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Parameters Identification of Induction Motor Using Bacterial Foraging Algorithm

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***Abstract*—This work proposed a multi-attribute optimization technique for identification the equivalent circuit parameters of a three-phase induction motor from the name plate data. A fitness function was obtained and compared with the computed steady-state performance of the exact equivalent circuit at prospective parameters set with rated manufacturer data. A biologically inspired algorithm called Bacterial Foraging Algorithm (BFA) was used in the optimization. The feasibility of the BFA optimization technique was tested and examined on a motor of rating 5 horse-power (*hp*). The performance of the BFA optimization scheme was tested by simulation and real-time experiments under challenging load variations. Simulation results demonstrate the ability the BFA to produce better results with less error values and good convergence characteristics.**

Keywords- Induction Motor, Parameters identification, Bacterial Foraging Algorithm, Optimization, Fitness Function, Steady-State Performance.

I. INTRODUCTION

In a world of ever-increasing growth of industries, increasing the usage of induction motor (IM) is currently at the forefront of this transformation. IM works on the principle of electromagnetic induction, with its rotor producing torque and the stator windings producing the excitation field and supplying the energy that is converted to mechanical output. The absence of sliding mechanical part in IM coupled with the consequent saving in terms of maintenance makes it the fastest growing industrial derive [1]. Also, IMs operate in harsh environmental conditions [2]. Typical motor classification is shown in Figure 1.

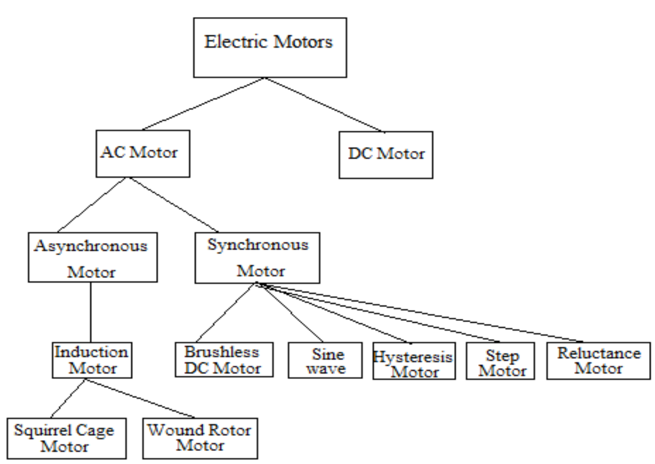

Figure 1. Electric Motor Classification

Currently, number IM drives are based on scalar control principle and the control algorithm is implemented on simple microcontroller. But the advanced control technique of the motor control requires fast processor which increases the price of drives [3]. Upon the high reliability and ruggedness of IMs, they suffer from various stresses leading to unavoidable modes of failures/faults. This is especially when supplied by AC drives where the winding insulation experiences potentially huge stress due to voltage containing high harmonics. So, accurate parameters identification (PI) of IM becomes imperative because it properly assesses machine performance [4] and for fault diagnosis which is a prerequisite to many applications such as sensor-less control [2] and model predictive control.

However, motor drives such as rolling mills, paper winding processes and hoist crane systems, IMs are connected to complex mechanical systems and the commissioning processes are performed after coupling of the mechanical structure. As such, it may not be possible to perform a pre-running test, owing to motor poor operation results from inaccuracy in the parameters. This may cause a potentially massive mechanical damage to the plant. Hence, standstill parameter identification techniques deemed necessary [5].

A. Overview of Induction Motor Parameter Identification

Induction motor parameter estimation is the science of building mathematical models of a dynamic system from observed input-output data. It is obvious that the interface between the real world of applications and the mathematical world of control theory and model abstractions [1]. The parameters of the equivalent circuit of the motor have to be estimated in order to tune the controllers, a process termed self-commissioning and done automatically by the controller [6]. Certainly, it is quite imperative to implement drive and control systems for IMs, and that requires the knowledge of motors' mechanical and electrical parameters. But these data are not immediately available in some cases, or the parameters' values may change due to the wear, work point, winding temperature [7] and even motor components. These problems can be overcome if an effective parameter estimation technique is available [8]. So, accurate identification process is imperative for proper operation of the motor [9][7]. The main purpose of the estimation of the motor's parameters is to determine the exact instantaneous values of the machine [10].

Ultimately, the fact that widespread industrial motors nowadays are induction motors; the analysis and control of the motors are actually based on its circuit parameters. So, accurate measurement of electrical parameters based on optimization is very important [11]. When developing a model-based approach for parameter identification (PI) of IM, it deems necessary to commence with correct model that sufficiently describes the measured data. It is also imperative to assess how well the actual parameters of the model are estimated from the measurements. If the real and identified model parameter values fail to match well, it may result in a wrong assessment of the motor performance. So, before using a motor model in a parameter estimation technique, it is quite worthy to test the identifiability of the model so as to be absolutely sure that its parameters are uniquely identifiable [1]. Nowadays, the PI methods of IMs are mainly off-line and online estimations. For obvious reasons, the off-line identification is mostly used. This is due to the fact that the basic parameters of vector control can be provided with less complex operation. [12]. Presently, however, complicated and accurate vector-controlled machines receive great development owing to the fact that the traditional steady-state parameters based on dynamic model is insufficient to represent the exact dynamic behaviors of the motor with high accuracy.

B. Research Motivation and Objectives

Actually, the accurate PI of IM is a hugely challenging issue for controlled drives system [13]. Researchers have done quite significant work to develop feasible method for IM parameter estimation. However, identification of the parameters using traditional methodologies is still not straightforward, because different researchers use different technique (as in literature). Recently, researchers have developed many optimization models for solving complex arrays of problems using BFA. This is because it produces better results [14]. The results obtained from its previous usage revealed that it may be a good choice for IM parameter estimation. For the mathematical modeling of the motor operation modes, it is necessary to come up with the machine parameters. The result of having wrong parameter values used in the controllers (as in vector control) give rise to error in both flux and torque. This thereby altered the motor dynamics performance. This is overcome using, methods (such as optimization) in control engineering. Lot of evolutionary (inspired by the natural evolution) optimization schemes were employed to solve the optimization problem. But, were less successful due to converge towards local optima rather than the global optimum (if the cost function is not properly defined). Also, another disadvantage of these optimization schemes is that the estimated parameters solely rely on initial guess of parameters, which is prone to change and results to totally different convergence values of the algorithm. Again, the amount of computation time or convergence period is another issue as it may pose a serious problem for system which demands faster convergence time. Sometimes, some evolutionary algorithms have their performance degraded when objective functions are highly co-related (as in GA). With these demerits, researchers explore more on collective intelligence of groups of simple animals based on the behaviour of real-world organisms (swarm-based algorithms), as a problem-solving complex intelligence technique which attempts to biologically emulate living organisms, from reasoning, self-organizing behavior, decision-making, learning ability, decentralized foraging process and optimization through special ability of parameter estimation [11].

The performance parameters data of an IM which are; breakdown torque, locked rotor torque, full-load power factor, full-load efficiency, etc (provided by the manufacturers in their data sheets) formed the basic requirement for the estimation of motor equivalent circuit parameters [15][16]. Since the IM drives demands the exact knowledge of its parameters, an effective PI method became essential in other to determine the motor parameters such as the stator and rotor resistances, leakage and magnetizing inductances [11].

II. Previous Work

Here we review previous approaches to parameters identification of induction motor. Several techniques have been proposed to estimate the speed and flux pattern of an induction motor. Also, vast literature exists on identification schemes have been studied so far and have been proposed for dynamic PI of IMs. [17] worked on algorithm for determination of parameters of induction traction motors in the presence of measurement errors. The errors result to biased estimates of motor parameters based on annulling the effect of noise that increases the accuracy of the estimated parameters, but [18] used artificial neural networks in a vector-controlled IM for online determination of the stator and rotor resistances.

Numerical simulations were given attention on several models to portray the effectiveness of the envisaged scheme [19]. [20], employed hybrid genetic algorithm and particle swarm optimization (HGAPSO) and determine the parameters of three-phase IM. They carried out the performance evaluation through comparison of the method with the results of the Classical, GA, DE and PSO. But [21] proposes a work on adaptive system PI of an IM based on PSO and measure the performance of the proposed algorithm by comparing the results with those of genetic algorithm (GA) and simulated annealing (SA) for the benchmark application with six unknown parameters identified. The dynamic inertia-weighted PSO algorithm used significantly outperforms the GA and SA techniques. A paper on simple PSO called modified PSO was also employed by [22] for the PI suggested the use of modified PSO optimization and came up with the best model parameter. They compared the performance of the method with, line search, conventional PSO and GA.

The Determination of National Electrical Manufacturers Association NEMA design IM parameters from manufacturer data [23], tested on more than 300 large-size HV IMs. The have shown that the method is effective through computing various external machine quantities based on estimated parameters compared with name-plat values. But [24] offered an intensive explanation on induction motor parameter identification based on vector control using MATLAB/SIMULINK tools. They simulate three-phase IM vector control system using the identified parameters. Another work by [25] described and demonstrated a method that determines the parameters of an electromechanical model of an IM. The parameters were estimated from poor guessing, restricted well within the range of magnitude of the physical parameters.

III. METHODOLOGY

A. Identification of Parameters

Without loss of generality, only the electrical parameters will be estimated. The accurate determination of the electrical parameters of the IM to achieve excellent performance is becoming a serious challenge owing to its importance, more especially when the end user buys separately; the inverter and the machine from different suppliers and that the parameters are not correctly known prior to start-up. As such, it is very important to estimate these parameters before any operation [26]. The on-line and off-line operations form the basis for induction motor parameter identification.

Five (5) control parameters were selected for the determination of defining features of the machine. These include: rated values (rotational speed, torque, phase voltage), motor efficiency and the power factor [27]. The IM parameters actually change with the changes in environmental factors. These parameters are; stator resistances (R_1), rotor resistance (R_2), stator inductances (L_1), rotor inductance (L_2), and the mutual inductance between stator and rotor (L_m). The factors responsible for changes of the IM running parameters are as follows:

1) ***Temperature changes:*** This is the energy in form of heat (influence mechanism) released during transformations from electrical energy into mechanical energy. Other are change of external environment, aging degree and the wear and tear degrees. The parameters are influenced by stator resistances (R_1), rotor resistance (R_2). It has the following change law;

$$R_a = \frac{235+t_a}{235+t_b} R_b \quad (1)$$

R_a is the resistance at initial temperature t_a, and R_b is the resistance at final temperature t_b [12].

2) ***Frequency changes:*** In this case, the influencing mechanism is the frequency changes of the current due to skin effect. This change is directly related to the rotor slot type of IM. The IM motor parameters are influenced by rotor resistances (R_2) and rotor inductance (L_2) [12].

3) ***The saturated magnetic factors:*** The influencing mechanism of the IM is well within the linear region of the *B-H* curve, for smaller values of iron core reluctances. In this case, the parameters influenced are; rotor resistance (R_2), rotor inductance (L_2) and the coefficient of leakage inductance (σ) [12].

4) ***The stray loss:*** In this case the influence mechanisms are the eddy current losses and the hysteresis losses. Also, there are higher-order harmonic losses. The IM parameters are affected by stator inductance (L_1), rotor inductance (L_2) and mutual inductance (L_x) [12].

Clearly, the IM's parameters change with temperature, frequency and saturation, hence, any parameter mismatched results to the induction motor performance degradation [28]. As a consequence, the IM's parameters deviate from their nominal values in operation [29].

B. Multiobjective Optimization

Multiobjective optimization (MOO) involves the adjustment of the input variables (or process) and came up with optimum value of the result. This process is shown in Figure 2.

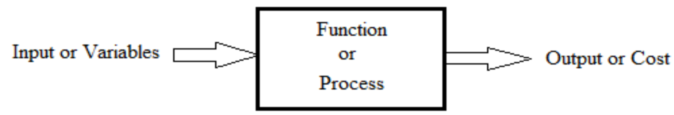

Figure 2. Optimization Process [30]

The Multiobjective optimization problem (MOO) can be formulated as;

$$\text{Minimize } F(x) = (f_1(x), \ldots, f_m(x))^T \quad (2)$$
$$\text{Subject to } x \in S,$$

where S is the decision space and $x \in$ S is a feasible set of decision variable vector. $F(x)$ consists of m objective functions or criteria f_k: $n \rightarrow m$, $k = 1,..., m$, with n-dimensional decision variable $x = \{x_1, \cdots, x_n\}$ in the space X, n is the decision variable space [30].

MOO seeks to find the optimal values of a vector-valued cost function through making trade-off between objective targets. Unlike the single objective optimization, in MOO, there does not exist a single utopian solution that can optimize all objective functions at the same time [30].

C. Bacterial Foraging Algorithm

Bacterial Foraging Algorithm (BFA) for distributed optimization and control is a swam-based computational technique developed by Kelvin M. Passino in 2002. As modern heuristic search technique, BFA has been developed based on E. *coli* bacteria foraging behavior [30].

The BFA method of searching along the neutral profile consists of four important stages, namely chemotaxis, swarming, reproduction and elimination-dispersal. These are briefly explained hereafter. More explanation can be found in [30].

1) ***In chemotaxis step***, the bacterium usually takes a step followed by step or tumble along the nutrient profile in search for nutrients while avoiding noxious substances. A maximum of swim with a chemotactic step length N_c is given by N_s. The actual number of swim steps is determined by the environment.

In the BFA, after one step motile, the position of the ith bacterium can be represented as:

$$\theta_i(j+1, r, l) = \theta_i(j, r, l) + C(i)\angle\varphi(j) \quad (3)$$
$$\theta_i(j+1, r, l) = \theta_i(j, r, l) + C(i) \quad (4)$$

where; $\theta_i(j, r, l)$ is the position of the ith bacterium at the jth chemotactic step in the rth reproductive loop of the lth elimination and dispersion event; $C(i)$ is the length of a unit walk, which is set to be a constant; and $\varphi(j)$ is the direction angle of the jth step [30].

2) ***Reproduction (Nre):*** After N_c chemotactic steps, a reproduction step is recovered. If N_{re} is the number of reproduction steps to be taken. It is assumed that half swim of the population members are well fit to reproduce without mutations. [30].

3) ***Elimination and dispersal:*** Due to the constant environmental changes for the bacteria in all time, it may get stuck around the initial positions or local optima. This has great influence to their living, in negative or positive sense. [30].

4) ***Swarming:*** Actually, in the motile process of bacteria during foraging, they form groups and move in concentric patterns of groups with high bacterial density. This is achieved through communication using cell-to-cell signaling via attractant or repellant, so as to search for optimum path towards nutrient [30].

The whole flowchart simulation process including the environmental changes is illustrated in Figure 3.

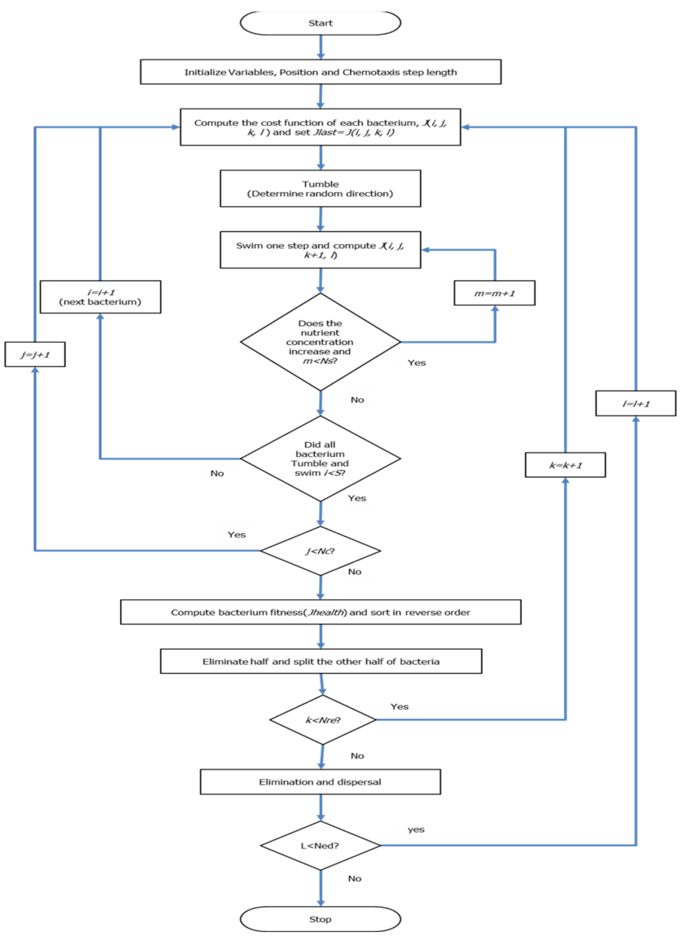

Figure 3. The BFA Flowchart

The basic goal of BFA optimization algorithm is aimed at finding the minimum of utility $\{J(\theta)\}$, $\theta \in R_p$ along the nutrient profile/gradient $\nabla J(\theta)$ [30].

D. *Performance Evaluation Criteria*

This is mainly concerned with the average best utility function used during the simulation process, so that the search process will be able to find the global optimum accurately within short time. It is good way of evaluating the performance of the BFA.

The fitness function used in this work is the mean squared error (MSE). It returned with a global error measure during the entire simulation period. The formulation of this cost function is as follows;

$$J(P) = \frac{1}{N}\sum_{k=1}^{N}[e(k)]^2 \quad (5)$$

where $e(k)$ is the error value, N is the number of points estimated in the searching period at kth time step [30].

E. *The Exact Equivalent Circuit Model*

In this method, the effects of R_2 and X_m are considered in the calculations. In its basic form, it uses the maximum torque (T_{max}), full load torque (T_{fl}), starting torque (T_{str}), and full load power factor (pf) for problem formulation so as to determine the five independent IM parameters. These parameters are; R_1, R_2, X_1, X_2, and X_m, [31]. It is always assumed that X_1=X_2 [32].

The exact equivalent circuit representing the steady-state operation of an IM is shown in Figure 4.

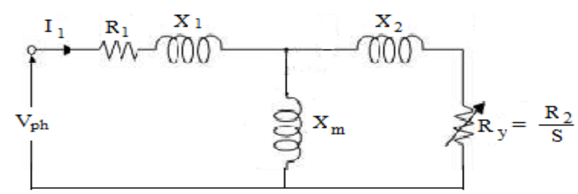

Figure 4. Exact Equivalent Circuit Model

Figure 4 can be formulated using Thevenin equivalent circuit based on *IEEE* standard 112. This is shown in Figure 5.

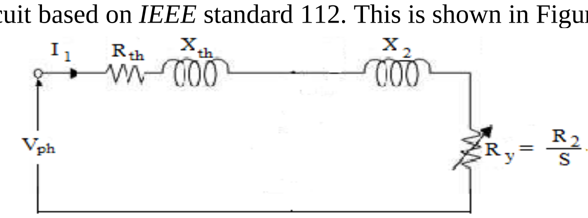

Figure 5. Thevenin Equivalent Circuit for Exact Equivalent Circuit Model

The motor identification task optimization formula based on exact equivalent circuit model can be express as follows:

$$Minimize\ J_E(x),\ x = (R_1, R_2, X_1, X_2, X_m, s) \quad (6)$$

Where,

$$J_E(x) = (\phi_1(x))^2 + (\phi_2(x))^2 + (\phi_3(x))^2 + (\phi_4(x))^2 \quad (7)$$

Subject to:

$$0 \le R_1 \le 1,\ \ 0 \le R_2 \le 1,\ \ 0 \le X_1 \le 1,\ \ 0 \le X_2 \le 1,$$
$$X_1^{min} \le X_1 \le X_1^{max}$$

where X_i^{min} and X_i^{max}, are the lower and upper bounds of the parameter X_i, which is the optimal value defined as the pareto optimal solution.

$$f_1(x) = \frac{\dfrac{K_t R_2}{s\left[(R_{th} + R_2/s)^2 + X^2\right]} - T_{fl}(mf)}{T_{fl}(mf)} \tag{8}$$

$$f_2(x) = \frac{\dfrac{K_t R_2}{\left[(R_1 + R_{th})^2 + X^2\right]} - T_{str}(mf)}{T_{str}} \tag{9}$$

$$f_3(x) = \frac{\dfrac{K_t R_2}{2(R_{th} + \sqrt{R_{th}^2 + X^2})} - T_{\max}(mf)}{T_{\max}(mf)} \tag{10}$$

$$f_4(x) = \frac{\cos(\tan^{-1}(\dfrac{X}{R_{th} + R_2/s})) - pf(mf)}{pf(mf)} \tag{11}$$

Where:

$$R_{th} = \frac{R_1 X_m}{X_1 + X_m} \tag{12}$$

$$V_{th} = \frac{V_{ph} X_m}{X_1 + X_m} \tag{13}$$

$$X_{th} = \frac{X_1 X_m}{X_1 + X_m} \tag{14}$$

$$K_t = \frac{3V_{th}^2}{\omega_s} \tag{15}$$

$$X = X_2 + X_{th} \tag{16}$$

Here, V_{th}, R_{th}, and X_{th} are the Thevenin equivalents of voltage, resistance and reactance, respectively. K_t is the constant coefficient, ω_s is the angular velocity, s is the motor slip, and V_{ph} is the phase voltage. Also, f_1, f_2, and f_3 are error between the calculated and manufacturer value of the full load torque, starting torque, and maximum torque, respectively. The pf is the full load power factor, while mf stands for manufacturer data index. Also, f_4 is error between the calculated and manufacturer value of the full load power factor. The sum of squares of moment error function: $J_E(x) = (\phi_1(x))^2 + (\phi_2(x))^2 + (\phi_3(x))^2 + (\phi_4(x))^2$ is called the suitability function [19].

Again, the efficiency balance constraint is formulated follows as (Equation 17):

$$\eta_{fl} = \frac{p_{fl} - (I_1^2 R_1 + I_2^2 R_2 + P_{rot})}{P_{fl}} \tag{17}$$

The rated values; P_{fl} and P_{rot} stand for the power and rotational losses, respectively [19]. Also, it is assumed that the core-losses are negligible in the analysis [20].

The efficiency of the IM can be determined by loading the motor and measuring the input and output directly [33]. This is expressed as follows (Equation 18):

$$\eta = \frac{P_{output}}{P_{input}} \times 100\% \tag{18}$$

F. *Experimental Measurements*

Actually, the input voltage, current and power (V_i, I_i and P_i) are recorded using digital voltmeter, digital ammeter and a wattmeter respectively. Also, power factor meter was used to measure the power factor (pf). The three phase induction motor works on no load condition and then connect it to work under varying mechanical loading condition still maintaining input parameters.

During the determination of the induction motor efficiency, the losses are obtained. So, to estimate the parameters of the IMs, the experimental samples are taken from the actual machine, so as to increase the accuracy of optimization algorithm [34]. Figure 6 shows the dialog box for inputting the motor parameters.

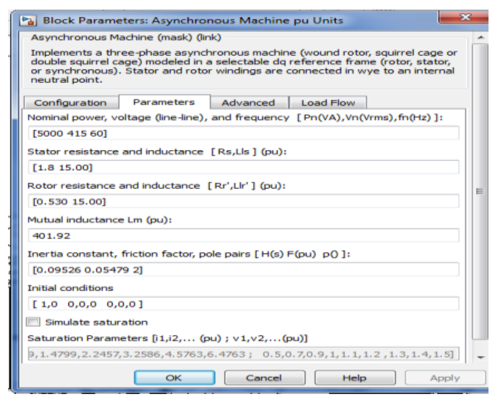

Figure 6. Editing Interface for Inputting the Motor Parameters

For the algorithm implementation, a program using the MATLAB/Simulink was developed. Features of the program are applicable for any number of variables that are bounded by imposing constraints (Figure 7).

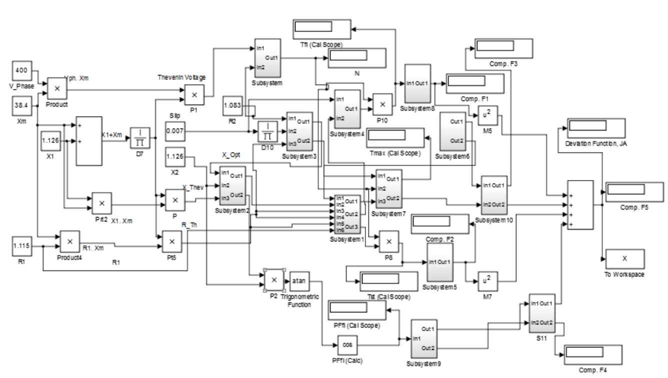

Figure 7. Simulink for the Optimization of a Three-phase IM

IV. Simulation and Discussion of Results

The choice of BFA parameters in this research is shown in Table I. The choice parameters were used to determine the optimal parameters of the motor considering the exact equivalent circuit model (J_E). The BFA algorithm parameter setting was initialized from the values obtained from the experiment. The algorithm was implemented using MATLAB/Simulink developed model.

TABLE I. BFA Parameter Selection for Optimization

Parameter	Value
Search space dimension (p)	$p = 3$
Population of bacteria (s)	$s = 4$
Chemotactic step length (N_c)	$N_c = 4$
Number of run (swim) steps (N_s)	$N_s = 4$
Reproduction steps number (N_{re})	$N_{re} = 4$
Number of elimination-dispersal events($N_{ed} = 4$)	$N_{ed} = 4$
Population of bacteria for production ($Sr = s/2$)	$Sr = s/2$
Probability of elimination/dispersal of bacteria (p_{ed})	$(p_{ed}) = 0.25$

Source: [30].

The 5 *h.p* three-phase IM specifications are listed in Table II.

TABLE II. Manufacturer Data for the Taste Motor

Specification	Motor
Capacity (HP)	5
Voltage (V)	400
Current (A)	8
Frequency (Hz)	50
Number of Poles	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

Certainly, the effect of the saturation, hysteresis and temperature variations were made quite extremely PI process [35]. In this paper, the IM parameters were assumed to be constant throughout the identification compared with the experimental values.

The extremum values and mean for the suitability function (based on the exact equivalent circuit) are depicted in Table III.

TABLE III. Rating Result of Suitability Function

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

It can be seen from Table III for the motor, the optimization algorithm (BFA), has less value of mean (average value) of suitability function, J_E (based on the exact equivalent circuit model).

In other to validate the effectiveness of the proposed BFA method for the PI (tasted on a 5 h.p three-phase IM in MATLAB/Simulink environment), the returned torque and power factor values of the motor (based on BFA) are compared with those of the manufacturer and experimental values so as to show the power of the proposed BFA scheme (Table IV).

TABLE IV. BFA, Experimental and Manufacturer Values Comparison

Torque	Manufacturer Value	Experimental Value	Error (%)	BFA	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

Percentage error was employed as a performance measure to show how the BFA yields lesser percentage errors. As observed from Table IV, the BFA works considerably better than the experimental values since it leads to (almost in all items) smaller torque and power factor percentage errors. In fact, the experimental method leads to the less accurate results compared to BFA. Note that in dealing with the algorithm the simulations are performed several times and the best result is used for comparison purposes.

The overall identified parameters based on the exact equivalent circuit model for the motor 5 *h.p* motor is depicted in Table V.

TABLE V. RESULT OF THE IDENTIFIED PARAMETERS BASED ON BFA

Parameters	Manufacturer Value	Experimental Value	Error (%)	BFA	Error (%)
R_1	01.80	03.00	66.67	01.81	00.56
R_2	05.27	07.89	49.72	05.30	00.57
X_1, X_2	14.81	17.30	16.81	15.00	01.28
X_m	409.6	82.11	-80.0	401.92	-01.88

From Table V, the BFA scheme yields lesser percentage errors, signifying better results than the manufacturer and experimental values.

It is clear that the most important performance measure of every algorithm in solving optimization problems is its convergence period. The performance of the BFA optimization tool in terms of its fitness value is shown in Figure 8. It is obvious that the fitness value reduces over few numbers of iterations and converges to minimum value (small run time). It also did not trap at local minimum, rather a global minimum.

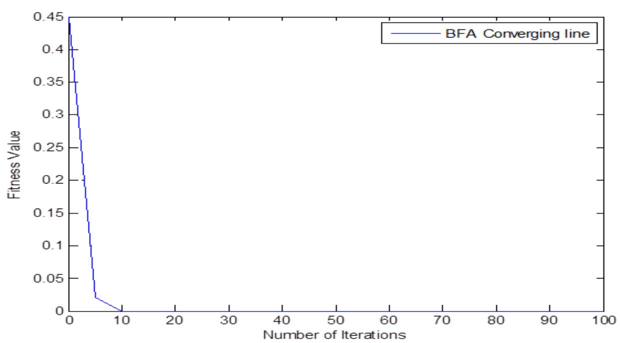

Figure 8. Fitness Evaluation versus Generation for the BFA

Figures 9 to 18 show the remarkable plots that clearly describe the characteristics of the proposed algorithm (BFA) for the motor along with the nameplate and the experimental results.

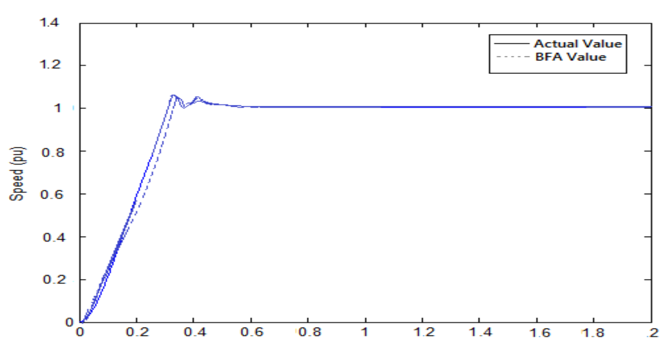

Figure 9. Transient Speed Characteristics of the Motor with No-Load

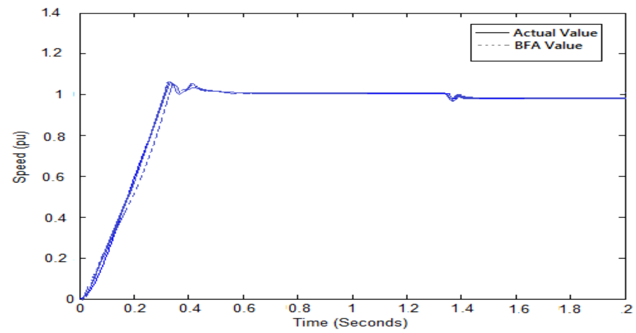

Figure 10. Transient Speed Characteristics of the Motor with Per Unit Step Load of 1

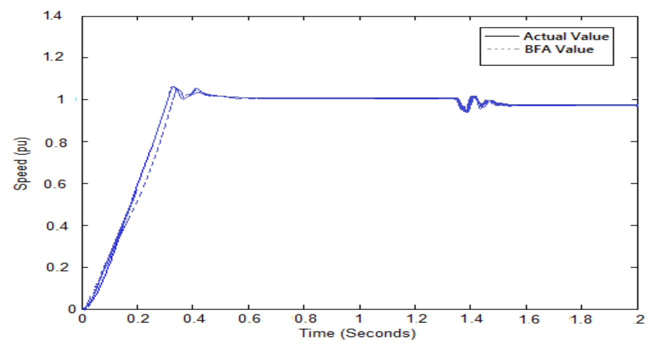

Figure 11. Transient Speed Characteristics of the Motor with Per Unit Step Load of 1.5

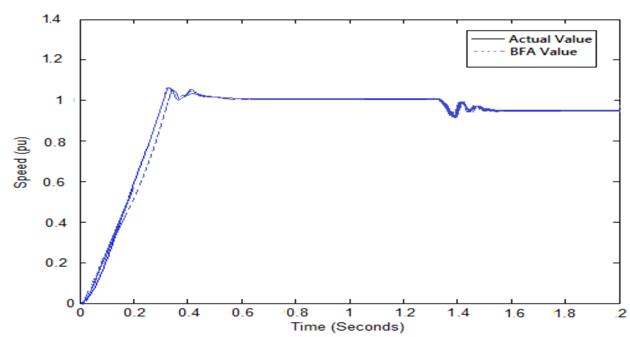

Figure 12. Transient Speed Characteristics of the Motor with Per Unit Step Load of 2.0

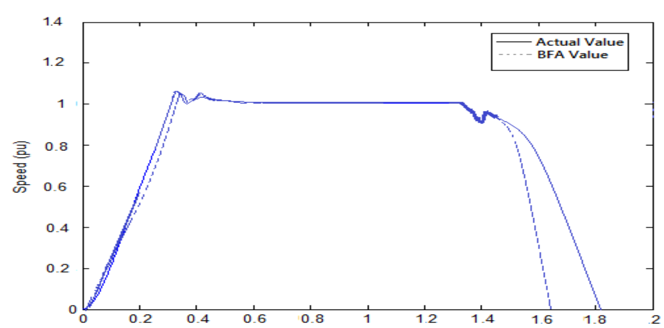

Figure 13. Transient Speed Characteristics of the Motor with Per Unit Step Load of 2.4

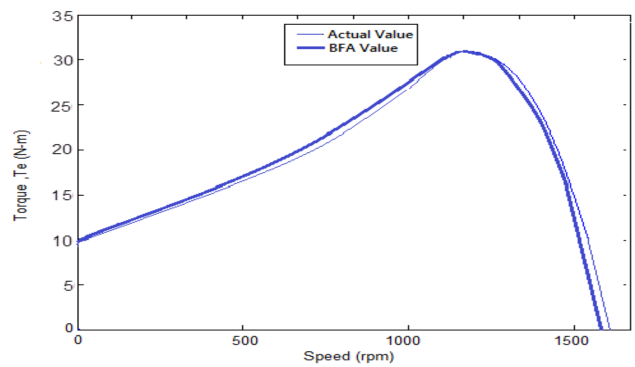

Figure 14. Plot of the Steady State Electromechanical Torque against Rotor Speed

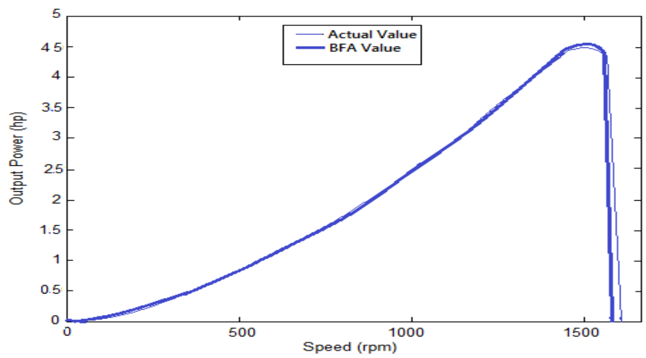

Figure 15. Plot of the Steady State Output Power against Rotor Speed

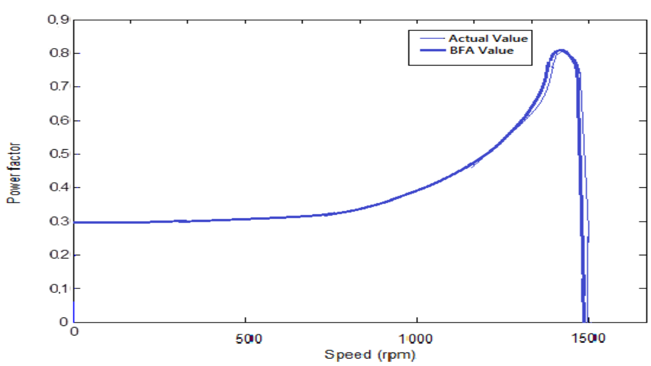

Figure 16. Plot of the Steady State Power Factor against Rotor Speed

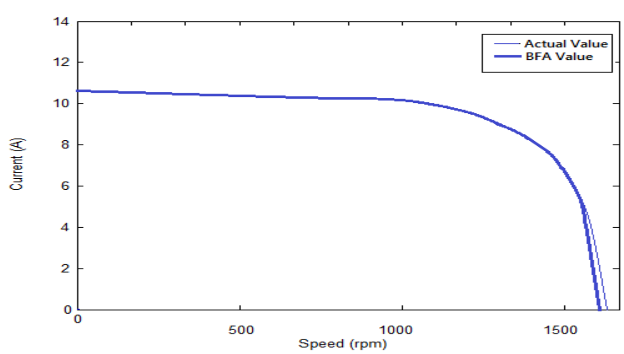

Figure 17. Plot of the Steady State Current against Rotor Speed

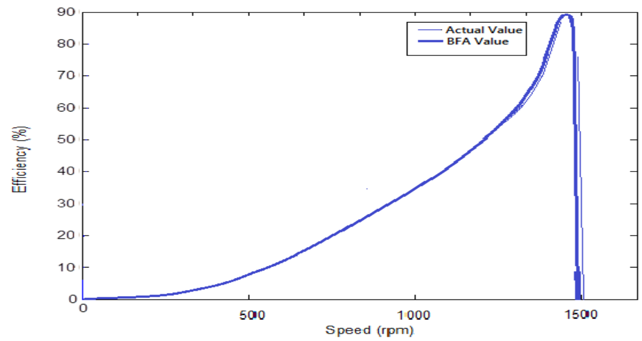

Figure 18. Plot of the Steady State Efficiency against Rotor Speed

V. CONCLUSION

In this paper, a bio inspired meta-heuristic technique, bacterial foraging algorithm, which is a distributed optimization and control method has been successful implemented for the parameter identification of a three-phase induction motor. A steady-state exact equivalent circuit model has been presented. The problem was formulated as a nonlinear optimization. MATLAB Simulink tool box have been immensely utilized for the estimation (electrical parameters of the induction motor) process. The error values obtained from the results of the BFA method are actually lesser than those using the experimental method. Figure 8 clearly shows that the BFA has faster convergence time (as it reaches its final value after about 10 iterations).Owing to the uniqueness of the BFA, coupled with its ability of fast convergence with less number of fitness evaluations and computational overheads (also been observed that even if the number of parameters increases, the run-time does not show any significant increase in that order), it is expected that it would be more suitable for parameters identification of induction motor.

This paper has presented the BFA as optimization tools for the parameters' identification of a three-phase induction motor. It is a broad step towards IM parameters identification based on the use of the algorithm and future work can involve in developing the algorithms further for solving more multi-attribute optimization problems in electrical engineering.

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