IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676, p-ISSN: 2320-3331, Volume 17, Issue 6 Ser. I (Nov. – Dec. 2022), PP 11-25
www.iosrjournals.org

Bacterial Foraging Algorithm Based Parameters Estimation of Induction Motor

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Abstract:
This paper presents a swarm-based optimization technique for the induction motor parameter estimation based on intelligent bio-mimicry of social foraging bacteria (Escherichia coli (E Coli)) called Bacterial Foraging Algorithm (BFA), a powerful distributed optimization control application. The proposed technique is based on the foraging behaviour of the bacteria as the multi-objective optimization technique to identify the equivalent circuit parameters of a 5 HP three-phase induction motor from the manufacturer name plate data. The basic chemotactic step length was adjusted with a view to have dynamic non-linear behaviour that improves global and local search balancing. From the proposed method computes the values of appropriate objective functions, then compare input-output data from induction motor and from simulation model. More precisely the parameters were obtained from minimization of those objective functions. With the bacteria exhibiting the property identified by their ability of social foraging strategy and to be able to climb noisy gradients in nutrients, the simulation results demonstrate the ability of the proposed scheme to capture the true values of the motor parameters and the superiority of the results obtained using the BFA where obtained.

***Key Word**:Induction Motor; Parameters estimation; Bacterial Foraging Algorithm; Escherichia Coli; Optimization; Cost Function; Steady-State Performance.*

I. Introduction

As is well known, the nomenclature of induction motor (IM)was derivedfrom windings of the machine such that it producesthe excitation magnetic field and supply energy that is converted to mechanical output at the prime mover. The absence of sliding mechanical parts is the consequent of saving in a typical IM in terms of maintenance and is a great merit [1].The unique attribute which distinguishes IM from other type of electric motors (synchronous and DC machines) is that its secondary currents are created solely by induction just as in a transformer instead of being supplied by a DC exciter or other external power sources [2].

High performance IM drives have attracted a great attention in industrial applications owing to their advantages such as low cost, less maintenance cost and high reliability [3][4];however, motor manufacturers do not provide the equivalent circuit parameters for their machines. It is clear that IM parameters are motor specific [5]. So, knowledge of IM parameters has become imperative for the interest of optimizing system performances. Accurate values of these machine parameters give room for improving the control of both electrical and mechanical (torque, speed and position) quantities of the motor. It manages power consumption and effectively predicts IM failures with great reliabilities [6].

II. Problems Definition and Objectives

Certainly, system identification has become an essential cardinal principle of control engineering. So certain considerable efforts weremade to develop techniques for the identificationof system models and their parameters [6]. Potential number of analytic methods surfaced in other to meet these demands. But relatively little developmentswererecorded for non-linear systems using the analytical methods. Obviously, huge changes occur in dynamic systems and leads to the ever-increasing demands for system identification and parameter estimation methodologies. Alternative approach to cope with the need to adapt with the changes in search for more-efficient method capable of handling large problemsevolved. These are the non-linear optimization techniques [7].The inaccurate parameters results to a potentially inefficient motor control. Even though several IM parameters estimateschemes where available, it is still a challenging task to ensure a good level of confidence in the IM estimation scheme. It is well known fact that these parameters are influenced by not only the loading magnitudes but also by environmental factors (such as temperature)[8].

Consequently,evolutionary algorithms (EAs) and other stochastic search techniques seem to be promising alternative to traditional classical techniques. First, EA do not rely on the assumptions of differentiability, continuity or unimodality. Second, EAs are very robust, as they can handle problems with non-linearity from the constraints to multiple objectives and the time-varying parameters. Thirdly, they exhibit high level performance and great confidentiality in solving problems [6]. Computational intelligence which attempts to biologically emulate the adaptive evolutionary nature of living beings like reasoning, decision-making, learning, and optimization via a series of techniques is one suitable technique for system identification and parameter estimation.Several algorithms based on evolutionary computation principles have been successfully applied to identify the optimal parameters of IMs. However, it suffers the limitation of turning up of sub-optimal solutions due to improper equilibrium between exploitation and exploration in search strategies.

Many researches on PIIM nowadays are based on heuristics optimization models in solving multiobjectiveoptimization problems.In this paper, swarm based intelligence-search algorithm with good convergence speed called Bacterial Foraging Algorithm (BFA) was employed for determining the IM parameters.

BFA algorithm produces promising results for real-world optimization problems nowadays [3][9]. The parameter identification of induction motor (PIIM) using BFA is based on computing the values ofattribute functions which compares input-output data from IM and from simulation model. Minimizing these functions leads optimal pareto front leading to a more accuratemotor parameters.

III. Previous Work

Several methods have been proposed for the estimation of IM parameters. In [10] steady-state analysis of a three phase induction motor (TIM) was proposed. It was based on MATLAB/Simulink which simulates the effects of DC resistance, no-load and blocked rotor tests and estimates the values of stator and rotor resistances and leakage reactances. Skin effect and temperature were not taking into consideration. Also, [11] presents a rather simple, flexible and accurate method with less mathematical computations and derivations based on laboratory test model on IM created using “Motor Solve 5”. Again, [12] offered an in-depth explanation on PIIMbased on vector control of IM and simulated using the identified parameters. [13] developed an efficient soft computing approach for parameter estimation of induction motor (PEIM) and validates the results obtained through hardware implementation and evaluation of model. In [14], a method is described based on online estimation of the stator and rotor resistances of IM in the indirect vector-controlled drive.

Estimation of TIM equivalent circuit parameters which employ data provided by manufacturers on catalogs and nameplates data for motors was envisaged [15]. It focuses on six analytical methodologies used in the context of efficiency estimation at steady-state operation of the motor which improve the accuracy of calculations for the studied motors. Another work on the recursive identification of IM parameters using computer simulations based on simple algorithm derived from least squares technique then benchmarked with experimental results [16].

[17]provides a survey on the methods of IM parameter estimation using meta-heuristic methods. Several methods were compared. From the obtained results, it was clear that an exact circuit approach can be made to compute the equivalent circuit parameters. Another work on IM equivalent circuit PI based on heuristic algorithms was proposed. In the study, Differential Evolution Algorithm (DEA) and Particle Swarm Optimization (PSO) were used to investigate and determine the changes in parameters and performance of two IMs. It was seen that proposed algorithms determined the electrical equivalent circuit parameters of the motors with minimum errors[18]. Based on Artificial Bee Colony Algorithm (ABC), [19] proposed an effective method for estimating the parameters of IM. The work focuses on determination of the electrical parameters of the machine. Effectiveness of the method was measured through comparison with the results obtained using genetic algorithm (GA), particle swarm optimization (PSO), and power asynchronous machine parameters command (PAMP). The results show thatABC has fast converges rate than GA and PSO. A paper based on BFA for the parameters identification of IM was envisaged by [3] that came up with good estimated parameters and display the fact that the BFA technique is quite superior in the optimization process owing to its good convergence characteristics.

IV. Material And Methods

4.1 1dentification of Parameters

Three-phase induction motors (TIM) operating under steady-state are commonly modeled using a per unit (p.u) equivalent circuit standard. This enables the computation of quantities include: line current, power factor, input and output power and efficiency simply as a function of supply voltage, frequency and slip [15].The detailed induction motor modeling can be found in [3].The idea of the induction motor model is based on the method of determiningall the parameters of a mathematical model of the motor simultaneously with the desired structure, so that thesystem modelconforms with the input-output behaviour of the machine, realized based on the following approach [20]:

a. Experimental test was conducted covering the motor transient from standstill to steady-state condition, at the right supply frequency(f_s) and free rotation to standstill, resulting to three stator voltage and current values, and rotor speed.
b. A mathematical model is developed so as to simulate the experimental test of step a
c. Utility (cost) function is computed (integral squared error in this case)with a view to compere the output variables obtained from the experiment and those obtained by simulation for the optimization process.
d. The unknown motor parameters are updated iteratively so as to minimize the cost function in step c above.

The third and fourth steps are performed using the powerful optimization algorithm, the BFA. A remarkable and attractive technique for the parameter identification based on BFA that mimic the foraging strategy of E. *coli* bacteria was presented here. An induction motor was mathematically modeled and then simulated using MATLAB/Simulink software to estimate the parameters. The use of BFA has attracted interest from not only electrical engineers, but also from those in the field of all management and operational research [20].

4.2 Multiobjectic Optimization

Right from the time of inception of optimization technique from the field of operational research, several attempts were made to scalarized objective functions in different ways, from simple weighted sum (classical technique) approaches to the use of stochastic techniques for solving multiobjective optimizationproblem [21].

A typical optimization composed up; the objective function, *f*, which is the quantitative measure of the performance of the system followed by the decision variable vectors, *x* (those defining the system characteristics) and the constrain functions, c (those parameters restricting the variables) [3][21]. The optimization modeling for a given problem involves identifying the objective function(s) variables and constraints. After the model formulation, the BFA optimization algorithm is employed to find the pareto optimal solution. Optimality conditions are employed as confirmatory condition to make sure that the set of variables is indeed the pareto solution of the problem [3], partial knowledge is provided in order to restrict the search strategy to only part of the Pareto frontier [22].

Many real world problems involve multiple measures of performance, or objectives, which are simultaneouslyoptimized [21].

The multi-objective optimization problem (MOOP) can be written as follows:

$$\min f(x) = (f_1(x), \ldots, f_m(x))^T \ldots \ldots \ldots \qquad (1)$$

Subject to $x \in S$.

S is the decision space and $x \in$ S is a feasible set of decision variable vector. *m* is the number of objective functions f_k: $n \rightarrow m$, $k = 1,\ldots, m$, with *n*-dimensional decision variable vector *x* in the solution space *x* [3][21].

4.3 Bacterial Foraging Algorithm

Once an optimization problem is formulated, an appropriate optimization algorithm is use to find the solution. The choice of the algorithm that fits well is an important step, because it determines whether the problem can be solve rapidly, slowly or, whether the solution exist at all. The convergence characteristics and searching strategy of a typical optimization algorithm is highly desired. For almost two decades, the emergence of another member ofthe swarm based biologically inspired algorithm family – bacterial foraging algorithm based on social foraging behavior of *Escherichia coli*(E. *coli*) bacteria has attract great attention from all field of engineering and beyond.

As an evolutionary computation technique, BFA is also an iteration based optimization tool where the foraging (methods for locating, handling, and ingesting food) behavior of E. *coli* bacteria is mimicked.The major driving force of BFA is the E. *coli* bacteria foraging process where bacteria undergo four stages,namely, chemotaxis, swarming, reproduction, and elimination and dispersal [3][21].

(*i*) Chemotaxes: This is the motion patterns that the*E*. coli bacteria perform in search for nutrients. It either performs a linear motion (run) or rotation (tumble) in the chemical attractants and repellents environment [23].

In BFA, after a single step movement, the position of the *i*th bacterium is:

$\theta_i(j + 1, r, l) = \theta_i(j, r, l) + C(i)\angle\varphi(j)$ … … … (2)
$\theta_i(j + 1, r, l) = \theta_i(j, r, l) + C(i)$ … … … (3)
where; $\theta i\ (j, r, l)$ is the position of the *i*th bacterium at the *j*th chemotactic step in the *r*th reproductive loop of the *l*th elimination and dispersion event; $C(i)$ is theunit walk length; and $\varphi(j)$ is the direction angle of the *j*th step [21].
(*ii*) Repoduction (N_{re}):From the rules of evolution, bacteria reproduce themselves in appropriate conditions in certain manner [23]. After all chemotactic steps, reproduction takes place. Least healthy bacteria dies out and the other healthier ones splits into two [21]. This is described by equation ().

$$\mathrm{J}_{\mathrm{h}}^{\mathrm{i}} = \sum_{J=1}^{Nc+1} J(i, j, k, l) \cdots\cdots\cdots \quad (4)$$

Where; $J^i_h$is the health of bacterium *i*. In other to keep the population of the bacteria constant, the ones with the highest J_{h} values die. The remaining ones are allowed to partinto two bacteria in the same point [21].
(*iii*) Swarming: This phenomenoninvolves the bacteria congregate into groups and move as concentric patterns (high bacterial density)in search for optimum food region using cell-to-cell signaling [21][23].The mathematical representation for E.*coli*bacteria swarming can be represented by equation x:

$$J_{cc}(\theta, p(\alpha,\beta,\gamma)) = \sum_{i=1}^{s} J_{cc}^{i}\left(\theta, \theta^{i}(\alpha,\beta,\gamma)\right) \cdots\cdots\cdots \quad (5)$$

$$J_{cc}(\theta, p(\alpha,\beta,\gamma)) = \sum_{i=1}^{s}\left[-d_a \exp\left(-w_a \sum_{\lambda=1}^{p}\left(\theta_\lambda - \theta_\lambda^i\right)^2\right)\right] + \sum_{i=1}^{s}\left[-h_r \exp\left(-w_r \sum_{\lambda=1}^{p}\left(\theta_\lambda - \theta_\lambda^i\right)^2\right)\right] \cdots\cdots \quad (6)$$

$J_{cc}(\theta, p(\alpha,\beta,\gamma))$ is the attribute function value to be added to the actual objective function,S is the bacteria population, p is the number of parameters to be optimize, d_{a} is the depth of attractant released by the cell,w_{a} is the measure of the width of the attractant signalh_{r} is the height of the repellant effect andw_{r} is the a measure of the width of the repellant.
(*iv*) Elimination and dispersal: This is an event where the bacteria population in a given environment/region changes gradually during foraging or suddenly due to certain environmental changes. Some are killed or dispersed into a new part of the environment [23]. Owing to the fact that the bacteria may get stuck around the initial positions or local optima, it is possible for the diversity of BFA to change either gradually or suddenly to eliminate the accidents of being trapped into the local optima [21]. The flowchart for the BFA is shown in Figure (1).

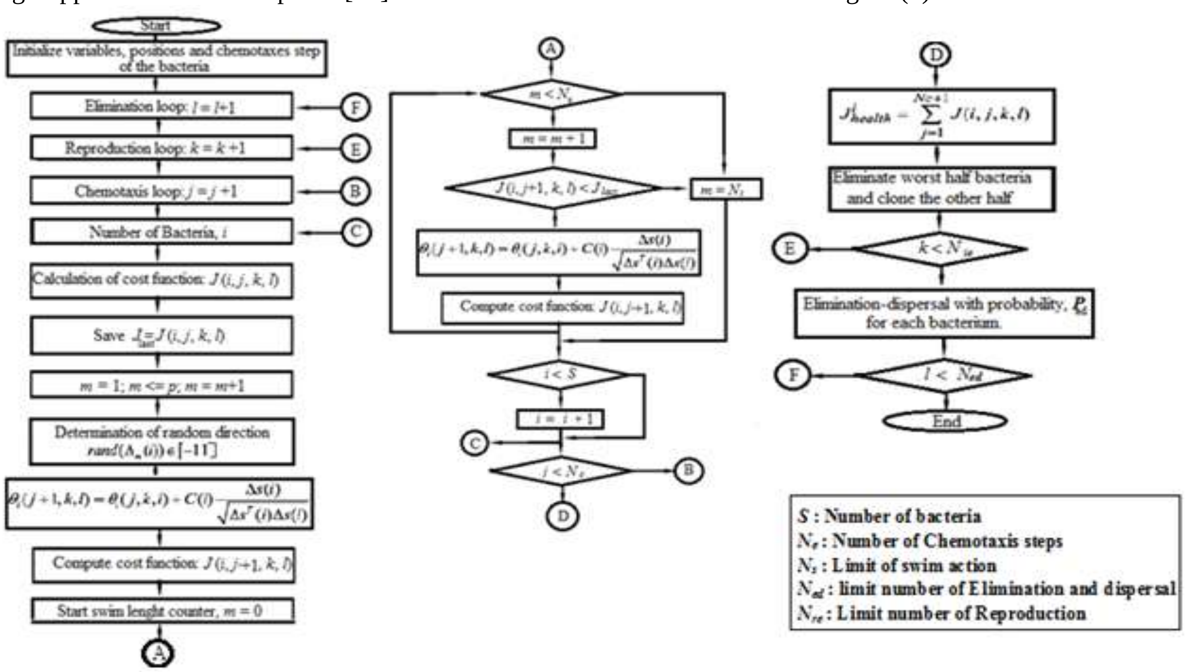


Figure (1): The BFA flowchart

4.4 Performance Evaluation Criteria

In its basic form the BFA optimization tool finds the minimum cost $\{J(\theta)\}$, $\theta \in R_p$ for the information about the nutrient profile$\nabla J(\theta)$, whilethe position of the bacterium and $J(\theta)$ represents an attractant-repellant profile which provides the cost value.

In sufficiently large samples, the cost function plays an important role forthe optimization procedure as it measures the quality of the represented solution and is always problem dependent. A proper cost function is very vital to achieve the desired performance through simulation [21].

In this work, the fitness function used is the mean squared error (MSE). The formulation of this cost function is as follows;

$$J(P) = \frac{1}{N}\sum_{k=1}^{N}[e(k)]^2 \dots \dots \dots \quad (7)$$

where $e(k)$ is the error value function, N is number of returned errors and k is counter [21].

Parameter identification of induction motor using bacterial foraging algorithm is based on computing the values of appropriate quality criterion which compare input-output data from IM and from simulation model. Minimization of these attributes leads to obtain more precise parameters.

Contrary to the single-objective optimization scheme, in multiobjective optimization, there does not exist a single solution that is optimal for all conflicting objectives, but front of solutions called Pareto frontiers, non-inferior, admissible, or efficient solutions [21]. The process to solve a constrained multi-objective parameter estimation using BFA technique was developed to obtain efficiently a high-quality solution. The BFA technique was used to determine the optimal equivalent circuit parameters of the IM, thus minimizing the error between the estimated and the manufacturer data. The position of the bacterium represents a candidate solution for solving the multi-objective parameter estimation problem.

4.5 Manufacturer Data of an Induction Motor

Actually, the name plate data of an IM is not sufficient to estimate the accurate parameters of themotor model over its entire operational range. To avoid this, the proposed estimation method uses the manufacturer data of the IM[24]. The manufacturer describes the IM behavior with data set which are: rated mechanical power, P_m, rated line-voltage, V, rated frequency, f, rated slip, S_n, rated current, I_n, rated power factor, pf, rated efficiency, η, maximum torque, T_M , starting current, I_s and starting torque, T_s [24].

Consequently, using the equivalent circuit model of IM in steady-state condition, the objective functions were formulated. Afterwards, using BFA, equivalent circuit parameters were estimated in a way to minimize the objective functions.

The various stages of the proposed work are given in Figure (2).

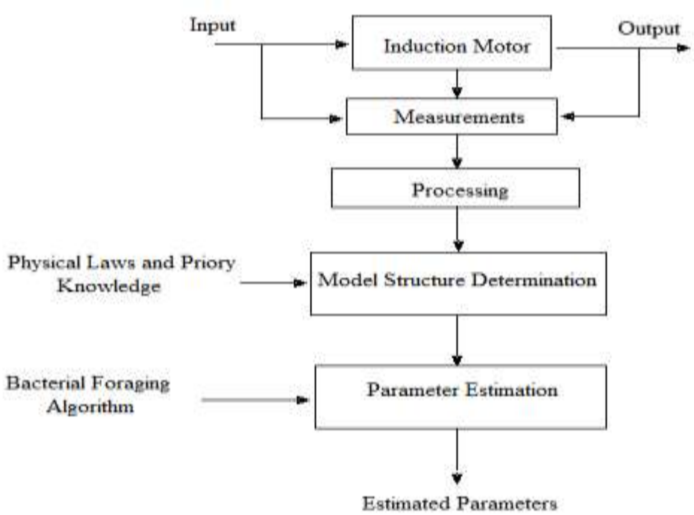


Figure (2): Stages for the proposed parameter estimation method

4.6 The Three Phase Induction Motor Model

A typical motor model consists of equations for voltage and current from the rotor and stator, the rotor and stator fluxes, the electromagnetic torque and the angular position of the rotor shaft. An idealistic machine is actually a symmetrical one with two poles. It has two phases and two pairs of identical windings on perpendicular axes in both the stator and the rotor fed its windings by two AC currents phase shifted by 90° angle as shown in Figure (3).It is treated as a two poles machine because the magnetic flux distribution repeats after each pole pair. In its basic configuration, the electrical and geometrical axes are identical, there by simplifying detecting the rotor position with reference to the stator during transient state [25].

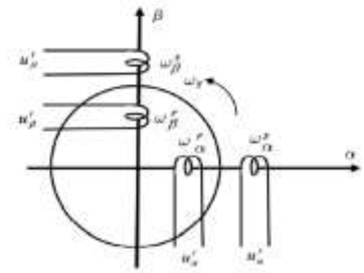


Figure (3): The ideal machine circuit

To be able to come up with the mathematical model, it is mandatory to use any of the rectangular coordinates commonly used in the motor analysis: the α and β coordinate system (fixed on the stator), the *d* and *q* coordinate system (fixed on the rotor and revolves with it in the same speed) and the *u* and *v* coordinate system (fixed on optional coordinates and revolves in an optional speed) [25].

Using the $\alpha - \beta$ coordinate system, the currents passing through the phases of the induction motor are given by:

$$i_a^s = i_\alpha^s \qquad \dots\dots\dots\dots\dots \qquad (8)$$

$$i_b^s = -\frac{1}{2} i_\alpha^s + \frac{\sqrt{3}}{2} i_\beta^s \dots\dots\dots\dots\dots (9)$$

$$i_c^s = -\frac{1}{2} i_\alpha^s + \frac{\sqrt{3}}{2} i_\beta^s \dots\dots\dots\dots\dots (10)$$

i_α^s : stator current on the axis alpha, i_β^s: stator currenton the axis beta, i_α^r : rotor current on the axis alpha, i_β^r : rotor current on the axis beta, u_α^s : stator voltage on the axis alpha, u_β^s: stator voltage on the axis beta, u_α^r : rotor voltage on the axis alpha, u_β^r: rotor voltage on the axis, $\omega_\beta^r = \omega_r$: the angular velocity.

The motor torque and speed equations are obtained using equation (x) and (m) respectively:

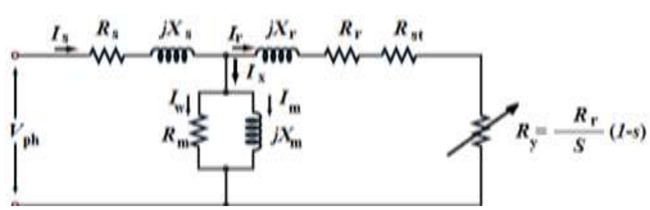
$$\frac{3}{2} pM = \left(i_\beta^s i_\alpha^r - i_\alpha^s i_\beta^r\right) \qquad \dots\dots\dots\dots \qquad (11)$$

$$\frac{d\omega_r}{dt} = \frac{p}{J}\left(T_{em} - T_m\right) \qquad \dots\dots\dots\dots \qquad (12)$$

Where: T_m: load torque, p: the number of pairs of poles, J: moment of inertia and T_{em}: electromagnetic torque.

4.7 The Exact Circuit Model

The problem formulation in exact equivalent circuit model uses the maximum torque (T_{max}), full load torque (T_{fl}), starting torque (T_{str}), and full load power factor (*pf*) to estimate the five independent parameters stator resistance (R_1), rotor resistance (R_r), stator leakage inductance X_s, rotor leakage reactance $X_r$and magnetizing leakage reactance X_m [26]. Generally, it is assumed that the stator and rotor leakage reactances are equal, X_1=X_2[24]. The detailed exact equivalent circuit model can be found in [3]. Figure (4) shows the exact equivalent circuit diagram.



Figure(4): Exact equivalent circuit model.

Using the *IEEE* 112 standard, Thevenin equivalent circuit was proposed and used for problem formulation, as shown in Figure (5).

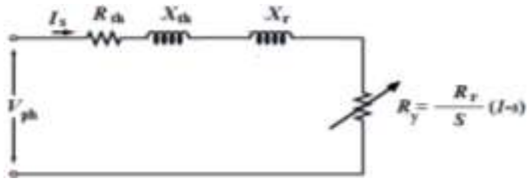


Figure (5): Thevenin equivalent for exact circuit of three phase induction motor.

Based on the exact equivalent circuit model, the estimation task can be formulated using the optimization problem of equations 6 and 7:

Minimize $J_e(x)$, $x = (R_s, R_r, X_s, X_r, X_m)$ … … … (13)

Where;

$J_e(x) = (g_1(x))^2 + (g_2(x))^2 + (g_3(x))^2 + (g_4(x))^2$ … … … (14)

Subject to:

$0 \le R_s \le 1,\ \ 0 \le R_r \le 1,\ \ 0 \le X_s \le 1,\ \ 0 \le X_r \le 1$

$X_i^{min} \le X_i \le X_i^{max}$

X_i^{min} and X_i^{max}, are the minimum and maximum values of the parameter X_i, which is the optimal value defined as the pareto optimal solution.

The values; g_1, g_2, and g_3 are error between the calculated and manufacturer value of the full load torque, starting torque and maximum torque, respectively. Also, g_4 represents the error between the computed and manufacturer value of the full load power factor. The sum of squares of moment error function $(g_1(x))^2 + (g_2(x))^2 + (g_3(x))^2 + (g_4(x))^2$ is called the suitability function and the BFA minimizes the error value in the optimization [27]. According to [27], we have the following equations:

Maximum torque constraint;

$$\frac{T_{\max}(c) - T_{\max}(mf)}{T_{\max}(mf)} \le \pm 2$$

$T_{max}(c)$ is the estimated maximum torque.

$$g_1(x) = \frac{\dfrac{K_t R_r}{s\left[(R_{th} + R_r/s)^2 + X^2\right]} - T_{fl}(mf)}{T_{fl}(mf)} \quad \text{… … …} \quad (15)$$

$$g_2(x) = \frac{\dfrac{K_t R_r}{\left[(R_s + R_{th})^2 + X^2\right]} - T_{str}(mf)}{T_{str}} \quad \text{… … …} \quad (16)$$

$$g_3(x) = \frac{\dfrac{K_t R_2}{2(R_{th} + \sqrt{R_{th}^2 + X^2})} - T_{\max}(mf)}{T_{\max}(mf)} \quad \text{… … …} \quad (17)$$

$$g_4(x) = \frac{\cos(\tan^{-1}(\dfrac{X}{R_{th} + R_r/s})) - pf(mf)}{pf(mf)} \quad \text{… … …} \quad (18)$$

The thevenin equivalent values of resistance R_{th} , voltage V_{th} , and reactance X_{th} are respectively given by Equations 19, 20 and 21 as follows;

$$R_{th} = \frac{R_s X_m}{X_s + X_m} \quad \text{… … …} \quad (19)$$

$$V_{th} = \frac{V_{ph} X_m}{X_s + X_m} \quad \text{… … …} \quad (20)$$

$$X_{th} = \frac{X_s X_m}{X_s + X_m} \quad \text{… … …} \quad (21)$$

Equations 22 and 23 explain further.

$$K_t = \frac{3V_{th}^{\ 2}}{\omega_s} \cdots \cdots \cdots \qquad (22)$$

$$X = X_r + X_{th} \cdots \cdots \cdots \qquad (23)$$

K_t is the constant coefficient, ω_s is the angular velocity, s is the slip, and V_{ph} is the supply voltage. For Equation 6 to be minimized, additional constraint condition for the values of the calculated parameters must besatisfied. This is called the efficiency balance constraint. This is expressed in Equation 24.

$$\eta_{fl} = \frac{p_{fl} - (I_s^{\ 2} R_s + I_r^{\ 2} R_r + P_{rot})}{P_{fl}} \cdots \cdots \cdots \qquad (24)$$

The P_{fl} and P_{rot} represent the rated power and rotational losses, respectively. With this restriction, the calculated efficiency is forced to be equal to the manufacturer efficiency. Hence, maintaining a balance [27].

Again, it is clear that the rotor parameters have been referred to as the stator side. Also, it is assumed that the core-losses are negligible [28].

Ultimately, in a typicalIM,the losses in stator are copper and core losses, while copper and frictional losses occur in the rotor. Also, small core losses occur in the rotor. The efficiency of the IM can be determined by connecting variable load toits rotor shaft and directly measure its input and output variations[2]. This is expressed in Equation 25 as follows.

$$\eta = \frac{P_{output}}{P_{input}} \times 100\% \cdots \cdots \cdots \qquad (25)$$

4.8 Experimental Structure

The method for PIIM was experimentally tested on a 3-phase IM. In the experimental measurements,input signals were obtained from the experimental test using 4 poles, 50 Hz, 240 V,5-*hp* and star connected induction motor. The input voltage (V_i), current (I_i) and the power (P_i) are recorded using digital voltmeter, digital ammeter and a wattmeter respectively. Also, power factor meter was used to measure the machine power factor (*pf*). The TIM is connected to speed encoder to torque-meter then to dc machine load. Signal conditioning that allows phase voltages and currents to be sent to the inputs of the data acquisition board (DAQ)and voltage variator form part of the experimental workbench requirements. The set-up was made tomonitor voltage (*V*), current (*A*), torque (*N-m*), speed (*rpm*) and the vibration of the TIM.

To estimate the parameters of the IM, experimental samples were taken from the actual motor. As it is known, by the load torque changing, motor speed, current and power factor change. The current, power factor and speed measurements are sampled so as to increase the accuracy of optimization algorithmsto have a good performance in searching the problem domain [29]. Figure (6) shows Simulink model for the parameter estimation optimization process.

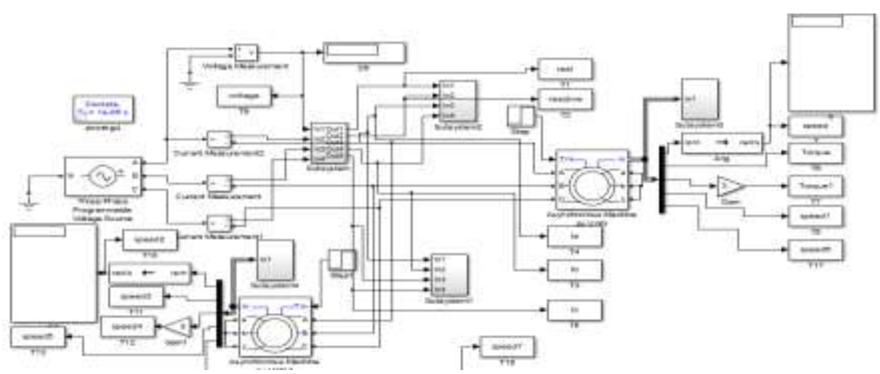


Figure (6): Simulink model for the parameter estimation optimization process.

V. Simulation Results and Discussion

In order to verify the effectiveness of the proposed scheme for the IMdrives parameter identification scheme, Matlab/Simulink software was employed to perform simulation tests of the overall drive.

5.1 Results

The BFA parameters choice used in this research is presented Table 1. The parameters were used to determine the optimal parameters of the motor based on the exact circuit model (J_e). The BFA was evaluated in comparison with a result obtained from the experiment. The parameter setting for the BFA was initialized from the values obtained from the experiment.In order to verify the feasibility and the performance of the BFA, computer simulations have been carried out using MATLAB/Simulink software.

Table 1: Selected Parameters for BFA Optimization

Parameter	Value
Search Space Dimension	p=3
BacteriaPopulation	s=4
Chemotactic Step Length (N_c)	N_c=4
Number of Runs Step (N_s)	N_s=4
Reproduction Step Number (N_{re})	N_{re}=4
Number of Elimination and Dispersal Events (N_{ed})	N_{ed}=4
Population of bacteria for production (S_r = s/2)	S_r = s/2
Probability of Elimination/Dispersal of Bacteria (p_{ed})	p_{ed} =0.25

Table 2 presents the technical characteristics (the original data) of the test motor used in the experiment. It is assumed that for simulation purpose, the IMis fed by source voltage inverter running in steady state at nominal speed condition.In this case, the induction machine parameters were assumed to be constant through the simulation compared with experimental values.

Table 2: Manufacturer (Original) Data for the Test Machine.

Specification	Motor
Capacity (*HP*)	5
Voltage (*V*)	400
Current (*A*)	8
Frequency (*Hz*)	50
Number of Poles (*N*)	4
Full-Load Slip (s)	0.07
Starting Torque, T_{str} (*N-m*)	15
Maximum Torque, T_{max} (*N-m*)	42
Stator Current (A)	22
Full-load torque, T_{fl} (*N-m*)	25

Source: [27].

The unmodeled dynamics such as saturation, hysteresis and temperature variations are neglected as in [16]. The values of J_e function obtained for the motor are reported in Table 3.

Table 3: Rating Results of J_E, Considering Motor.

Suitability Function (J_E)	BFA
Minimum	0.0030
Maximum	0.0030
Mean	0.0030

It can be seen from Table 3, the BFA has lower values of mean suitability function, J_E .

The motor estimated parameters were compared for starting torque (T_{str}), maximum torque (T_{max}), full load torque (T_{fl}) and full load power factor (pf_{fl}) values provided by the manufacturer. The percentage errors between the nameplate, experimental and the calculated (BFA) values were given in Table 4.

Table 4: Comparison of Experimental and BFA with Manufacturer Data, J_E, for the Motor.

Motor Torque	Manufacturer Value	Experimental Value	Percentage Error (%)	BFA	Percentage Error (%)
T_{st}	15	16.70	11.3	14.92	-0.53
T_{max}	42	42.00	0.00	42.00	0.000
T_{fl}	25	27.01	8.04	25.07	2.800
pf_{fl}	0.87	0.875	0.575	0.872	0.172

The main objective of the comparison in Table 4 is to evaluate the accuracy of the BFA approach with regard to the actual motor parameters.The errors between the calculated and original values of the parameters were shown. The magnitudes of the torque errors obtained using the BFA method are comparatively lesser than those obtained using the experimental method.

The simulated estimated parameters results given in Table 6 show that the BFA method provides lesser percentage errors. Percentage error was employed as a performance measure to show the clear deviation of the torque and power factor values for the BFA and experimental with respect to the true value (Manufacturer value). So, BFA works considerably better than the experimental values since it leads to (almost in all items) smaller torque and power factor percentage errors.

The overall summary of the exact circuit model estimated parameters for the motor (5 *h.p*) is depicted in Table 5.

Table 5: Summary of Exact Circuit Model Identified Parameters for the Motor (5 *h.p*).

Motor Torque	Manufacturer Value	Experimental Value	Percentage Error (%)	BFA	Percentage Error (%)
R_s	01.80	03.00	66.67	01.81	00.56
R_s	05.27	07.89	49.72	05.30	00.57
R_s ,R_r	14.81	17.30	16.81	15.00	01.28
X_m	409.6	82.11	-80.0	401.9	-01.88

According to the results from Tables 5 the proposed approach (BFA) provides better performance than the experimental method in all tests as the parameter values deviates with smaller values from the true manufacturer value and it has lesser percentage errors.

Due to the fact that the convergence rate of EAs is an important characteristic to assess their performance for solving optimization problems, the convergence of the algorithm's functions J_e was compared in terms of the fitness function versus number of iteration. Figure (7) shows the convergence graph for the BFA.

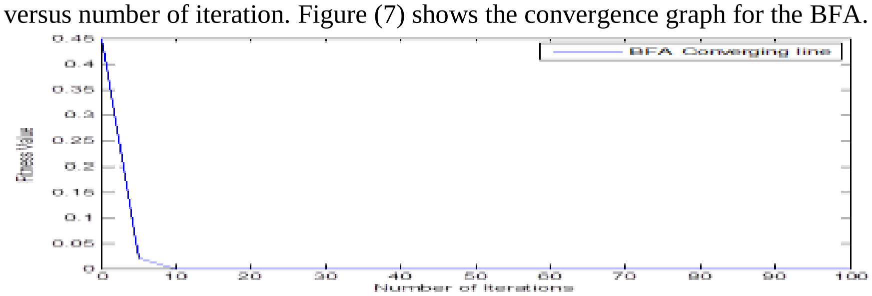


Figure (7): Convergence characteristics for the BFA.

The performanceoftheoptimizationtechniqueinterms of fitnessvalue of the BFA for the best run out of 25 trials of the motor is shown (Figure (7)). It can be observed thatthefitnessvalue reduces over the iterations and convergestominimumvalues after just 10th iterations for the IM parameter estimation. This confirms that BFA is very much suitable tool for multi-parameter optimization problems. Because more number of objectives to be optimized has less significant change in the execution time which is achieved not by increasing the bacteria population, but through increasing the chemotactic steps length.

Figures (8) down to (22) show the remarkable plots that certainly describe the characteristics of the BFA for the motor along with the nameplate and the experimental results.

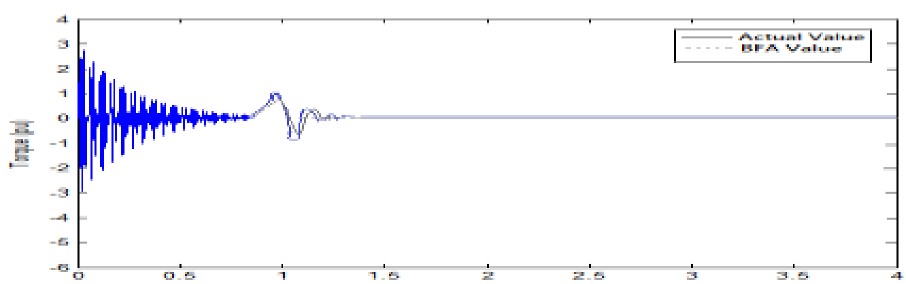


Figure (8): Dynamic behavior of transient torque characteristics with No Load.

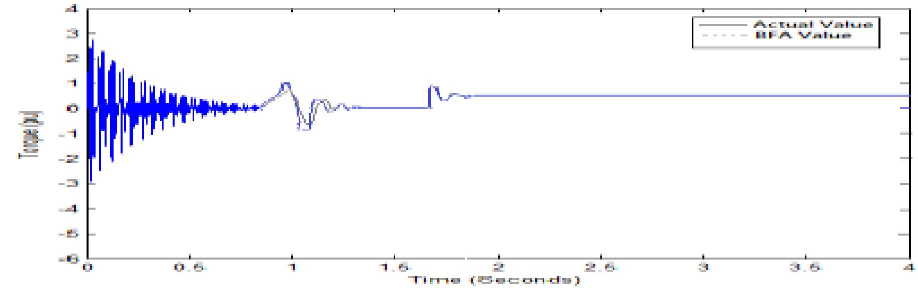


Figure (9): Dynamic behavior of transient torque characteristics at per unit step load of 1.

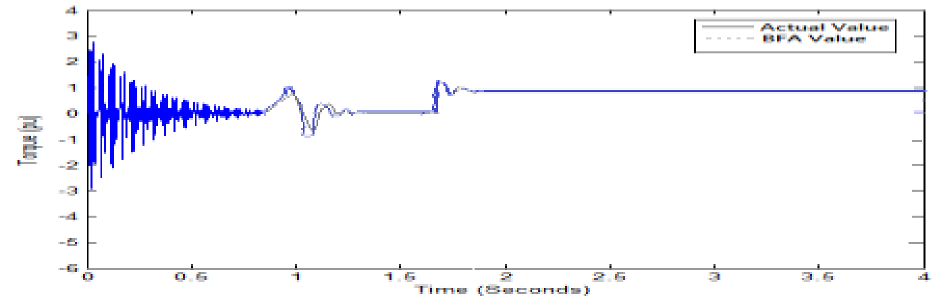


Figure (10): Dynamic behavior of transient torque characteristics at per unit step load of 1.5.

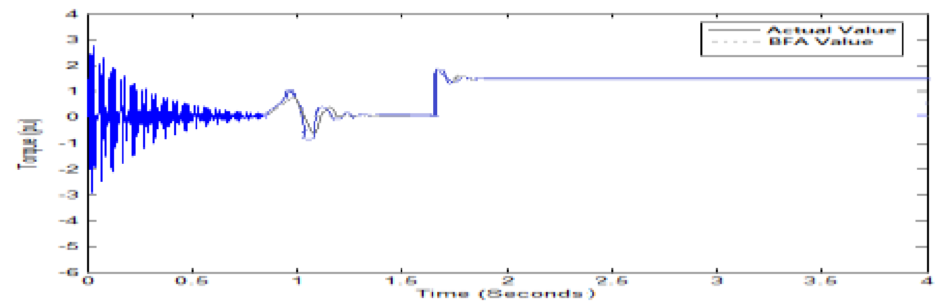


Figure (11): Transient torque characteristics at per unit step load of 2.0.

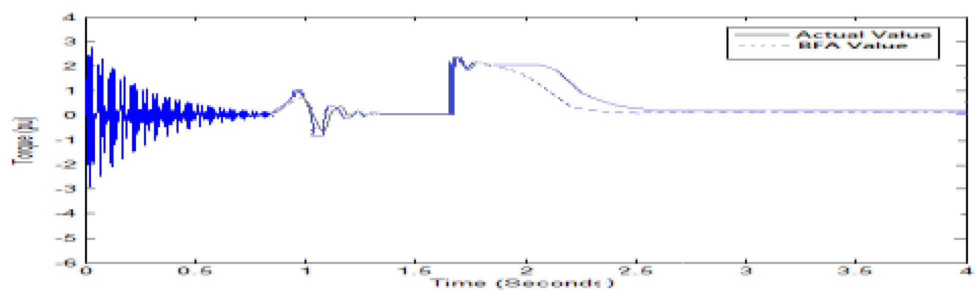


Figure (12): Dynamic behavior of transient torque characteristics at per unit step load of 2.4

The torque-speed behavior of the induction motor is shown in Figure (13), where the comparison has been made between the experimental and the BFA results. Also, the steady state output power against rotor speed was plot in Figure (14). So also, Figure (15) shows the comparison of the power factor against speed for the motor.

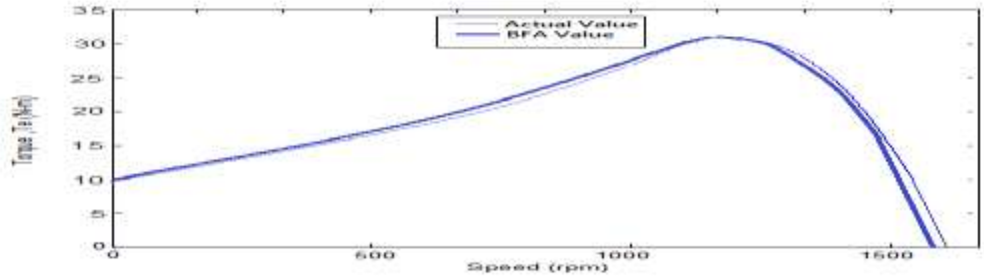


Figure (13): Steady state electromechanical torque-rotor speedcurve for the motor.

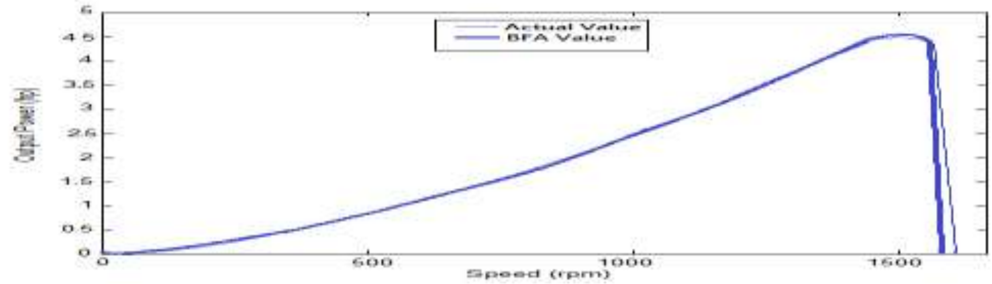


Figure (14): Plot of the steady state output power against rotor speed.

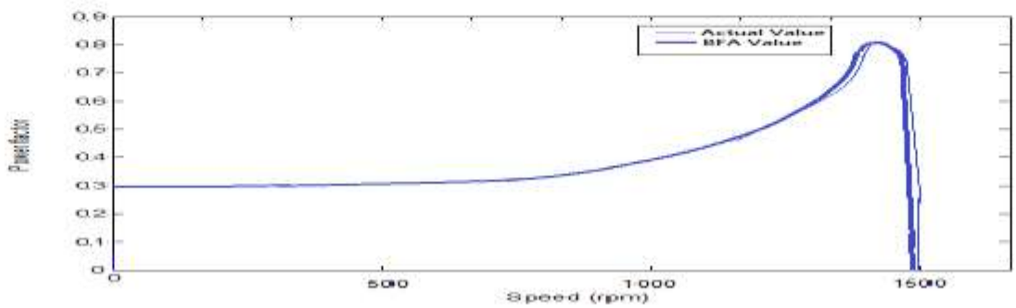


Figure (15): Steady-state power factor against rotor speed.

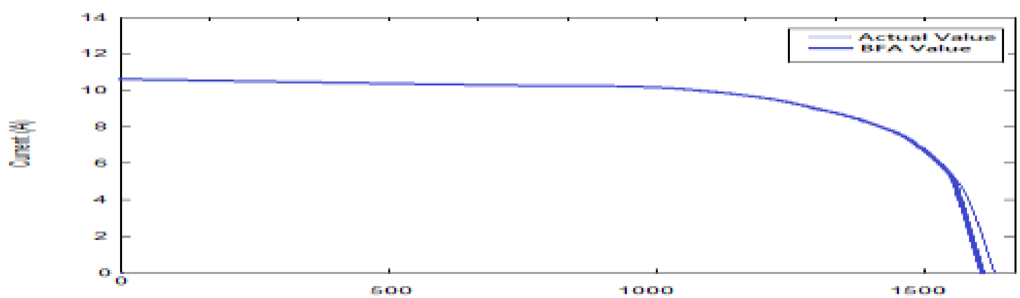


Figure (16): Steady-state current against rotor speed.

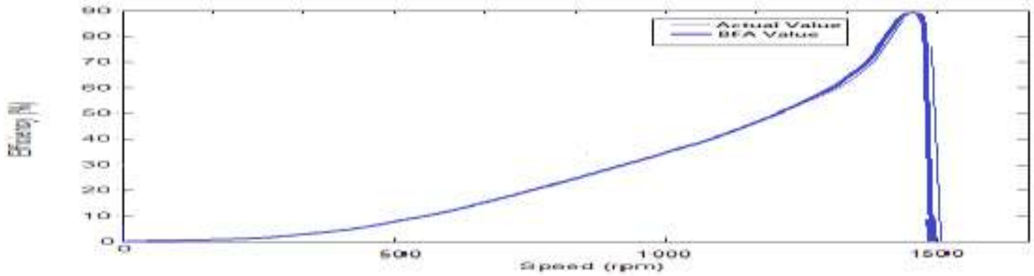


Figure (17): Steady-state efficiency against rotor speed.

From the all the plots (Figures 13, 14 and 15), it is clear that the BFA model yields great accuracy.

The accuracy of the IM parameter identification relies on the frequency of the applied input voltage, number of generations and the accuracy of simulation model employed. Also, the size of the sampling period which in turn depends on the available computing resources is also another factor [30].

The validation test is made in other to test the robustnessof the BFA method. This is done when the IM is subjected toinput load disturbances. Testwas carried out and the motor torque was provided by the direct current motor coupled by the shaft to theinduction motor. From no-load condition to 0 per unit load (p.u) after a period of time to per unit step load of 2.4 were applied. Figures (18) to (22) show the comparison of the simulated transient behaviors of the test motor stator phase currents as a function of time for the actual and the BFA.

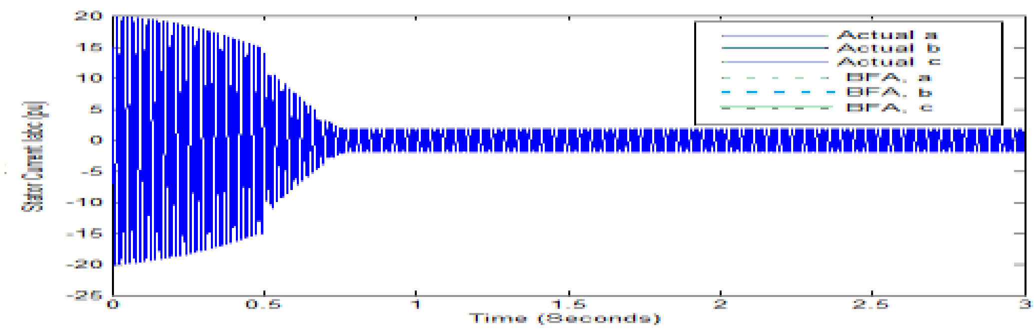


Figure (18): Transient characteristics for stator current versus time on no-load.

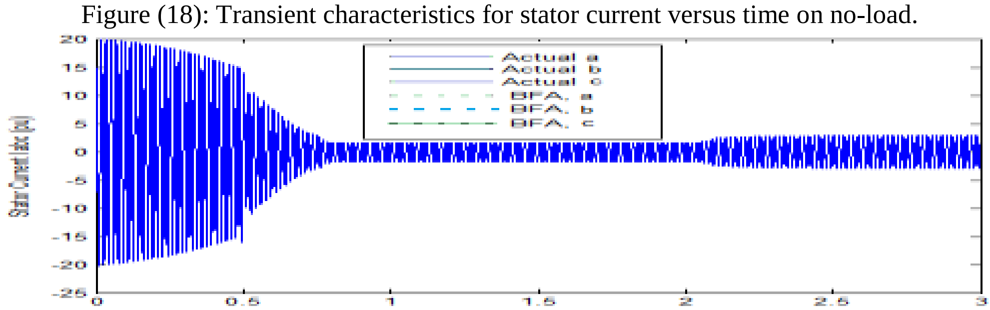


Figure (19): Transient characteristics for stator current versus time with per unit step load of 1.

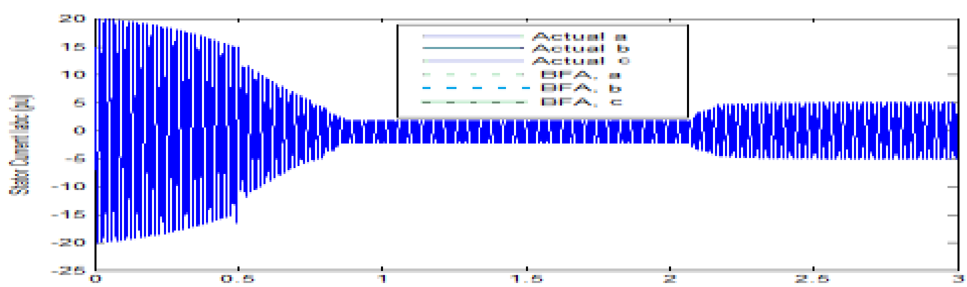


Figure (20): Transient characteristics for stator current versus time with per unit step load of 1.5.

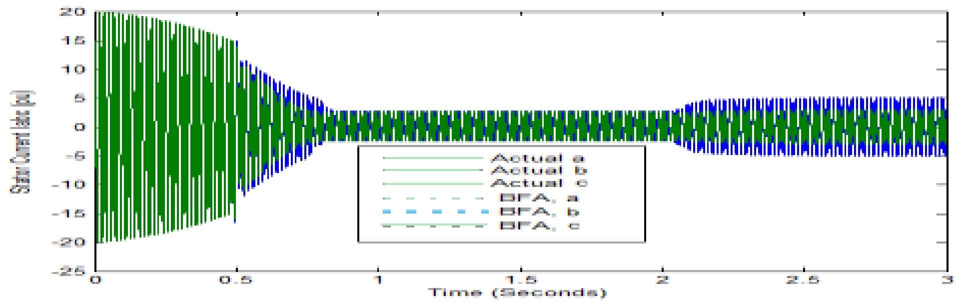


Figure (21): Transient characteristics for stator current versus time with per unit step load of 2.0.

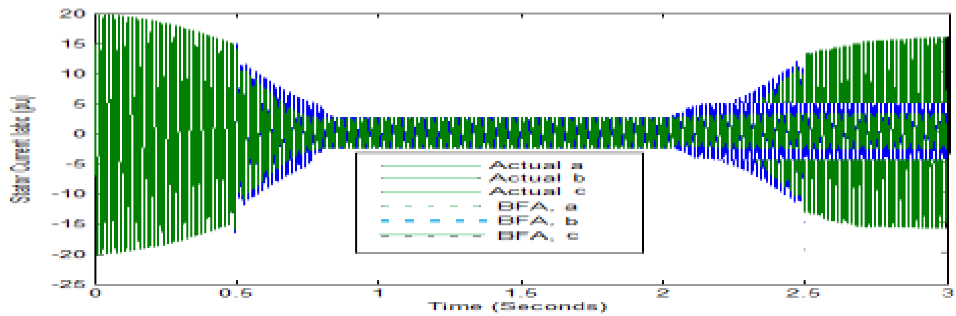


Figure (22): Transient characteristics for stator current versus time with per unit step load of 2.4.

5.2 Discussion

MATLAB/Simulink tool box have been immensely utilized to estimate electrical parameters of the induction motor. The plot depicted in Figures 7 clearly shows the faster convergence of BFA as it reaches its final value after just10 iterations. The results obtained from the plots in Figures 10 to 22 show that BFA can be used for the PIIM. Furthermore, BFA shows both more robust results and faster convergence capabilities with the 5 *h.p* motor. Additionally, it is a lot simpler to implement and appears to require less parameter tuning. Also, the method proves to be effective for the control of IMs and as well the analysis of mechanical loads connected to the motor. Since the aim of this study is to determine if BFA is a feasible approach to PIIM,its success on the problems certainly underlines that it is a promising candidate for parameter identification using real motor data.

VI. Conclusion

The results of the parameteridentification using BFA method shows good parameters, low starting current, there by less voltage drop, hence minute disturbance to voltages on the supply lines. These improve the operational performance of the IM. Also, the results shows that the BFA is a quite accurate method owing to the fact that it provides large starting torque in a short transient period; thereby external starter is not necessary, then external equipment charges reduced. It also shows smooth startup with fewer disturbances, hence lesser jerks practical machine would be obtained. These features give the BFA an edge over lot of stochastic algorithms counterparts as reliable and accurate multi-objective optimization tool andits inherent ability to escape from trapping at local minima. Again, it proves to be an accurate on-line algorithm and it is a good approach for identifying the electrical parameters of induction motor if appropriate experimental measurements and good objective functions were available. The BFA method for estimating the asynchronous motor parameters can further be improved by the use of modified BFA techniques to increase the convergence speed and further increase the accuracy of the algorithm. Also, by examining different performance measures in order to come up with the best fitted objective function that rhymed up with the problem. Again, chosen appropriate mathematical model (such as the coordinate system, circuit model etc) produce good system response and less computational overheads, thereby shorten the simulations run time.It is recommended that further research has to focus on evaluating the efficiency of induction motor through the measured current, power factor and the input power to be applied to the proposed method along with the objective function without any intrusive test.

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