ESTIMATING EQUIVALENT CIRCUIT PARAMETERSOF AN INDUCTION MOTOR USING CHAOS EMBEDDED FIREFLY ALGORITHM

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ABSTRACT

Induction motors consume the maximum percentage of energy in industrial facilities. This consumption is dependent on operating conditions (imposed by internal parameters) of the motor. Obviated by the need to avoid the hard-to-perform experimental tests & the tedium of numerical methods, the parameters of induction motor can be estimated by minimization of normalized squared error function between the manufacturer's and the estimated data. In this paper, a novel chaos embedded firefly algorithm is used to estimate equivalent circuit parameters of an induction motor using the motor name plate data & its performance characteristics. Comparison of performance of standard firefly algorithm with chaos embedded firefly algorithm using different chaotic sequences has been made. Results show that the use of chaotic sequences in firefly algorithm improves the overall parameter estimation and can be used effectively for energy management system of induction motor, thus resulting in saving of overall energy in an industry.

Keywords: *Equivalent Circuit Parameters, Induction motor, Chaos, Firefly algorithm, Chaotic sequences*

INTRODUCTION

Environmental issues caused by the overuse of electrical energy have attracted the researchers towards improving the efficiency of machinery as well as elements having high level of consumption of electrical energy (Omar Avalos et. al., 2016). Due to their less price and ruggedness, induction motors are being preferred by most of the industries. Nearly 60% of electric energy in the industries is changed into the mechanical energy by using induction motors mounted in fans, machine tools, pumps and adjustable speed drives (V.P. Sakthivel et. al., 2010). Hence, researchers are increasingly concentrating on developing models and estimation of parameters of induction motors(Huynh and Dunnigan, 2010).

Equivalent circuit parameters of induction motors (reactance and resistances of rotor and stator (including the magnetizing branches)) are normally determined by using no load tests and locked-rotor tests. But, these techniques require experimental studies; that are hard to perform. Another option is to use numerical methods, but, these are generally tedious. In literature, induction motor parameter estimation has been reported by using least square technique (Y. Koubaa, 2006), Kalman filter (Kumar, Prakash et. al., 2011), artificial neural networks (Wishart, R.G. Harley, 1995), neuro- fuzzy techniques (Desouza Ribeiro et. al., 1999), etc.

Recently, evolutionary algorithms such as genetic algorithms (Mohammadi and Akhavan, 2014), particle swarm optimization (Huynh and Dunnigan, 2010; Sakthivelet. al., 2010), shuffled frog-leaping algorithm (Gomez-Gonzalez et. al., 2013), gravitational search algorithm (Omar Avalos et. al., 2016), artificial immune system (V.P. Sakthivel et. al., 2010), Artificial Bee Colony Algorithm (Abro and Mohmad-Saleh, 2011), bacterial foraging algorithm (Sakthivel, R. Bhuvaneswari and S. Subramanian, 2011), differential evolution (Giri, A. Chowdhary and Ghosh, 2010), ant colony optimization (Chen et. al., 2008), big bang-big crunch (Erol and Eksin, 2006), etc. have been proposed to solve the problem of induction motor parameter estimation.

Firefly algorithm, a member of the family of swarm intelligence algorithms was introduced in 2008 (Fister Jr., Percet. al., 2015; Xin-She Yang, 2009). Since then, a number of its modified versions were suggested and applied for getting the efficient and fast solutions of multimodal optimization (Xin-She Yang, 2009), continuous optimization (Xin-She Yang, 2010), constrained optimization(Szymon Lukasik, Slawomir Zak, 2009) and real-world problems (Saini and Saini, 2012). Some versions of firefly algorithm have also used chaotic maps (Gandomi, 2013).

Chaotic approach for optimization is able to bypass local optima stagnation in contrast to the conventional approaches. Taking advantage of the ergodic and stochastic properties of chaotic maps, a number of chaos-embedded optimization algorithms have been proposed and hybridization of chaotic search with other techniques has been done by a few researchers (Saini and Saini, 2012; Liu, Wang et. al., 2005; Sneh Lata and Sanju Saini, 2013; Chen and Yu, 2008; Alatas et.al., 2009; Wei et.a.l., 2011). In this work, chaotic search is embedded in a novel manner in a firefly optimization algorithm to improve the latter's capabilities to optimize the parameters of equivalent circuit of an induction motor. It utilizes chaotic sequences to improve the efficiency of search process.

Rest of the paper is organized as follows: Details of the design problem is given in the Section 2. A review of the conventional firefly algorithm is given in Section 3. In next section, chaos embedded firefly algorithm using chaotic sequences is explained. Further, simulation results have been given followed by conclusions & list of references.

DESIGN PROBLEM

As induction motor parameters can not be measured directly, identification techniques are commonly used to estimate them. Here. induction motor's behavior is represented by the equivalent (nonlinear) circuits (Omar Avalos et. al., 2016)& the problem of parameter's estimation is converted to a multidimensional problem of optimization. Objective becomes to minimize error in between the manufacturer's and estimated data by adjustment of equivalent circuit parameters.

Five main parameters of steady state equivalent circuit of a single phase induction motor are rotor and stator resistances (R_1& R_2), their leakage reactances (X_1& X_2) and magnetizing leakage reactance Xm as shown in Figure 1.

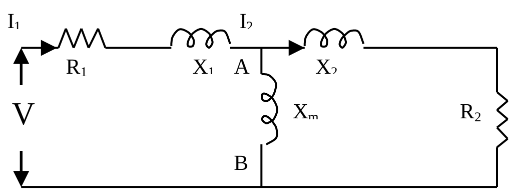

Figure 1: Steady state equivalent circuit of an induction motor

Assuming $X_1 = X_2$ (for simplification), problem of parameter estimation (of induction motor) can be converted to an optimization problem. Aim is to determine those values of four parameters, which lead to minimization of the difference between the estimated values and manufacturer supplied data values of full load torque, starting torque, maximum torque and full load power factor.

OBJECTIVE FUNCTION

Mathematically, the objective function is chosen as given in eqn. 1.

$$\text{Minimize } W = W_1+W_2+W_3+W_4 \qquad (1)$$

Where,

$$W_1 = \frac{T_{flc} - T_{flm}}{T_{flm}}, \qquad W_2 = \frac{T_{stc} - T_{stm}}{T_{stm}},$$

$$W_3 = \frac{T_{mc} - T_{mm}}{T_{mm}} \quad \text{and} \quad W_4 = \frac{T_{pfc} - T_{pfm}}{T_{pfm}}$$

T_{flc}, T_{stc} , T_{mc} and T_{pfc} are the calculated values (from motor parameters) and T_{flm}, T_{stm}, T_{mm} and T_{pfm} are the manufacturer supplied values of full load torque, starting torque, maximum torque and full load power factor respectively. Expressions for the stator and rotor currents can be given by eqn.2& eqn.3 respectively.

$$\vec{I_1} = \frac{\vec{V_{ph}}}{R_1 + jX_1 + \vec{Z}} \quad \text{where} \quad \vec{Z} = \frac{jX_m \times (\frac{R_2}{s} + jX_2)}{\frac{R_2}{s} + j\,(X_2 + X_m)} \tag{2}$$

$$\vec{I_2} = \frac{\vec{Z}.\vec{I_1}}{\frac{R_2}{s} + jX_2} \tag{3}$$

By using slip, s = sfl (full load slip), 1 and s_{max} respectively, the values of the full load torque, starting torque and maximum torque are determined by using eqn. 4. s_{max} can be calculated by using eqn. 5.

$$\text{Torque (T)} = \frac{1}{\omega_s} 3I_2^2 \frac{R_2}{s} \tag{4}$$

Here,

$$\omega_s = 2\pi N_s \quad \text{and} \quad N_s = \frac{120\,f}{p}$$

Ns is the synchronous speed in r.p.s , f and p are the frequency in hertz and number of poles respectively.

$$s_{max} = \frac{R_2}{\sqrt{R_{th}^2 + (X_{th} + X_2)^2}} \tag{5}$$

where R_{th} and X_{th} are the resistive and reactive components of the Thevenin equivalent impedance when part of the circuit (shown in Figure 1) to the left of the terminals AB is replaced by its Thevenin equivalent. As already assumed, $X_1 = X_2$, there are four parameters to be optimized to minimize the objective function defined by eqn. 1. Following constraints [10] are also taken into account while solving the problem of optimization:

$$\frac{T_{mc} - T_{mm}}{T_{mm}} \leq \pm 0.02$$

and values of R_1, R_2, X_1, X_2 and $X_m$are greater than zero. The complexity of this problem results in error surfaces, which are multimodal and it becomes very difficult to minimize the cost function. In this work, a chaos embedded firefly algorithm is used to solve this problem. This algorithm has been discussed in details in the next sub-section.

FIREFLY OPTIMIZATION ALGORITHM

Developed by X.-S Yang in 2010, firefly optimization algorithm is based on the flashing characteristics of fireflies & is applicable to a number of engineering optimization problems. Flashing lights are produced by fireflies to attract their partner or to protect themselves from predators. Intensity of this flashing light decreases as distance from the source increases. This behavior has been modeled as Firefly optimization algorithm, where, light intensity is directly proportional to fitness function of the optimization problem. In fact, this algorithm is inspired from the social behavior of fireflies. It uses the following three rules:

1. All fireflies are assumed to be unisexual, i.e., one firefly will be attracted to other fireflies irrespective of their sex.

2. Attractiveness is directly proportional to brightness, i.e., less bright firefly moves towards a brighter one; also, brightness reduces with increasing distance between fireflies. I(r), the light intensity at a distance r, can be defined by eqn. 6.

$$\mathrm{I(r)} = I_0 e^{-\gamma r^2} \tag{6}$$

here, I_0 is the original light intensity, γ is the light absorption coefficient. Attractiveness of a firefly can be defined by eqn. 7.

$$\beta\,(\mathrm{r}) = \beta_0 e^{-\gamma r^2} \tag{7}$$

β_0 represents the attractiveness at r =0. Eqn. 8 represents the movement of ith firefly (at x_i) to more brighter jth firefly (at x_j).

$$\Delta x_i = \beta_0 e^{-\gamma r_{ij}^{\,2}} (x_j^t - x_i^t) + \alpha \varepsilon_i, \qquad x_i^{t+1} = x_i^t + \Delta x_i \tag{8}$$

First term of eqn. 8 represents attraction & the second term represents randomization, α is the randomization parameter and ε_i is a vector of random numbers drawn from Gaussian distribution. A firefly moves randomly in the space if none of the other fireflies is brighter than it.

3. Brightness of a firefly is directly related to the cost function.

CHAOS EMBEDDED FIREFLY ALGORITHM

A deterministic system with an unpredictable behavior is said to be chaotic. 'Order' is not completely absent in such system, rather, it has some element of randomness. Chaos is considered to be a part of nonlinear dynamical systems (Fister, Perc et. al., 2015). In mathematics, chaotic phenomenon is detected by iterated functions returning random value during each iteration. Sequence of numbers generated by chaotic functions constitutes chaotic maps (or orbit). Such orbits show aperiodicity and have sensitive dependence on initial conditions.

Chaotic functions can provide structured randomness. In swarm intelligence based algorithms, randomness plays an important role by exploration of new solutions. Thus, chaotic functions can replace random generators in a number of applications & increase the exploration power of the search process. Most commonly used chaotic maps have been listed in TABLE 1.

From eqn. 8, it can be observed that β and γ are two important parameters of firefly algorithm. In chaotic firefly algorithms, these parameters can be tuned by using chaotic maps (Fister, Perc et. al., 2015). For the present problem of parameter estimation of equivalent circuit of induction motors, it was observed (via extensive simulations) that tuning of γ by chaotic maps was not much effective to improve the quality of solution. However, tuning of attractiveness coefficient, i.e., 'β' was quite effective.

Hence, the used chaos embedded firefly algorithm performs following two additional operations with standard firefly algorithm:

1. Tuning of attractivenessβ by using eqn. 9[Iztok Fister et al. , 2015].

$$\beta_i = \beta_0\, \mathrm{Ki(N)} \tag{9}$$

Here, Ki(N) is the Nth chaotic map (given in TABLE 1).

2. A novelty is added to the process by performing chaotic search around the best solution after the end of each iteration, as shown in flowchart of Figure 2.

Table 1:Description of some 1-d chaotic maps	
Name	Equation
Logistic map	$x_{k+1} = \alpha x_k(1 - x_k)$ for $\alpha < 0$
Kent map	m=0.3 for 0<m<1 $x_{k+1} = \frac{x_k}{m}$ for $0<x_k<m$ $x_{k+1} = \frac{1-x_k}{1-m}$ for $m<x_k<1$
Intermittency map	$x_{k+1} = \in + x_k + c x_k^n$ $for\ 0<x_k \le P$ $\frac{x_k - P}{1-P}$ $for\ P<x_k<1$ where, P=0.6, ∈=0.001, n=2 & c=$\frac{1-\in-P}{P^m}$
Tent map	$x_{k+1} = \begin{cases} \frac{x_k}{0.7} for x_k < 0.7 \\ \frac{10(1-x_k)}{3}\ for\ x_k \ge 0.7 \end{cases}$
Sine map	$x_{k+1} = \frac{a}{4}\sin(\pi x_k)$ where, a = 4
Chebyshev map	$x_{k+1} = \cos(k\cos^{-1}(x_k))$
Gauss map	a = 4.9 b = -0.58 $x_{k+1} = \exp(-a x_k^2) + b$ $x_k = \frac{x_{k+1}}{2}$
Iterative map	$x_{k+1} = \sin(\frac{a\pi}{x_k})$ Here, 'a' belongs to [0,1]
Piecewise map	$x_{k+1} = \begin{cases} \frac{x_k}{P} for\ 0 \le x_k < P \\ \frac{x_k - P}{0.5-P} for P \le x_k < \frac{1}{2} \\ \frac{1-P-x_k}{0.5-P} for \frac{1}{2} \le x_k < 1-P \\ \frac{1-x_k}{P} for\ 1-P \le x_k < 1 \end{cases}$ Here, 'P' belongs to [0,5]
Singer map	$x_{k+1} = \mu(7.86 x_k - 23.31 x_k^2 + 28.75 x_k^3$ - 13.3028.75$x_k^4)$ where, μ=1.07

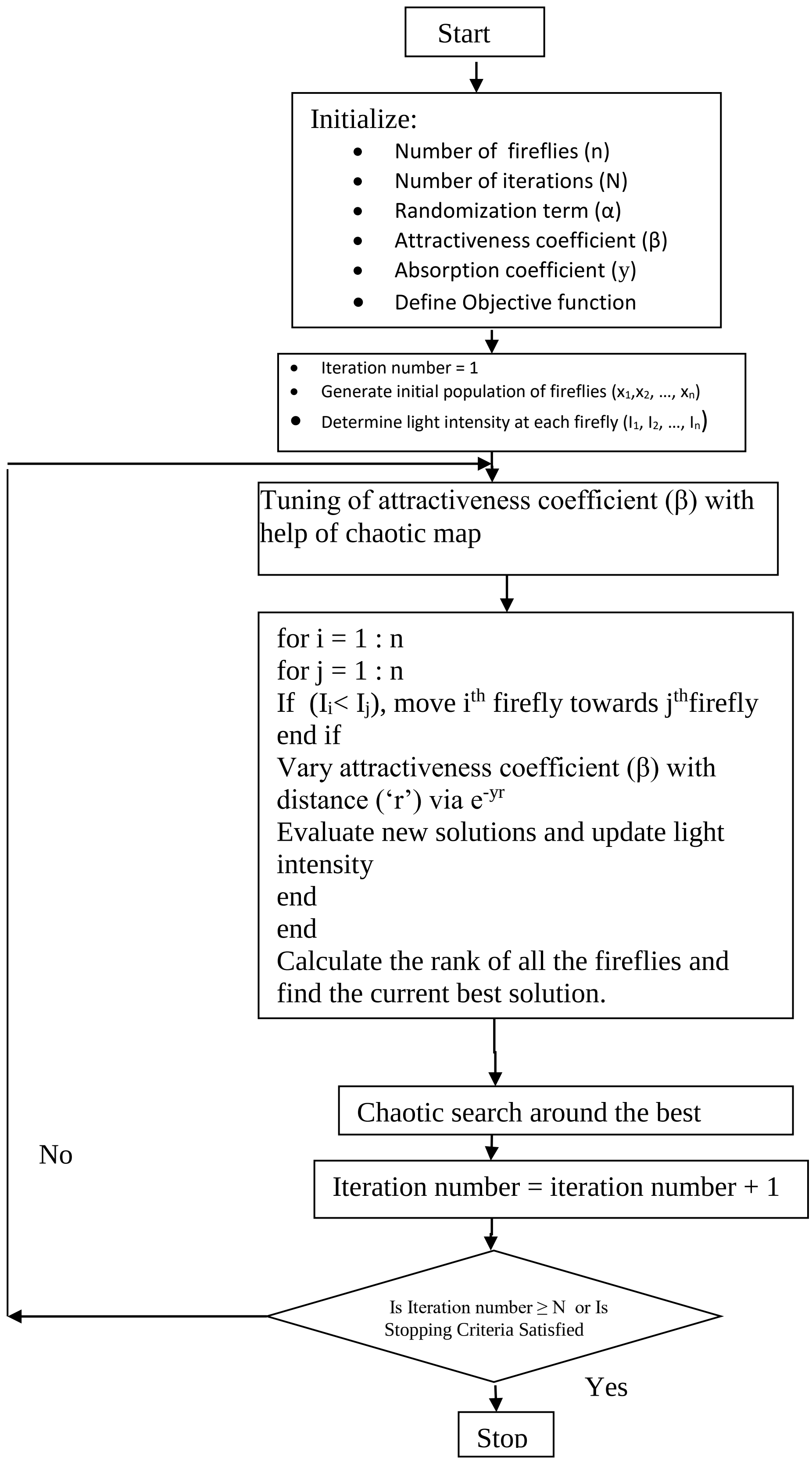

Figure 2: Flowchart of chaos embedded firefly algorithm

SIMULATION RESULTS

The proposed algorithm is tested on a motor of 40 H.P. The manufacturer data for the motor is shown in TABLE 3. In TABLE 2, comparative study of performance of chaos embedded algorithm has been done with standard firefly algorithm. In the same Table, effect of using different chaotic maps in the proposed algorithm has been given.

Initial parameters used for the canonical firefly algorithm are as follows:

$\alpha = 0.1$;
minimum value of $\beta = 0.20$;
absorption coefficient $\gamma = 1$,
number of fireflies = 20
and number of iterations = 400.

The estimated values of the design parameters (rotor and stator resistances (R_1& R_2), their leakage reactances (X_1& X_2) and magnetizing leakage reactance Xm), by use of canonical firefly algorthm and chaos embedded firefly algorithms (using different chaotic maps) have been given in TABLE 4. Range of values of all the four parameters to be optimized (R_1, R_2, X_1=X_2, X_m) is between 0.1 ohms to 10 ohms. From TABLE 2, it can be observed that the performance of the chaos embedded firefly algorithm (except in the case of Chebyshev map) is better than that of the canonical firefly algorithm as the errors (between values of starting torque, full load torque, maximum toque and full load power factor respectively as calculated from estimated values and manufacturer's data) are reduced by embedding chaos in firefly algorithm. Best results have been given by the use of piecewise map as it results in the minimum value of objective function.

Table 2:Comparison of performance

	Starting torque (Nm)	Full load torque (Nm)	Maximu torque (Nm)	Full load power factor	Objective function value
Manufacturer Data	260	190	370	0.8	-
Standard Firefly algorithm	259.82	189.43	369.39	0.7992	0.0074
Logistic map	258.91	189.89	369.81	0.7995	0.0066
Kent map	259.61	189.67	370.27	0.7993	0.0058
Intermittency map	260.35	189.24	369.88	0.8000	0.0057
Tent map	260.18	189.96	369.84	0.8010	0.0039
Sine map	260.18	190.05	369.43	0.8004	0.0035
Chebyshev map	258.73	189.72	369.93	0.7985	0.0106
Gauss map	260.00	189.34	369.90	0.8002	0.0042
Iterative map	259.92	190.57	369.83	0.7997	0.0045
Piecewise map	259,77	190.15	370.42	0.7997	0.0034
Singer map	261.16	189.88	370.01	0.7997	0.0058

Table 3:Manufacturer data of induction motor

Rated Power (P)	40 HP
Voltage (V)	400 volts
Frequency (f)	50 Hz
Number of poles (p)	4
Starting Torque	260 Nm
Full load Torque	190 Nm
Maximum Torque	370 Nm
Full load power factor	0.8
Full load slip	0.09

Table 4 :Estimated parameters values

	R_1 (Ohms)	R_2 (Ohms)	X_1=X_2 (Ohms)	X_m (Ohms)
Standard Firefly algorithm	0.2785	0.3621	0.4802	7.5876
Logistic map	0.2725	0.3618	0.4833	7.6429
Kent map	0.2712	0.3627	0.4833	7.6501
Intermittency map	0.27624	0.3632	0.48107	7.6466
Tent map	0.2804	0.3610	0.4786	7.6231
Sine map	0.2845	0.3600	0.4765	7.5564
Chebyshev map	0.2691	0.3626	0.4850	7.6409
Gauss map	0.2746	0.3632	0.4821	7.6690
Iterative map	0.2830	0.3588	0.4765	7.5179
Piecewise map	0.2742	0.3612	0.4811	7.6209
Singer map	0.2843	0.3604	0.4755	7.5281

CONCLUSION

In this paper, the problem of equivalent circuit's parameter estimation of induction motor has been transformed to a multidimensional optimization problem. Ten different chaotic sequences have been used to tune the attractiveness coefficient, i.e., 'β' of the standard (canonical) firefly algorithm to improve its estimation results. Novelty is added to the optimization process by performing chaotic search around the solution after each iteration of firefly algorithm. Through simulations, the potential of the proposed methodology stands demonstrated & it has been concluded that the best result in this problem is achieved by the use of piecewise (chaotic) map along with the standard firefly algorithm.

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REFERENCES

Omar Avalos, Erik Cuevas and Jorge (2016). Induction Motor Parameter Identification Using a Gravitational Search. *Computers*, 5 (6), 1-12.

V.P. Sakthivel, R. Bhuvaneswari and S. Subramanian (2010). Artificial immune system for parameter estimation of induction motor. *Expert Systems with Applications*, 37, 6109-6115.

D. C. Huynh and M. W. Dunnigan (2010). Parameter estimation of an induction machine using advanced particle swarm optimisation algorithms. *IET Electic Power Applications*., 4(9), 748-760.

Y. Koubaa (2006). Application of least-squares technique for induction motor parameters estimation. *Mathematical and Computer Modelling of Dynamical Systems*, 12, 363-375.

S. Kumar, J. Prakash, P. Kanagasabapathy(2011). A critical evaluation and experimental verification of extended Kalman filter, unscented Kalman filter and neural state filter for state estimation of three phase induction motor. *Applied Soft Computing*, 11, 3199-3208.

M.T. Wishart, R.G. Harley (1995). Identification and control of induction machines using artificial neural networks. *IEEE Transactions on Industry Applications*. 31, 612-619.

L. A. Desouza Ribeiro,C.B. Jacobina and A.M.N. Lima. (1999). Linear Parameter estimation for induction machines considering the operating conditions. *IEEE Transactions on Power Electronics*, 14,. 62-73.

H. R. Mohammadi, A. Akhavan (2014). Parameter Estimation of Three-Phase Induction Motor Using Hybrid of Genetic Algorithm and Particle Swarm Optimization. *Journal of Engineering*, 1–6.

V. P. Sakthivel, R. Bhuvaneswari, and S. Subramanian (2010). Multi-objective parameter estimation of induction motor using particle swarm optimization. *Engineering Applications of Artificial Intelligence*, 23(3) . 302–312.

I. Perez, M. Gomez-Gonzalez, and F. Jurado (2013). Estimation of induction motor parameters using shuffled frog-leaping algorithm. *Electrical Engineering*, 95(3), 267–275.

A.G. Abro, J. Mohmad-Saleh (2014). Multiple global best guided artificial bee colony algorithm for induction motor parameter estmation. *Turkish Journal of Electrical Engineering and Computer Sciences*, 22, 620-636.

V. P. Sakthivel, R. Bhuvaneswari, and S. Subramanian(2011). An accurate and economical approach for induction motor field efficiency estimation using bacterial foraging algorithm. *Journal of the International Measurement Confederation*, 674-684.

R. Giri, A. Chowdhary, A.Ghosh, B.K. Panigrahi, S. Das (2010). Offline parameter estimation of induction motor using a meta heuristic algorithm. *Lecture Notes in Computer Science*, 6466, 523-530.

Z. Chen, Y. Zhong, J. Li (2008). Parameter identification of induction motors using ant colony optimization.*IEEE world Congress on Computational Intelligence*, 1611-1616.

O.K. Erol, I. Eksin (2006). New optimization method:big bang-big crunch. *Advances in Engineering Software*, 37, 106-111.

Iztok Fister Jr., Matjaz Perc, Salahuddin M. Kamal,Iztok Fister (2015). A review of chaos-based firefly algorithms: Perspectives and research challenges. *Applied Mathematics and Computation*, 252, 155-165.

Xin-She Yang (2009). Firefly algorithms for multimodal, optimization. *Stochastic Algorithms: Foundations and Applications, Springer*, 169-178.

Xin-She Yang (2010). Firefly algorithm, stochastic test functions and design optimization. *International Journal on Bio-Inspired Computation*,2(2), 78-84.

Szymon Lukasik, Slawomir Zak (2009). Firefly algorithm for continuous constrained optimization tasks.*Proceedings of First International Conference, Wriclaw, Poland*, 97-106.

Xin-She Yang, Seyyed Soheil Sadat Hosseini, Amir Hossein Gandomi(2012). Firefly algorithm for solving non convex economic dispatch problems with valve loading effect. *Applied Soft Computing*, 12(3), 1180-1186.

Sanju Saini and J. S. Saini (2012). Chaotic queue-based genetic algorithm for design of a self-tuning fuzzy logic controller.*Journal of AIP Conference Proceedings*, 1499, 191-195.

B. Liu, L. Wang, Y. H. Jin, D. ian X. Huang, and F. Tang (2005). Improved particle swarm optimization combined with chaos. *Chaos, Solitons & Fractals*, 25(5), 1261–1271.

Sneh Lata, Mrs. Sanju Saini (2013). Chaotic search based genetic algorihm for economic dispatch problem. *Proc. of Int. Conf. on Emerging Trends in Engineering and Technology*, 685-689.

R. Q. Chen and J. S. Yu (2008). Study and application of chaos-particle swarm optimization based hybrid optimization algorithm. *J. Syst. Simul.*,20(3), 685–688.

B. Alatas, E. Akin, and A. B. Ozer(2009). Chaos embedded particle swarm optimization algorithms. *Chaos, Solitons and Fractals,* 40(4), 1715–1734.

Z. Wei, F. Ge, Y. Lu, L. Li, and Y. Yang (2011). Chaotic a nt swarm for the travelling salesman problem. *Nonlinear Dynamics.,* 65(3), 271–281.

Q. Zuo and Y. S. Fan (2006). Chaotic search based immune algorithm for function optimization. *Control Theory Applications,* 23 (6), 957–960.

A.H.Gandomi, X.-S.Yang , S.Talatahari and A.H.Alavi (2013). Firefly algorithm with chaos. *Communications in Nonlinear Science and Numerical Simulation*, 18(1), 89-98.