EFFICIENT OPTIMIZATION TECHNIQUES FOR PARAMETER ESTIMATION IN THREE PHASE INDUCTION MACHINE

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Abstract—*Prediction of a three phase induction motor's characteristics from its equivalent circuit is very familiar and widely used methodology. Computation of equivalent circuit parameter is usually done by no-load and blocked rotor test. The results obtained from the test may not give accurate values of the parameter and it has a wide variation in the operating condition. The obtained values were not precise and effective when analyzing the machine under various operating condition so we are urge to implement any other methodologies which makes the estimation of parameter precise. In this paper two optimization techniques i.e., Artificial Bee Colony Algorithm (ABC), Fireworks Algorithm (FWA), are applied for parametric estimation. The obtained results are compared with the actual values supplied by the manufacturer.*

Key Words—*Induction Machine, Parameter Estimation, Artificial Bee Colony Algorithm, Fireworks Algorithm,*

1.INTRODUCTION

The Induction motor is the most commonly used electric motor. It is robust and rather cheap motor that hardly need less maintenance. In fact, more than 60% of the connected load in the World is comprised of induction motors of different sizes. It is of great interest for the user to know the performance characteristics of the motor for various load conditions. Based on these characteristics the user may determine the relative efficiency and economics of the motors. Unfortunately, performance characteristics are, in general, not supplied by the manufacturer. However, these characteristics of an induction motor can be obtained from its equivalent circuit. The equivalent circuit parameter of an induction motor is determined using the three tests: (1) DC test (2) No-Load Test (3) Blocked Rotor test. The main drawback of this method is that the motor has to be locked mechanically and tests have to be carried out by experienced operator. The Conventional method can reveal significant differences in the entire range of slip. To illustrate the performance of the induction machine more precisely and to reduce the differences between the estimated and real performances, one must modify the parameters obtained from the classical method.. [1] Haque suggested an iterative procedure for calculation of all Single Cage with Core Loss (SCM-CL) and mechanical losses from catalog data, presented the superiority of the resulting efficiency and power factor curves. [2] M.Akbaba proposed an iterative numerical algorithm and the results obtained demonstrate the considerable influence of skin effect on the rotor resistance and rotor leakage reactance and saturation effects on the magnetizing and rotor leakage reactance with the parameter obtained from the proposed algorithm, the machine performance error was less than 0.5% at any operating point. [3] Christiaan Moons suggested the two estimation methods such as normal general total least square method and constrained general total least square and concluded that the second method is more robust and well suitable under high noise conditions. [4] F.Alonge introduced the Least Square(LS) technique and Genetic Algorithm(GA) using stator voltages, stator currents and velocity as input-output data, that is well suited for off-line parameter estimation of electric motors supplied by static electric converters and also computed the mechanical time constant, ratio of coulomb's and viscous friction coefficient and computing the mechanical time constant. [5] Hamid A.Toliyat reviewed on thevarious technique of parameter estimation. [6] Yassine Koubaa proposed the Least Square method using the information of stator currents, voltages and rotor angular speed as input-output data and it is applicable only for steady state operation and also suggested the future research for on-line identification. [7] And also extended(2006) for transient state operation to estimate rotor resistance, leakage stator reactance and inductance for incorporating into any flux and speed estimation. [7] K.Ursem analyzed performance of eight stochastic optimization algorithm and the eight algorithms were represented in four main groups of algorithms. They are Local Search(LS), Evaluation Strategies(ES), Generational Evolutionary Algorithm(GEA) and Particle Swarm Optimizers(PSO).The simple population-based approaches had rather good performance, while the advanced algorithms had the best performance .Diversity-guided EA showed the best average performance for both problems. [8] V.P.Sakthivel proposed offline parameter estimation of induction motor, using particle swarm optimization(PSO). Three different circuit models such as approximate, exact and deep bar circuit models are considered. [9] V.P.Sakthivel also proposed an Immune Algorithm(IA) to optimize the parameter estimation. [10] V.P.Sakthivel further extended the parameter estimation by bacterial foraging technique the feasibility of bacterial foraging technique has been tested and examined on 2 sample motors and the results were benchmarked with that obtained using PSO, IA and classical parameter estimation method. [11] Gomez Gonzalez analyzed the estimation of induction motor double cage model parameter from standard manufacturer data: full load power factor, full load current, maximum torque, starting torque, and starting current. Modified Shuffled Frog-Leaping Algorithm (MSFLA) gives better quality and the errors or deviations than the classical estimation method, PSO and the GAs. [12] E.Boudissa estimated the parameters of induction motor using the starting current and the phase voltage by a real-coded genetic algorithm. [13] Arezki Menacer determined the electrical parameter of induction motor by non-linear parametric identification technique based on the output error method and the Levenberg Marquardt algorithm. Recently, in solving induction motor parameter estimation problems, optimization techniques seems to be a promising alternative to the classical approaches. Although the past researchers have attempted optimization techniques, so far, there is no specific algorithm to achieve the best solution. Therefore in this regard to improve the optimal results of three phase induction machine equivalent circuit parameters Artificial Bee Colony (ABC) algorithm and FireWorks Algorithm (FWA) were presented in this paper. Further the proposed method was tested on a sample motor and the obtained results are encouraging.

The remainder of the paper is organized as follows: Section 2 describes the problem formulation, In section 3 the optimization procedure using ABC Algorithm and FWA algorithm for parameter estimation has been discussed, Section4 analyses the numerical results and discussion followed by the conclusions in section 5.

2. Problem Formulation

Three phase induction motor can be modeled with approximate circuit model, Exact circuit model and deep bar circuit model. The problem is formulated as a least squares optimization problem, the objective function being the minimization of deviation between the estimated and the manufacturer data. The problem formulation for estimating the parameter is described below.

2.1APPROXIMATE EQUIVALENT CIRCUIT

The approximate equivalent circuit model of an induction motor is shown in "Fig.1". The problem formulation uses the starting torque, maximum torque and full load torque manufacturer data to estimate the stator resistance, rotor resistance and stator leakage reactance parameters.

2.1.1 Objective Function

Using the equivalent circuit model of an induction motor, the objective function can be formulated as,

$$\text{Minimize } F = f_1^2 + f_2^2 + f_3^2 \tag{1}$$

Where

$$f_1 = \frac{\frac{K_t R_2}{s\left[\left(R_1+\frac{R_2}{S}\right)^2+X_1^2\right]} - T_{fl}(mf)}{T_{fl}(mf)}$$

$$f_2 = \frac{\frac{K_t R_2}{(R_1+R_2)^2+X_1^2} - T_{lr}(mf)}{T_{lr}(mf)}$$

$$f_3 = \frac{\frac{K_t}{2\left[R_1+\sqrt{R_1^2+X_1^2}\right]} - T_{max}(mf)}{T_{max}(mf)}$$

$$K_t = \frac{3V_{ph}^2}{\omega_s}$$

$T_{fl}(mf)$, $T_{lr}(mf)$ and $T_{max}(mf)$ are the manufacturer values of full load torque, locked rotor torque and maximum torque respectively.

2.1.2 Constraints

Minimum and maximum parameter limits

$X_{i,min} \leq X_i \leq X_{i,max}$

where $X_{i,min}$ and $X_{i,max}$ are the minimum and maximum values of the parameter X_i.

Maximum torque constraint

$$\frac{\text{Tmax(c)} - \text{Tmax(mf)}}{\text{Tmax(mf)}} \leq \pm 0.2$$

Where Tmax(c) is the estimated maximum torque.

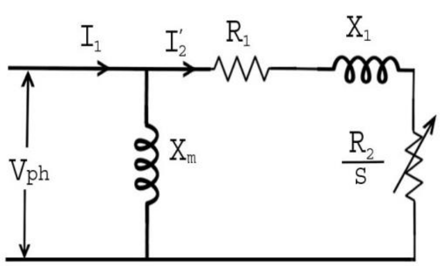

Fig. 1. Approximate circuit model

2.2 EXACT CIRCUIT MODEL FORMULATION

The problem formulation uses the starting torque, maximum torque, full load torque and full load power factor manufacturer data to estimate the stator resistance, rotor resistance, stator leakage reactance, rotor leakage reactance and magnetizing leakage reactance parameters. Equivalent circuit representing steady state operation is shown in Fig. 2

2.2.1 Objective function:

Minimize $F = f_1 + f_2 + f_3 + f_4$ (2)

Where

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

$$f_2 = \frac{\frac{K_t R_2}{(R_{th}+R_2)^2+X^2} - T_{lr}(mf)}{T_{lr}(mf)}$$

$$f_3 = \frac{\frac{K_t}{2\left[R_{th}+\sqrt{R_{th}^2+X^2}\right]} - T_{max}(mf)}{T_{max}(mf)}$$

$$f_4 = \frac{\cos\left(\tan^{-1}\left(\frac{X}{R_{th}+\frac{R_2}{s}}\right)\right) - pf_{f1}(mf)}{pf_{f1}(mf)}$$

$$V_{th} = \frac{V_{ph}X_m}{X_1+X_m}, \quad R_{th} = \frac{R_1 X_m}{X_1+X_m}, \quad X_{th} = \frac{X_1 X_m}{X_1+X_m}$$

$$K_t = \frac{3V_{th}^2}{\omega_s}, \quad X = X_1 + X_{th}$$

2.2.2 Constraints

Minimum and maximum parameter limits

$X_{i,min} \leq X_i \leq X_{i,max}$

Maximum torque constraint

$$\frac{\text{Tmax(c)} - \text{Tmax(mf)}}{\text{Tmax(mf)}} \leq \pm 0.2$$

Efficiency balance

$$\frac{\text{Pfl} - (I_{1fl}^2\text{R1} + I_{2fl}^2\text{R2} + \text{Prot})}{P_{fl}} = \eta_{fl}(mf)$$

where P_{fl} and P_{rot} are the rated power and the rotational losses respectively.

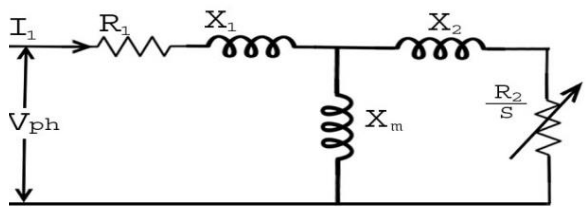

Fig.2. Exact circuit model

2.3 DEEPBAR CIRCUIT MODEL FORMULATION

The problem formulation uses the starting torque, the maximum torque, the full load torque, the full load current and the full load power factor manufacturer data to estimate the parameters of the deep bar circuit model. The deep bar or double cage induction motor equivalent circuit model is shown in Fig.3

2.3.1 Objective function:

Minimize $F = f_1 + f_2 + f_3 + f_4 + f_5$ (3)

Where

$$f_1 = \frac{\frac{K_t|Y_{\infty t}|^2(R_{21}|Y_{21}|^2+R_{22}|Y_{22}|^2)}{s|Y_1+Y_m+Y_{21}+Y_{22}|^2} - T_{fl}(mf)}{T_{fl}(mf)}$$

$$f_2 = \frac{\frac{K_t|Y_{\infty t}|^2(R_{21}|Y_{21}|^2+R_{22}|Y_{22}|^2)}{|Y_1+Y_m+Y_{21}+Y_{22}|^2} - T_{lr}(mf)}{T_{lr}(mf)}$$

$$f_3 = \frac{\frac{K_t|Y_{\infty t}|^2(R_{21}|Y_{21}|^2+R_{22}|Y_{22}|^2)}{s_{max}|Y_1+Y_m+Y_{21}+Y_{22}|^2} - T_{max}(mf)}{T_{max}(mf)}$$

$$f_4 = \frac{\frac{(R(Y_{21})+R(Y_{22}))|Y_1|+R_1|Y_1||Y_m+Y_{21}+Y_{22}|^2}{|Y_m+Y_{21}+Y_{22}||Y_1+Y_m+Y_{21}+Y_{22}|} - pf_{fl}(mf)}{pf_{fl}(mf)}$$

$$f_5 = \frac{V_{ph}|Y_{tot}| - I_{fl}(mf)}{I_{fl}(mf)}$$

$$Y_1 = \frac{1}{R_1+jX_1}, \qquad Y_{m} = \frac{1}{jX_m}$$

$$Y_{21} = \frac{1}{\frac{R_{21}}{s}+jX_1}, \qquad Y_{22} = \frac{1}{\frac{R_{22}}{s}+jX_2}, \qquad K_t = \frac{3V_{ph}^2}{\omega_s}$$

2.3.2 Constraints

Minimum and maximum parameter limits

$X_{i,min} \leq X_i \leq X_{i,max}$

Inner and outer cage leakage reactance constraints

$X_{21} > X_{22}$

Inner and outer cage rotor resistance constraints

$R_{22} > R_{21}$

Maximum torque constraint

$$\frac{Tmax(c) - Tmax(mf)}{Tmax(mf)} \leq \pm 0.2$$

Efficiency balance

$$\frac{Pfl - (I_{1fl}^2 R1 + I_{2fl}^2 R2 + Prot)}{P_{fl}} = \eta_{fl}(mf)$$

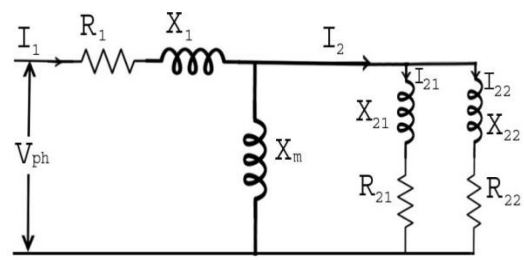

Fig.3. Deepbar circuit model

3. OPTIMIZATION METHODOLOGY FOR PARAMETER ESTIMATION PROBLEM

In this proposed work equivalent circuit parameters of three phase induction machine is estimated by various optimization techniques. The various optimization techniques are,

- Artificial Bee colony(ABC)
- FireWork Algorithm(FWA)

3.1 ARTIFICIAL BEE COLONY ALGORITHM(ABC)

3.1.1 Introduction to ABC

ABC is a bio-inspired meta-heuristic algorithm that mimics the foraging behavior of bee and it is applied to solve variety of optimization problems[13-18]. ABC categorize bees in to three main groups: employed bees, onlooker bees and scout bees. Employed bees exploit the nectar sources and shares the information via waggle dance to the onlooker bees waiting in the hive about the quality of the food source sites which they are exploiting. Onlooker bees stay at the hive and decide on a food source to exploit based on the information shared by the employed bees. Scout bees either randomly search the environment in order to find a new food source depending on an internal impulse or based on possible external hint.

3.1.2 ABC for Parameter Estimation

ABC algorithm consists of five phases namely initialization phase, employed bee phase, onlooker bee phase, scout bee phase and termination phase.

(1)Initialization phase: The algorithm randomly produces food sources. Each food sources defined as $X_i = \{x_{i1}, x_{i2}, x_{i3,\ldots}, x_{ij,\ldots} x_{iD}\}$ is generated by

$$x_{ij} = x_j^{min} + K(0,1)(x_j^{max} - x_j^{min}) \quad (4)$$

where i={1,2,..SN} SN is the number of food sources ; j = {1,2, . . ., D}; D is the dimensionality of the search space; x_j^{min} and x_j^{max} are predefined minimum and maximum values of parameter j.

(2)Employed bee phase: The employed bee alter the position ofits concerned food source to find a new potential food source

$$\upsilon_{ij}=x_{ij}+\varphi_{ij}(x_{ij}-x_{mj}) \quad (5)$$

where i represents the index of current food source(X_i); m represents the index of neighbour food source(X_m),which is randomly chosen among all sources except for i ;j is the randomly selected parameter for modification ; φ_{ij} is a random number uniformly distributed within [-1,1]. When $\upsilon_i$is generated its fitness value is evaluated. If the fitness value of υ_i is better than fitness value of X_i, the employed bee memorizes the new food position and leaves the old one.

(3)*Onlooker bee phase*: Employed bees share the information related to its food source such as nectar amount and position of food source. Onlooker bee selects the food source depending on the probability according to the fitness values through roulette-wheel selection strategy, where potential food sources have a higher probability than others.

The selection scheme based on the fitness value is given by

$$p_i = \frac{\text{fitness}_i}{\sum_{i=1}^{SN} \text{fitness}_i} \quad (6)$$

fitness_i is the fitness value of source X_i.

After the calculation of probability (p_i) , a random number in the range of 0 and 1 is generated for each food source i .If p_i>rand(0,1), X_i is chosen and the searching process is carried out similar to the employed bee phase.

(4)*Scout bee phase*: If the solution cannot be improved for a predetermined number of trials specified by user then that food source becomes abandoned is called "limit" or "abandonment criteria". Scout bees randomly create new solutions using equation4and replace the abandoned one.

(5)Termination phase: When the termination condition is satisfied the best solution with high fitness value is presented as output. If not the algorithm repeats from employed bee phase to scout bee phase.

The implementation of ABC algorithm is illustrated step by step and of ABC

Step 1: Input the manufacturer data of the three phase induction motor .

Step 2: Generate an initial population randomly.

Step 3: Compute the corresponding fitness value for each individual.

Step 4: Generate the neighbor solutions for the employed bees and evaluate them.

Step 5: Select the best individuals with the lowest fitness value.

Step 6: If all the onlooker bees are distributed then proceed to step 9, otherwise proceed to the next step.

Step 7: Calculate the probability values P_i for the solutions X_i

Step 8: Generate the neighbor solutions for the selected onlooker bee, depending on P_i and evaluate them.

Step 9 : Replace the abandoned solutions with a new solution randomly generated by the scout bees.

Step 10: Memorize the best solution achieved so far.

Step 11: Stop the process if the termination condition is satisfied .

Step 12:Output the optimal machine parameter.

3.2 FIREWORKS ALGORITHM(FWA)

3.2.1 Introduction to FWA

FireWorks Algorithm is comparatively a new global optimization technique preferred for variety of applications [19-22] inspired by the phenomenon of fireworks explosion. When a firework is set off, a shower of sparks fill the local space around the firework shown in Fig.4.The explosion process of a firework is viewed as a search in the local space around a specific point where the firework is set off through the sparks generated in the explosion. To find a point x_i satisfying $f(x_i) = y$, continuously set off 'fireworks' in potential space until one 'spark' targets or is fairly near the point x_i . In the FWA, for each generation of explosion, first select n locations, where n fireworks are set off. After explosion process, the locations of sparks are obtained and evaluated. When the optimal location is found, the algorithm stops. If not, n other locations are selected from the current sparks and fireworks for the next generation of explosion.

3.2.2 FWA for Parameter Estimation

In the Fireworks algorithm , explosion operator, mutation operator ,mapping rule and selection strategy are the four components. The explosion operator generate sparks around fireworks, the number and amplitude of the sparks are influenced by the explosion operator. The next stage of sparks are produced by mutation operator utilizing Gaussian operator in the Gaussian distribution. If the sparks produced by the effect of these two operator are not in the feasible region ,then the mapping rule will map the new generated sparks in to the feasible region. Selection strategy is preferred to select the sparks for next generation. The most significant attribute of fireworks is the explosion types. It can be divided in to two types "good" explosion and "bad" explosion as shown in Fig.5Good firework can generate a larger population of explosion sparks within a small range with better fitness. In contrary Bad fire work can only generate a smaller population within a larger range with lower fitness. This technique is the key aspect of the algorithm to balance between the exploration and exploitation process. Hence this behavior is quite suitable for parameter estimation problem; since the method has to confine its search by exploration followed by exploitation process. The search process continues until the stopping condition is met as shown in Fig. 6.

The number of sparks (S_i) and the amplitude(A_i) for each firework x_i is given by:

$$S_i = m.\frac{y_{max} - f(x_i) + \xi}{\sum_{i=1}^{n}(y_{max} - f(x_i)) + \xi} \tag{7}$$

$$A_i = \hat{A}.\frac{f(x_i) - y_{min} + \xi}{\sum_{i=1}^{n}(f(x_i) - y_{min}) + \xi} \tag{8}$$

where m and $\hat{A}$ denotes the control parameters, $f(x_i)$ is the value of objective function (fireworks)at location x_i, y_{max},y_{min} are the maximum(worst) and minimum(best) value of the objective function among the n fireworks and ξ is a smallest constant in the computer utilized to avoid zero-division-error

To restrict the spark evaluation within the limits, constraints are defined as follows

$$S_i = \begin{cases} S_{min} if S_i < S_{min} \\ S_{max} if S_i < S_{max} \\ round(S_i) \quad\quad otherwise \end{cases} \tag{9}$$

In case of a d-dimensional problem, the location of each spark x_j generated by x_i can be obtained by randomly setting z directions (z<d), and for each dimension k setting the component $x_j^k (1 \leq j \leq S_i, 1 \leq k \leq z)$.

There exist two ways for setting x_j^k . For most sparks a displacement h=A_i* rand(-1,1) is added to x_j^k as

$$x_j^k = x_j^k + h \tag{10}$$

To maintain the diversity, for a few specific sparks, an explosion coefficient based on Gaussian distribution is applied to x_j^k and is given as

$$x_j^k = x_j^k.Gaussian(1,1) \tag{11}$$

If in both the ways the obtained new location falls out of the search space the it is mapped to the search space according to Eqn(12)

$$x_j^k = x_{min}^k + |x_j^k| \% (x_{max}^k - x_{min}^k) \tag{12}$$

During each iteration of firework, among all the current sparks and fireworks, the best location is always kept for the next explosion generation. Then n-1 locations are selected with some probabilities proportional to their distance to other locations.

The selection probability of a location is given by the following equations,

$$R(x_i)=\sum_{j\in k} d(x_i, x_j) =\sum_{j\in k}\left\|x_i - x_j\right\| \qquad (13)$$

$$p(x_i)=\frac{R(x_i)}{\sum_{j\in k} R(x_j)} \qquad (14)$$

where k is the set of all current locations of both fireworks and sparks.

The algorithmic framework of FWA to optimize the three phase induction motor are presented as follows:

Step-1: Initialization of the FWA parameters

Number of iteration, dimension of search space, number of location, parameter controlling total number of sparks, maximum explosion amplitude etc

Step-2: Randomly select n locations of sparks for fireworks.

Step-3: Fireworks loop started: For the selected n locations, objective function is calculated

Step-4: For each firework

Calculate the number of sparks that the firework yields, i.e. number of feasible solutions with best fitness value according to eqn. (9). Unfeasible solution that violates the operating constraints will not be considered further. Then, obtain the new location of i^{th} sparks of the firework using displacement eqn.(10) and (12).

Step-5: Randomly select a firework and generate a specific spark for the firework using Gaussian explosion method as in eqn.(10) and (12).

Step-6: Evaluate the quality of all the above locations and select the best location that gives minimum F and keep it for the next explosion generation.

Step-7: Randomly select n-1 locations from the two types of sparks generated and the current fireworks according to the probability shown in eqn.(14)

Step-8: If fireworks loop less than maximum number of iteration go to step-3. Otherwise end and display the results of the best location.

Fig.4 Search Process of Fireworks Algorithm

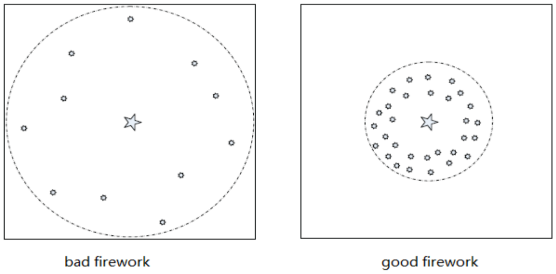

Fig.5 Solution Search for Optimization Problems

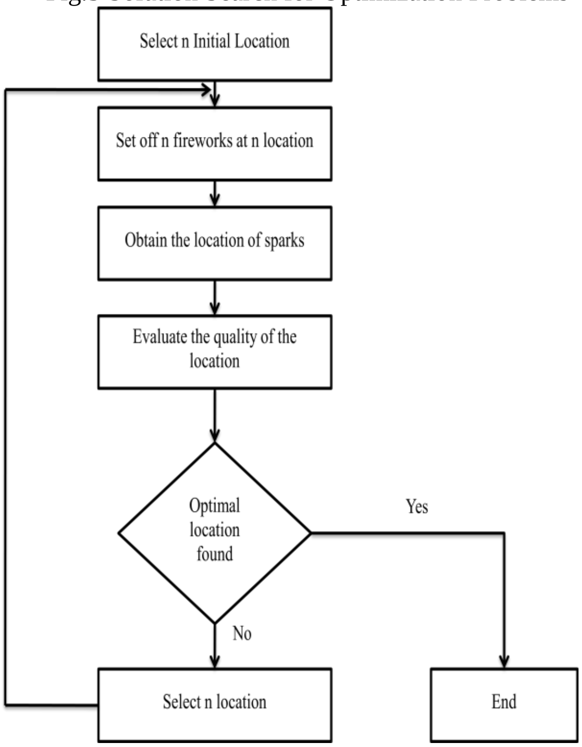

Fig.6 Flow Chart of FA

4. NUMERICAL RESULTS

The proposed technique was tested on a sample motor. Optimal design parameters were determined by implementing three different models. The obtained results are compared with the classical parameter estimation method.

The population size and the number of iterations are selected as 10 and 50.The manufacturer details of the test machine are presented in Table 1. In order to test the robustness of the proposed approach 20 independent trials are performed to observe the variation during the evolutionary process and to compare their solution quality and convergence characteristics. The best torque values obtained during the evolutionary process is shown in Table 2&3. In Table 4 the classical parameter estimation results are presented. From Table 2 & 3 it is evident that the proposed ABC and FWA has the least error deviation compared with IA method. It is also evident from table 4 that compared with ABC, FWA has the least error deviation. The classical parameter results are presented in Table 5. Fig.7 depicts the torque versus slip characteristics obtained from ABC and FWA method for the test machine specified in Table 1.It can be visualized that there exist a good agreement between the curves generated by the FWA method and the manufacturer data. Fig. 8 shows the standard deviation results of the three models and techniques for the 20 trials. It is clear from the figure that the FWA method standard deviation fitness values for all the trials performed was lesser than the ABC method. Convergence tendency of ABC and FWA methods for the sample motor is plotted in Fig.9.The convergence curve shows that the FWA method converges faster and also results minimum fitness value.

TABLE-1 MANUFACTURER DATA OF THE TEST MACHINE

Specification	Motor
Capacity(HP)	5
voltage(V)	400
Current(A)	8
Frequency(Hz)	50
Number of Poles	4
Full load slip	0.07
Starting torque(N m)	15
Maximum torque(N m)	42
Starting Current(A)	22
Full load torque(N m)	25

TABLE -2 COMPARISON OF IA AND ABC WITH MANUFACTURER DATA

Torque	Actual Value	IA						ABC					
		MODEL1		MODEL2		MODEL3		MODEL1		MODEL2		MODEL3	
		Estimated Data	Error (%)	Estimated Data	Error (%)	Estimated Data	Error (%)	Estimated Data	Error (%)	Estimated Data	Error (%)	Estimated Data	Error (%)
T_{st}	15	15.44	-2.9	16.03	7	16	6	14.68	2.13	14.72	1.86	15.23	-1.53
T_{max}	42	38.44	-8	41.08	-0.4	42.98	2	42.94	-2.23	42.66	-1.57	41.6	0.96
T_{fl}	25	20.36	-18	27.44	9.7	25.46	2	22.72	9.12	22.62	9.52	23.67	5.32

TABLE -3 COMPARISON OF IA AND FWA WITH MANUFACTURER DATA

Torque	Actual Value	IA						FWA					
		MODEL1		MODEL2		MODEL3		MODEL1		MODEL2		MODEL3	
		Estimated Data	Error (%)	Estimated Data	Error (%)	Estimated Data	Error (%)	Estimated Data	Error (%)	Estimated Data	Error (%)	Estimated Data	Error (%)
T_{st}	15	15.44	-2.9	16.03	7	16	6	14.82	1.2	15.24	-1.6	14.88	0.8
T_{max}	42	38.44	-8	41.08	-0.4	42.98	2	42.66	-1.57	42.3	-0.71	41.71	0.69
T_{fl}	25	20.36	-18	27.44	9.7	25.46	2	22.62	9.52	25.12	-0.48	24.58	1.68

TABLE – 4 COMPARISON OF ABC AND FWA WITH MANUFACTURER DATA

Torque	Actual Value	ABC						FWA					
		MODEL1		MODEL2		MODEL3		MODEL1		MODEL2		MODEL3	
		Estimated Data	Error (%)	Estimated Data	Error (%)	Estimated Data	Error (%)	Estimated Data	Error (%)	Estimated Data	Error (%)	Estimated Data	Error (%)
T_{st}	15	14.68	2.13	14.72	1.86	15.23	-1.53	14.82	1.2	15.24	-1.6	14.88	0.8
T_{max}	42	42.94	-2.23	42.66	-1.57	41.6	0.96	42.66	-1.57	42.3	-0.71	41.71	0.69
T_{fl}	25	22.72	9.12	22.62	9.52	23.67	5.32	22.62	9.52	25.12	-0.48	24.58	1.68

TABLE- 5 COMPARISON OF CLASSICAL PARAMETER ESTIMATION RESULT WITH MANUFACTURER DATA FOR SAMPLE MOTOR

Torque	**Sample motor**		
	Actual value	Estimated data	Error(%)
T_{st}	15	14.37	-5
T_{max}	42	36.46	-13.18
T_{fl}	25	27.415	9.66

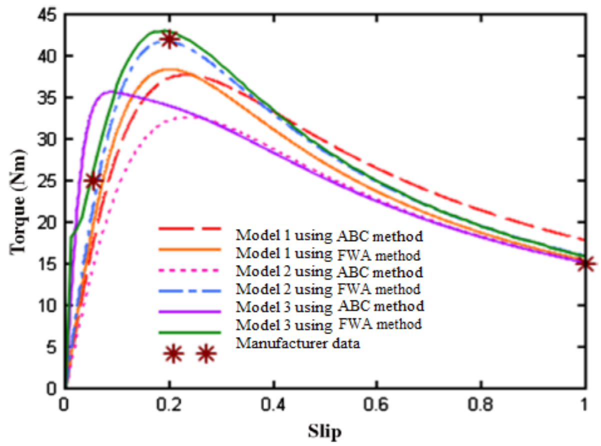

Fig.7 Torque Vs slip characteristics of the Induction motor specified in Table 1

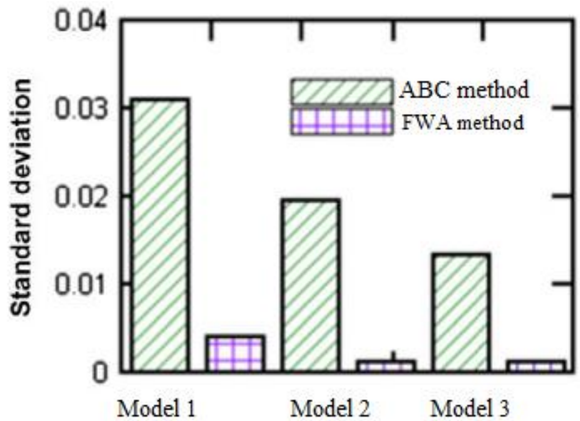

Fig.8 Comparison of standard deviation for ABC and FWA method for Induction motor specified in Table1

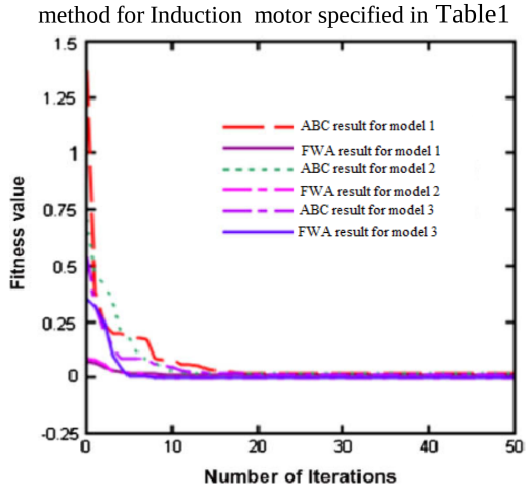

Fig.9 Convergence diagram of a sample motor by different models and techniques

5.CONCLUSION

In this paper, we have proposed two non-conventional optimization techniques i.e., ABC and FWA algorithm are applied for optimizing the parameters of three phase induction motor. The proposed ABC and FWA method have been tested and examined on a sample motor, and the results were compared with that obtained using the IA parameter estimation method. The computational results show that the results obtained by the proposed algorithms are encouraging and found to be better than the other methods compared. It is also observed that the FWA has outperformed the other methods as it gave minimum standard deviation of the solution obtained from multiple random trials. The proposed algorithm can be applied for any large rating of the machine to compute the parameters accurately.

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