown in Fig. 1 [6, 9, 16-19].

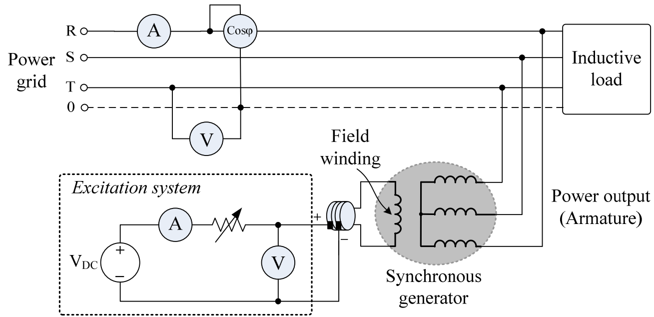


Figure 1. The block diagram of experimental setup [6, 9, 16-19]

The nameplate data of SM used in this study was Y/Δ 400 / 231 V, 5.8 / 10 A, cosφ = 0.8, 4 kVA, 1000 rpm. Firstly, SM was accelerated by an external prime mover up to synchronous speed. When the speed of the motor value was provided to synchronous speed, the auxiliary mover was disconnected from system. The excitation current of SM was set to the normal value which leads to SM operation at unity power factor. The excitation current was then gradually increased from the normal value to the new value corresponding to the unity power factor of power system using the field rheostat without changing the load on the motor. Five variables of load current (I_L), power factor (*pf*), power factor error (e), change of excitation current (dI_f) and excitation current (I_f) was recorded for each increment. Then the load on the motor was increased and the excitation current value was set to the normal value for this new load. The excitation current was again increased step by step starting from the normal value to the unity power factor of system using the field rheostat. This experiment was repeated many times for different load values on the motor and the data set consisting 557 distinct values was created [6, 9, 16-19]. The variables constituting data set was obtained for the load current from 3 A to 6 A and the power factor value between 0,66 and unity.

The data set, which was prepared to reveal the relationship between the excitation current of SM and other variables, was summed up in an array of 557×5. In the linear equation utilized to determine the relationship between the parameters of SM, load current (I_L), power factor (*pf*), power factor error (*e*) and change of excitation current (dI_f) were input parameters and the excitation current (I_f) was output parameter [16, 18]. A novel hybrid algorithm can determine the excitation current of motor to provide the reactive power required by the power system when there is any load on the motor shaft using this data set.

A. Proposed algorithm and its application to considered problem

Inspired from the powerful search performance of GA and keeping in mind the dependency of SA algorithm upon its neighborhood search, an idea of combining two algorithms in a proper way has been arose to enhance the search performance of the basic SA algorithm. In SA, there are many ways for generating trial solutions in a neighborhood of the current solution and conventionally the neighboring solution is generated randomly. This type of random search not based on a systematic approach for the next candidate generation mechanism is more likely to fail to find out the optimal or near-optimal solution in a reasonable time. Therefore, rather than totally randomized search for neighbor solutions, a systematic way that makes progress in increasing trial solution qualities while with good computational cost is required.

The presented GASA algorithm differs from the original SA algorithm only with regard to the neighboring solution generation strategy [41]. After a number of solutions are generated randomly around the best solution found so far, a crossover operation is performed in order between the best solution and those generated randomly previously. Then, mutation is invoked in GASA algorithm. The reason behind the crossover operation is to increase the chance of obtaining better solutions than the best solution, which is associated with the exploitation property of the algorithm. As for mutation, it is applied after invoking crossover in order to introduce random modifications in the hope of preventing being mired in local optima. Meanwhile, after new individuals are generated using crossover, the fitness of each is computed to attain the best point among all points. This best solution is then taken as elite individual in order not to mutate it in the mutation phase for possible deterioration in solution quality. The following block diagram outlines the above explanation.

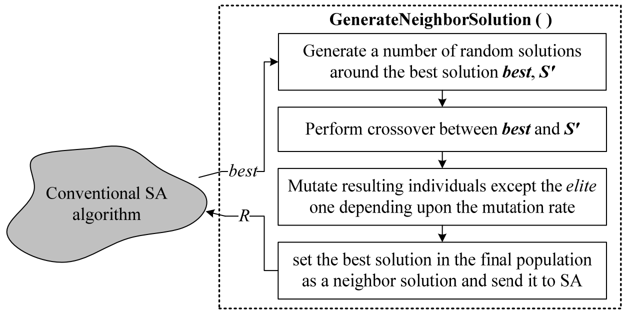


Figure 2. The block diagram of neighboring generation algorithm in GASA

As shown in Fig. 2, the best solution found at the end of the neighboring generation algorithm is sent to SA algorithm to be evaluated for the next iteration. In the present work, the use of GASA algorithm is devoted to attain more optimal weight values of the selected features with the hope of predicting excitation current of SM more accurately.

B. Problem formulation

In the article, as the relation of excitation current (I_f) is tried to be acquired with regard to the motor variables such as load current (I_L), power factor (*pf*), error (*e*), and excitation current change (dI_f), all these predictor variables are gathered together and combined linearly to estimate I_f as defined in Eq. 1, where w_1, w_2, w_3, w_4 and w_5 are interpreted as regression coefficients. As there is more than one factor that linearly influences a single response variable, (1) is usually referred to as a multiple linear regression model.

$$\begin{aligned} I_f^{estimated} &= f\left(I_L, pf, e, dI_f\right) \\ &= w_1 I_L + w_2 pf + w_3 e + w_4 dI_f + w_5 \end{aligned} \tag{1}$$

According to (1), the excitation current depends linearly upon four predictor variables I_L, *pf*, *e*, dI_f by varying degrees. For example, a higher value of w_4 means that the effect/weight of dI_f on excitation current is greater than other features and vice versa. As the authors of this article are encouraged to estimate excitation current of SM with less error compared to that offered by a recently published study, a new hybrid algorithm is deployed in the present study in order to find out better regression coefficients so that the linear regression function *f* can map the input parameters I_L, *pf*, *e* and dI_f to target parameter I_f in a more accurate sense.

To apply GASA algorithm for searching the regression coefficients, it is required first to encode these parameters into an array presented as a numeric string. As there are five coefficients to be optimized, each set of them composes an individual vector W in GASA by $W = [w_1, w_2, w_3, w_4, w_5]$. Thus, there are five elements in an individual, which are represented by real numbers. In order to obtain a quantitative measure regarding how well each individual performs, the following cost function J is defined and used in the study. This cost function is chosen to minimize the deviation between the actual and estimated excitation current for each training sample.

$$J(W)=\sum_{i=1}^{N}\left(I_{f_i}^{estimated}-I_{f_i}^{actual}\right)^2 \qquad (2)$$

Where N is the number of training samples used during optimization process, $I_{f_i}^{estimated}$ and $I_{f_i}^{actual}$ speak for the estimated and the actual excitation current for the ith training sample, respectively. In optimization problem, for each cost function evaluation, it is assumed that the selected predictor variables change in a certain range in order to form the training data set as will be explained in the forthcoming chapter. In this regard, a total of N different combination of the four input parameters are obtained, which accordingly leads to N different costs. The final cost regarding each individual is the sum of these costs which is mathematically given in (2). As a result, the concerned real-world problem of estimating SM excitation current has been tried to be solved by formulating it as a constrained optimization problem subject to the following constraints of weight bounds:

Minimize J
Subject to:

$$\left.\begin{array}{l} w_1^{\min}\le w_1\le w_1^{\max} \\ w_2^{\min}\le w_2\le w_2^{\max} \\ w_3^{\min}\le w_3\le w_3^{\max} \\ w_4^{\min}\le w_4\le w_4^{\max} \\ w_5^{\min}\le w_5\le w_5^{\max} \end{array}\right\} \qquad (3)$$

where the superscripts min and max stand for the minimum and maximum values of the corresponding weights. The typical ranges of these weight values used in the earlier studies are (0.0, 1.0) (see [16] and [18], for example). To widen the search space and to attain better regression coefficients, all the weights are assumed in the range (−0.1, 1.0). One understands that several optimization algorithms can be applied to solve the above-formulated optimization problem i.e. GSA [16], ABC [16] and GA [16]. We introduce GASA algorithm for the first time as a powerful alternative to solve the concerned problem in a more efficient and simpler way. At the end of the study, optimized weight parameters w_1, w_2, w_3, w_4, and w_5, which result in comparably less cost function value, may be considered as optimal or near-optimal expected to yield desired level of estimating performance. The flowchart of optimization of weight parameters using GASA algorithm is visualized in deep in Fig. 3.

The proposed algorithm begins the search from an initial random feasible solution after setting the initial temperature T_{init}. Provided that temperature does not fall below zero, best solution found by the SA algorithm is fed into the GA-based neighboring generation module in order to realize effective search in the neighborhood of the given solution at current temperature. In this module, first a number of individuals or chromosomes are generated from the normal distribution with mean parameter 'best' and a small standard deviation value, which allows to have a population whose members spread around the best solution. Then, crossover is performed between the best and each of the previously generated solutions which causes the population size to be doubled. After identifying solution with the least fitness value which is preferable, it is preserved and the remainder of the individuals is exposed to mutation depending upon the mutation rate. In this phase, randomly selected genes of randomly selected chromosomes are altered within the minimum and maximum bounds of the regression coefficients to lead an efficient exploration of the problem space. At the end of the neighboring generation algorithm, only the best generated chromosome is considered and it is fed back into the conventional SA algorithm to proceed. Notice in Fig. 3 that the inner loop of SA searches the current solution's neighbors recursively for a number of trials L and when promising solutions are attained ($\Delta E<0$), they are unconditionally accepted as the new solution. Even for inferior trial solutions, there is a chance to be accepted with a probability $p=\exp\left[\left(J(w_k)-J(w_{k+1})\right)/T\right]$, which depends on the process temperature and cost difference between the trial solution and the current solution. When inner loop is completed, outer loop reduces temperature gradually limiting the acceptance of inferior trial solutions, and thereby allowing a more concentrated search toward the global optima. In this way, the search process is iterated until the temperature value reaches nearly zero.

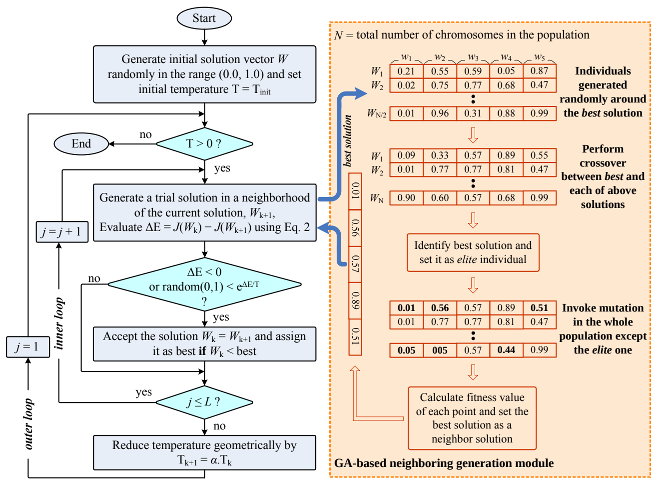


Figure 3. The detailed flowchart of optimization of weight parameters using GASA algorithm

III. Experimental Validation Course

In this section, the results of applying GASA algorithm to the addressed problem of exploring better weight parameters are reported and they are also compared with those provided by the reported algorithms GSA [16], ABC [16] and GA [16] in order to validate the superiority and effectiveness of the presented technique. To optimize the regression coefficients under identical conditions, the same experimental data is used in this article. In this regard, a total of 557 data samples are collected including I_f as an experimental output data with respect to I_L, pf, e, and dI_f. 390 samples are selected from the dataset homogenously in a random fashion to form the training dataset, and the remaining 167 samples are preserved as the test dataset. The training data is for optimizing coefficients of the selected features of synchronous machine under various situations and the estimation accuracy of the resulting linear regression model with its weights optimized using GASA algorithm is tested using the test data that is not experienced before during optimization process. Seven of the training data and test data are tabulated in Table I. It is also possible to access the GASA algorithm and the entire experimental dataset by using addresses in Appendix. In this regard, researchers can test their algorithms using the same dataset and compare the results to the ones reported in this paper under identical conditions.

TABLE I. SEVEN EXAMPLE MEASUREMENTS IN THE TRAINING SET AND TEST SET

Exemplars of training data					
No	I_L	pf	e	dI_f	I_f
1	3.0	0.66	0.34	0.383	1.563
74	3.4	0.68	0.32	0.402	1.582
100	3.5	0.84	0.16	0.225	1.405
215	4.1	0.66	0.34	0.522	1.702
375	5.1	0.89	0.11	0.347	1.527
448	5.4	0.97	0.03	0.166	1.346
520	5.8	0.97	0.03	0.218	1.398
Exemplars of test data					
No	I_L	pf	e	dI_f	I_f
3	3.0	0.70	0.30	0.360	1.540
76	3.4	0.72	0.28	0.345	1.525
113	3.8	0.96	0.04	0.119	1.299
222	4.3	0.98	0.02	0.14	1.32
382	5.1	0.73	0.27	0.615	1.795
445	5.4	0.91	0.09	0.159	1.339
555	6.0	0.95	0.05	0.160	1.340

In order to give a better picture regarding the excitation current evolution in the training data and in the test data, Fig. 4 is provided for the excitation current value versus sample number, where each sample collected from the experiment is indicated by the black point.

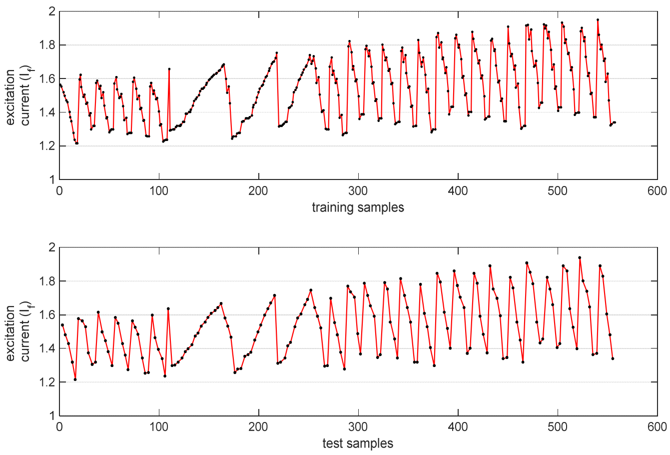


Figure 4. Evolution of excitation current values in the training data and test data against sample number

The GASA search algorithm whose parameter settings are shown in Table II has been written in *.m file* in the Matlab 8.5.0 (R2015a) program installed on an Intel Core i5-3.30Ghz processor and 8GB memory computer. As proposed in literature [46, 47], GASA is independently run 25 times under random initial conditions. When finding a cost function value J below 1E−3, the program is terminated, and otherwise it is iterated until the iteration number reaches 1000 iterations.

TABLE II. PARAMETER SETTINGS OF GASA ALGORITHM

Specification	Method/Value
Maximum iteration number	1000
Initial temperature, T_{init}	100
Cooling factor, α	0.996
Inner loop iteration number in SA, L	20
Particle length, W_l	5
Number of chromosomes in the neighborhood, N	30
Crossover technique	Uniform
Mutation rate, p_m	0.13
Cost function, J	Equation 2

The statistical results of GASA obtained by 25 independent runs are summarized in Table III where the best value, mean value and standard deviation regarding the cost function value and iteration number are delineated. From Table III, it is obvious that the presented algorithm is consistent across the problem since the calculated standard deviation is very small (i.e., close to zero), indicating that the obtained solutions have a tendency of spreading out in a narrow range around the mean of the set. It can be also said that GASA can find a good result of 4.26E−04 after 314 iterations in average.

TABLE III. THE STATISTICAL RESULTS OF GASA

Feature	Measure	Value
Cost function value	Best	0.000116
	Mean	0.000426
	Worst	0.000520
	StdDev	0.000245
Iteration number	Best	15
	Mean	314
	StdDev	186

A comparison of the optimized regression coefficients of the multiple linear regression model and the value of J are reported in Table IV, where the **bold** number signifies best fitness value. From this table, it is inferred that GASA performs better than GSA, ABC and GA because less J value is offered by GASA algorithm (J=1.16×10^{-4}), compared to GSA (J=7.62×10^{-3}), ABC (J=10.8×10^{-4}), and GA (J=5.58×10^{-4}). This outcome proves that the coefficients found by GASA are more optimal than those offered by the existing approaches.

Now that the best weight values are acquired, we can constitute the linear correlation of excitation current I_f of SM with regard to its variables including I_L, pf, e and d_{If} by substituting the GASA-optimized weight values in Table IV into (1) as seen in (4).

TABLE IV. COMPARATIVE REGRESSION COEFFICIENTS AND THE CORRESPONDING COST FUNCTION VALUE FOR VARIOUS ALGORITHMS

Algorithms	w_1	w_2	w_3	w_4	w_5	Cost function J
GASA	0.000763	0.619446	0.628955	0.992026	0.558231	**0.000116**
GSA [16]	0.069097	0.135676	0.815564	0.575546	0.824279	0.007626
ABC [16]	0.010779	0.637809	0.637809	0.946734	0.533464	0.010840
GA [16]	0.117146	0.286163	0.999948	0.304766	0.557133	0.005586

$$I_f^{estimated} = 0.000763 I_L + 0.61944 pf + 0.628955 e + 0.992026 dI_f + 0.558231 \quad (4)$$

It is noticeable from (4) that two variables *pf* and *e* of SM have similar influence on I_f because their respective weights are approximately the same. This is reasonable because both are related to the power factor. The effect of dI_f is the highest of all, and I_L is the least significant in the regression model.

After optimizing the regression coefficients by means of GASA using 390 different operating circumstances realized in the experiment, the next step is to test the generalization capability of presented approach whether to respond to an unseen input data satisfactorily. For this reason, the SM excitation current is estimated using the test data which is not utilized during the optimization. The total number of test data is 167. The comparative estimation results using the weights in Table IV based on GASA, GSA, ABC and GA are demonstrated in Fig. 5 in a superimposed manner with the real excitation current. The real excitation current and the estimated excitation current are indicated with the solid red and dashed black traces, respectively. Three existing approaches show favorably good estimation performance for certain test samples, but they fail to do so particularly for the test samples greater than 250. On the other hand, the estimation result obtained in this paper with the presented technique is quite promising and shows an excellent match between the real/measured excitation current and the output from the multiple linear regression model, as compared to other indicated optimization algorithms. As a result of applying our suggested algorithm to the concerned estimation problem, it can be realized that optimized weight parameters of SM variables in the linear equation form are made closer to the optimal ones.

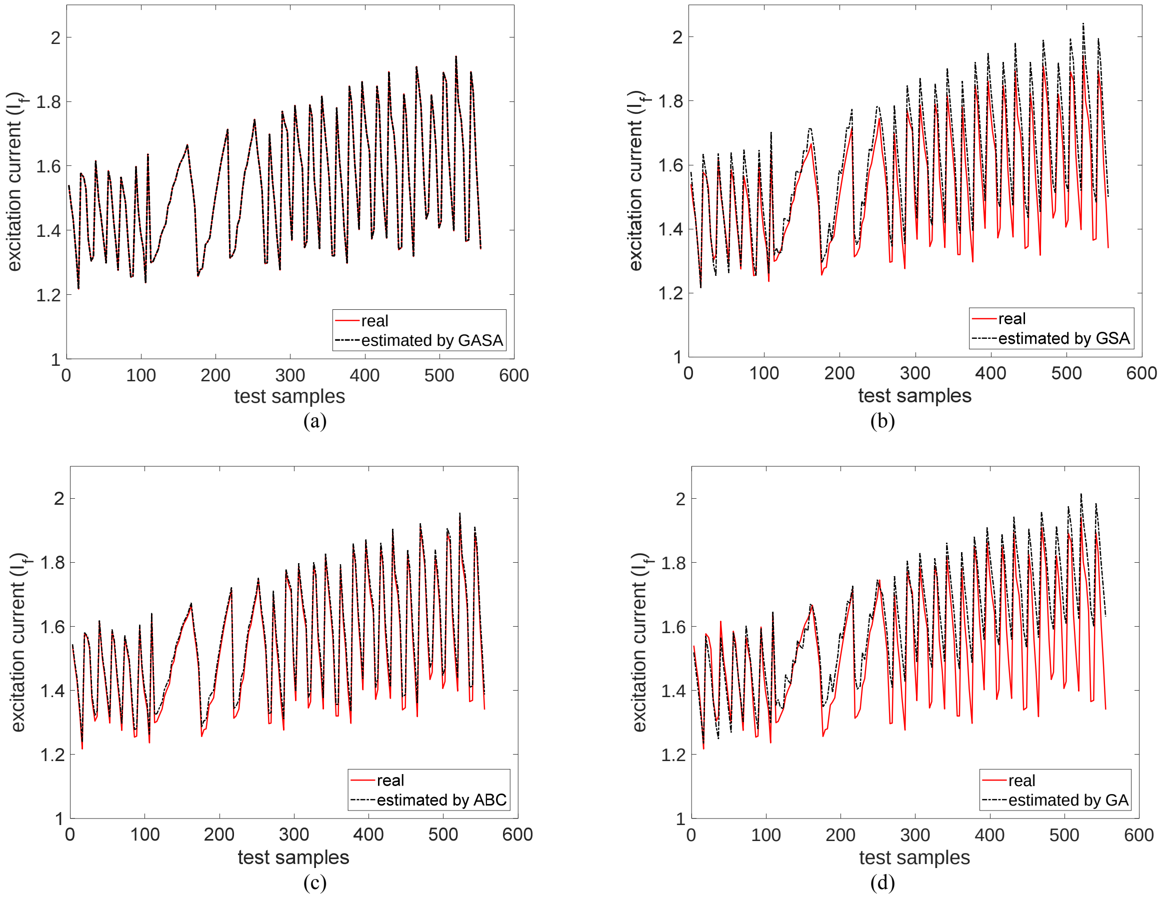


Figure 5. Comparative estimation results for the concerned test samples using the linear estimator optimized by (a) GASA (b) GSA (c) ABC (d) GA

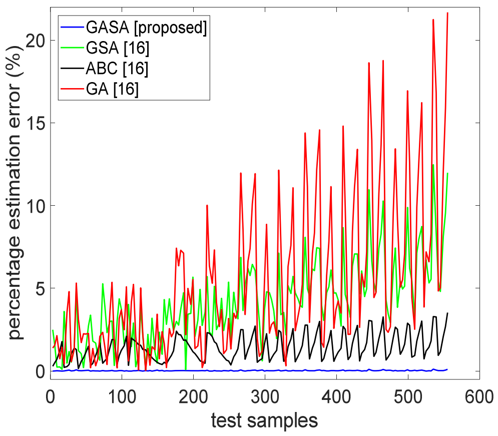


Figure 6. Comparative estimation results for the test samples

In Fig. 6, a comparison is given among the algorithms to present the percentage estimation error emerged in estimating excitation current for each of the test samples According to Fig. 6, the maximum percentage errors computed are 0.11% for GASA, 12.5% for GSA, 3.5% for ABC and 21.7% for GA algorithm. This confirms the pioneering of our proposal in excitation current estimation with an accuracy significantly higher than the other approaches.

One may recognize that the estimation results taken from the published study [16] do not exactly comply with the ones reported in this study, though the same regression coefficients are adopted. This is attributed to the fact that the data used for testing the estimator performance is not chosen similarly from the pool of collected experimental samples.

Nonetheless, this does not diminish the comparison fairness since the testing samples do not have to be the same when the applied technique is changed. As GASA-based estimator outperforms the other published approaches, the remainder of the article is forwarded with our proposal to avoid unnecessary increase in the manuscript length.

After performing a series of runs with GASA technique, it has appeared that the weight value of the predictor variable I_L is found in much smaller value at each optimization attempt, which indicates that the effect of I_L on I_f is not important. Inspired from this idea, I_L is no longer considered and removed from (1). Thus, we can arrive at the reduced form of the multiple linear regression model given in (5), which now depends on three predictors.

$$I_f^{estimated} = g\left(pf, e, dI_f\right) = w_1 pf + w_2 e + w_3 dI_f + w_4 \quad (5)$$

The new multiple linear regression model that we introduce has multiple advantages as listed below:

i. It is computationally simpler than its previous version as less number of terms are linearly combined.
ii. Reactive power correction system does no longer need for measurement of the load current using an expensive current sensor. Hence, the new model offers a cost-friendly solution.
iii. The optimization of its coefficients is easier to implement owing to the fact that optimization dimension is reduced to four from five.

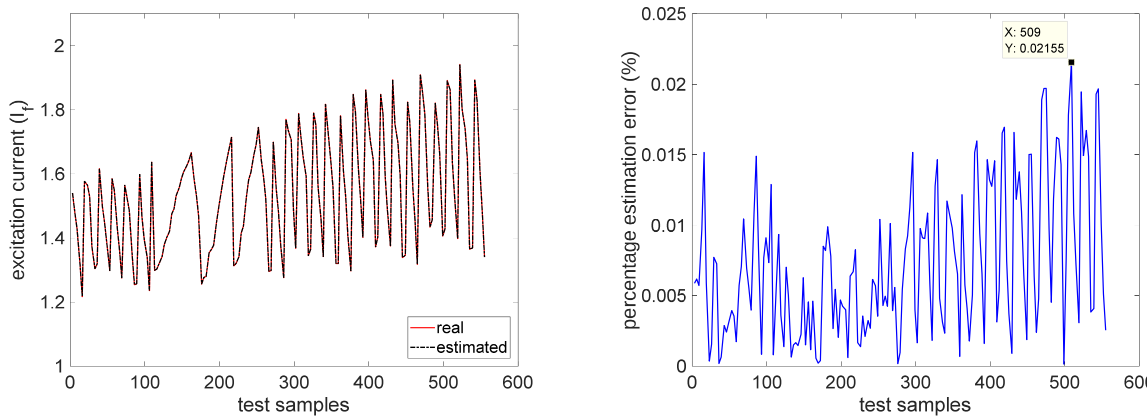
For the desire of exploring the most appropriate regression coefficients w_1, w_2, w_3 and w_4, the optimization process explained comprehensively above is repeated using the same algorithm parameters, but with four members in an individual in this case. The optimized weight values for the reduced form of the linear regression model are reported in Table V as well as their associated cost function value.

TABLE V. THE OPTIMIZED WEIGHT VALUES AND CORRESPONDING COST FUNCTION VALUE FOR THE REDUCED FORM OF SIMPLIFIED MODEL

w_1	w_2	w_3	w_4	Cost function J
0.330070	0.331357	0.998673	0.850112	0.0000091

The results in Table V are toward supporting our claim made for Table IV, in that, the weights corresponding to pf and e are still equal to each other roundly, and dI_f is the one that affects I_f most significantly. Thanks to such modification realized, the cost function value is reduced to 9.1×10^{-6} from 1.16×10^{-4}, which may be a prior indicator that estimation performance of the test data is boosted further.

Finally, estimation capability of the proposed regression model with its optimized coefficients shown in Table V is tested in presence of identical set of test data, and the results are given in Fig. 7. As we can see in Fig. 7(a), there is indeed perfect agreement between the real excitation current and the estimated one using our proposal. As regards Fig. 8(b) which shows the percentage estimation errors for different test samples, the maximum percentage error is found to be 0.02% as highlighted on the Fig. 7(b), which was 0.11% for the previous regression model including four predictor variables. As a result of this outcome, we conclude that thanks to the reduced form of the regression model with its optimized coefficients by deploying GASA algorithm, mapping or generalization capability of the estimator is improved not only for the training set, but also for the test set.



(a) (b)

Figure 7. Estimation result using the proposed regression model (a) real and estimated excitation currents (b) percentage estimation errors

A. *Effect of parameter* p_m

The adjustable parameters, such as initial temperature T_{init}, cooling factor α, inner loop iteration number L, neighborhood chromosome number N, mutation rate p_m, and crossover technique have certain roles in affecting the search performance of the presented GASA algorithm. In practice, the approximate optimal values of these parameters are tuned based on the problem at hand by trial and error. In literature, it is possible to find many research works that have analyzed and reported the effects of T_{init}, α, L, N on the classical SA algorithm, and also crossover technique and mutation rate on the operation of GA. Usually, the greater the values of L and N, the better the obtained solutions are, yet the heavier computational cost of the presented algorithm is. In other words, L and N yield a trade-off between computational effort/time consumption and solution accuracy or convergence rate. Additionally, uniform crossover technique, which was shown to work well on various interesting problems [48], is adopted in the algorithm, which produces offspring values coming from a combination of the two respective parent variable values. Mutation satisfies the GA's exploration (or diversification) property. It is required to prevent the algorithm from converging too fast before exploring the entire cost surface. If a low mutation rate is selected, the needed population diversity could not be introduced, and the algorithm distraction to converge on a promising solution may be destroyed if the mutation rate is higher necessary. In the following exercise, we have investigated the pure effect of mutation rate p_m of the performance of GASA for the specified optimization problem. For this, we try 5 values of p_m (i.e., p_m = 0.1, 0.2, 0.3, 0.4, and 0.5) while all other parameters in Table II remain the same. The statistical performance of GASA under this condition is recorded in Table VI for each value of p_m after 25 independent runs.

TABLE VI. THE EFFECT OF MUTATION RATE ON THE STATISTICAL PERFORMANCE OF GASA ALGORITHM

p_m	Best	Mean	Worst	StdDev
0.1	0.000116	0.000426	0.000520	0.000245
0.2	0.000252	0.000457	0.000717	0.000180
0.3	0.000194	0.000252	0.000454	0.000114
0.4	0.000163	0.000291	0.000445	0.000103
0.5	0.000207	0.000228	0.000281	0.000062

Moreover, the corresponding statistical findings are plotted in error bar in Fig. 8. It is noticeable from this figure that the mean value of the fitness results tend to decrease as p_m is increased, and the algorithm found the best fitness when p_m = 0.1, which judges that our selections in Table II are fine. It is also noticed that GASA does not give birth to very different results with a good robustness to changes in mutation rate.

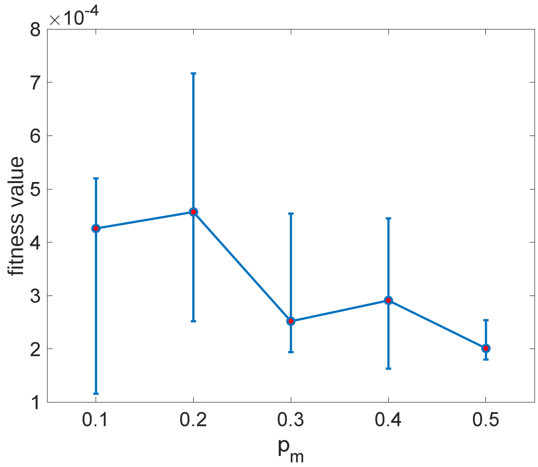


Figure 8. The effect of p_m on the statistical fitness value

IV. CONCLUSION

In this paper, a hybrid optimization algorithm called GASA that combines different strength and weakness of GA and SA is presented to find more optimal weight parameters regarding the motor variables with an aim to estimate the excitation current of SM with less error. To affirm the usefulness, first, a multiple linear regression model which describes the relationship of SM excitation current with regard to four predictor variables such as load current, power factor, error and excitation current changing is considered, and then GASA technique is applied to optimize five regression coefficients in such regression model. Results in comparison with those offered by recently published approaches confirm the superiority of GASA algorithm. Afterwards, owing to the fact that the coefficient of load current is obtained in very small value at each time of executing the algorithm, which indicates that load current has trivial importance over excitation current, it is removed from the regression model, and the remaining four coefficients are optimized in the same way to accommodate new condition. Thanks to this modification, both training and test performance are improved further, which reveals that SM excitation current does not actually depend on its load current in the current form of the regression model. This important modification contributes more simplicity to the estimator structure and accordingly reduces its response time at least by one microcontroller clock cycle. Another significant advantage of our proposal is that it offers reduced-cost solution since it does not any longer require the measurement of load current via an expensive current sensor.

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APPENDIX

Codes regarding the GASA algorithm and the entire dataset are downloaded from addresses below:
http://www.websitem.gazi.edu.tr/site/okaplan
http://www.websitem.gazi.edu.tr/site/emrecelik

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