

Optimization of Induction Motor Design using Five Artificial Intelligence Techniques

Abdulraheem T¹, Ike S.A.² & Agbontaen F.O.³

¹Research and Development Department, Power Equipment and Electrical Machinery Development Institute, Okene, Kogi State Nigeria

^{2,3}Electrical and Electronic Engineering Department, University of Benin, Benin, Edo State Nigeria

Abstract— This work optimizes material cost of a 10HP, 4 Pole, 3- phase, 50Hz squirrel cage inductor motor design using five different Artificial Intelligence (AI) techniques with a view to determining the best technique. Material cost optimization selects the optimal values of the design variables which give the least cost while satisfying some constraints. Seven design variables and six constraints were used in the optimization process. The optimization was implemented using MATLAB software. The results show that the best optimized material cost of ₦83,300 was achieved with the Genetic Algorithm technique, while Chicken Swarm Optimization, Cuckoo Search Algorithm, Artificial Bee Colony and Bat Algorithm gave ₦83,763, ₦84,375, ₦85,414 and ₦88,528, respectively. Comparisons of these results show a difference of ₦5,228 between Genetic Algorithm which gives the best result and Bat Algorithm which performed the least. This demonstrates the efficiency of GA over others being compared. This outcome can serve as a guide for induction motor designers and manufacturers that use AI techniques and whose goal is to roll out cheaper products and make more profit.

Keywords— Artificial intelligence, Optimization, Induction motor, material cost.

I. INTRODUCTION

The induction motor (IM) is no doubt the most used electrical motor and a great energy consumer. Three-phase induction motors consume 60% of industrial electricity and it takes considerable efforts to improve their cost of production. The vast majority of induction motor drives are used for heating, ventilation and air conditioning (HVAC) [1]. Squirrel cage Induction motor (SCIM) which is a type of induction motor is widely used due to its low cost, simplicity and robustness. Therefore, the study of reduction in the amount of materials used in manufacturing SCIM through the optimization of its design is very important as it will lead to reduction in cost [2]. Optimization is central to any problem involving decision making regardless of whether in engineering, technology, software development, or in economics. The task of decision making involves selecting between various alternatives. The measure of goodness of the alternatives is described by an objective function. Optimization theory and methods deal with selecting the best alternative in the sense of the given objective function. The area of optimization has received enormous attention in recent years, primarily because of the rapid progress in computer technology, including the development and availability of user-friendly software and high-speed processors. The optimization process involves creating a suitable model. Modeling is the process of identifying and expressing the objective, the variables and the constraints of the problem, mathematically. An objective is a quantitative measure of the performance of the system to be optimized, the variables are the components of the system whose values are to be found while the constraint is a condition of an optimization problem that the solution must satisfy [3]. One of the ways to optimize a problem is the use of artificial intelligence (AI) techniques. This work, therefore, seeks to optimize material cost in the design of a 10HP, 4 Pole, 3- phase, 50Hz squirrel cage induction motor using five different AI techniques.

Artificial intelligence is a branch of science which deals with helping machines find solutions to complex problem in a more human-like fashion. This is accomplished by studying how human brains think, learn, decide and work while trying to solve a problem and using the outcomes of this study as a basis of developing intelligent software and system [4]. It involves borrowing characteristics from human intelligence and applying them as an algorithm in a computer friendly way. The application of AI is endless. The technology can be applied in many different sectors and industries. AI is used in healthcare industry for dosing drug and different treatment in patient. AI also finds its application in areas like robotics, predictive search engines, e-mail spam filtering, self driving cars, optimization of processes and machines. Genetic Algorithm, Artificial Bee Colony, Ant Colony Optimization, Cuckoo Search Algorithm, Firefly Optimization, Invasive Weed Optimization, Grey Wolf Optimization, Whale Optimization, Chicken Swarm Optimization, Bat Optimization, Fuzzy Logic, Artificial Neural Network are all examples of artificial intelligence techniques. Some of these techniques are being inspired by the behavior of social animals like ants, bee, firefly etc.

II. ARTIFICIAL INTELLIGENCE TECHNIQUES EMPLOYED

Five AI based techniques were used in the optimization of a 10HP, 4 Pole, 3- phase, 50Hz squirrel cage inductor motor. An overview of these techniques is presented.

A. Genetic Algorithm (GA)

It is an optimization strategy that mimics natural selection. GA is based on survival of the fittest concept. It simulates biological evolution but in the domain of numbers. GA handles a population of possible solutions with each solution represented through a chromosome, which is just an abstract representation. In the most general sense, GA-based optimization is a stochastic search method that involves the random generation of potential design solutions. For GA to find a best optimum solution, it is necessary to perform certain operations over these individuals. It involves initialization, selection of parents, cross-over to create offspring, mutation of offspring, merging of main population and offspring, evaluation, sorting and selection. It then comes to an end when a stopping criterion is met. The stopping criteria could be when best solution has not changed over certain number of generation or when maximum number of iterations is attained. [5, 6]

B. Artificial Bee Colony (ABC)

Artificial Bee Colony (ABC) is an optimization concept based on the intelligent foraging behaviour of honey bee swarm. The ABC is made up of three groups of artificial bees: employed bees, onlookers and scouts. The employed bees make the first half of the colony whereas the second half comprise of the onlookers. The employed bees are connected to particular food sources. The number of employed bees is equal to the number of food sources for the hive. The onlookers watch the dance of the employed bees within the hive to select a food source, whereas scouts search randomly for new food sources. Analogously in the optimization context, the number of food sources (which is the employed or onlooker bees) in ABC algorithm is equivalent to the number of solutions in the population. Also, the position of a food source signifies the position of a promising solution to the optimization problem, whereas the quality of nectar of a food source represents the fitness cost (quality) of the associated solution. [7]

C. Bat Algorithm (BA)

Bats are grouped into mini bat, ghost bat and mega bat. Bat algorithm is based on echolocation behavior of micro bats which uses echolocation to detect prey. The bats create sound wave which echoes back to detect the prey. They create an echo to determine the distance of the prey. The bats have frequency, velocity, position, loudness and pulse rate. The frequency is the number of wave produced per unit time, its position is where the bat is located, its velocity is the speed of the bat in the direction of the target and loudness of sound determines the intensity of the wave.

The first step is to initialize the bat population. Random values are assigned to position, velocity, loudness and pulse rate to each bat. If the number of iterations is less than the maximum iteration, a new solution is generated by adjusting the frequency and updating the velocity and position for all bats. If a random number (between 0 and 1) is greater than the pulse rate, a solution is selected among the best bat. The best bat is based on the frequency of the bat. The higher the frequency the better. The frequency increases as the bat moves closer to the prey while the loudness decreases.[8]

D. Chicken Swarm Optimization (CSO)

Chickens are sociable birds that live in groups [9]. Chicken Swarm Optimization represents the behavior of chicken swarm, to optimize a computational problem's solution. In other words, it extracts the hierarchal characteristic of chickens to optimize the problem. CSO is designed by the following rules:

- In the chicken swarm, there exist several groups. Each group consists of a dominant rooster, a couple of hens, and chicks.
- How to divide the chicken swarm into several groups and determine the identity of the chickens (roosters, hens and chicks) all depend on the fitness values of the chickens themselves. The chickens with best several fitness values would be assigned as roosters, each of which would be the head rooster in a group. The chickens with worst several fitness values would be designated as chicks. The others would be the hens. The hens randomly choose which group to live in. The mother-child relationship between the hens and the chicks is also randomly established.
- The hierarchal order, dominance relationship and mother-child relationship in a group will remain unchanged. [10, 11]

E. Cuckoo Search Algorithm (CSA)

Cuckoo search algorithm is inspired by some cuckoo species laying their eggs in the nest of other species. Therefore, a pattern corresponds to a nest and similarly each individual attribute of the pattern corresponds to a cuckoo egg. In each computational step, the new and potentially improved solutions replace the worse solutions (eggs in the nests) [12]. Authors defined the CSA algorithm by setting three rules that idealize behaviour of cuckoos in order to become appropriate for implementation as a computer algorithm:

- Each cuckoo lays one egg at a time, and abandons it in a randomly chosen nest.
- The best nests with high-quality eggs will be carried over to the next generations.
- The number of available host nests is fixed and the egg laid by a cuckoo may be discovered by the host bird with a probability $pa \in (0, 1)$. In this case, the host bird can either get rid of the egg, or simply abandon the nest and build a completely new nest.

With regards to the mentioned rules, the CSA is implemented as follows. Each egg in a nest represents a candidate solution. Hence, each cuckoo can lay only one egg into a nest in original form although each nest can have multiple eggs representing a set of solutions [8]. More intricate cases like multiple eggs in a nest, symbolizing a set of solution, can be incorporated in this algorithm. The task of CSA is to generate the new and potentially better solutions that will replace the worse solutions in the current nest population [13].

III PROBLEM DEFINITION

The main specifications of the squirrel cage induction motor are 10HP, 415V, 3-phase, 50Hz, 4 pole and delta connected.

A. input parameters

Output power = 10HP

Type of connection, Δ = Delta.

Supply frequency, $f = 50\text{Hz}$.

Number of phase, $m = 3$.

Supply voltage, $V = 415\text{V}$.

Phase voltage, $V_{ph} = 415\text{V}$

Power factor, $p.f = 0.87$

Number of poles, $P = 4$.

Stator winding factor, $K_w = 0.955$.

Efficiency = 0.85

Specific magnetic loading $B_{av} = 0.45 \text{ Wb/m}^2$.

Specific electric loading, $Q = 22,000 \text{ AT/m}$.

Number of slots per pole per phase, $q = 3$

Ratio of core length to pole pitch, $K = 1$

Stacking factor $K_s = 0.9$

Flux density of the stator core, $B_{sc} = 1.2 \text{ Wb/m}^2$

Stator current density, $J_s = 4 \text{ A/mm}^2$

Current density of end ring, $J_e = 7 \text{ A/mm}^2$.

Current density of rotor bar, $J_b = 5 \text{ A/mm}^2$

Flux density of the stator tooth, $B_{st} = 1.6 \text{ Wb/m}^2$

Number of rotor slots $S_r = 44$

Resistivity of copper, $= 0.021 \Omega/\text{m and mm}^2$

Resistivity of copper, $= 7.874 \Omega/\text{m and mm}^2$

Cost factor for copper = N5, 200

Cost factor for iron=500

B. Design variables

1. Stator bore diameter, D
2. Stator core length, L
3. Depth of stator slot, d_{ss}
4. Depth of stator core, d_{sc}
5. Stator tooth width, W_{st}
6. Mean turn length of stator winding, L_{mt}
7. Length of air gap, L_g

C. Objective Function Formulation

Material cost which is the objective function, covers only the cost of copper for stator and rotor windings as well as the cost of iron for the stator core.

$$\text{Material cost } c_m = c_{cu} + c_{fe} \quad (1)$$

c_{cu} = cost of copper (stator and rotor windings)

c_{fe} = cost of iron (stator)

$$C_{cu} = k_{fe} d_{cu} \left[\frac{I N_{ph} L_{mt}}{J_s} + A_b L_b S_r + 2 A_e \pi D_e \right] \quad (2)$$

$$C_{fe} = k_{fe} d_{fe} L \{ [\pi D_{sc} (D + 2 D_{ss} + D_{sc})] + W_{st} D_{ss} S_s \} \quad (3)$$

Material cost $C_m = C_{cu} + C_{fe}$

$$C_m = k_{cu} d_{cu} \left[\frac{I N_{ph} L_{mt}}{J_s} + A_b L_b S_r + 2 A_e \pi D_e \right] + k_{fe} d_{fe} L \{ [\pi D_{sc} (D + 2 D_{ss} + D_{sc})] + W_{st} D_{ss} S_s \} \quad (4)$$

Where,

d_{cu} = Density of copper

N_{ph} = Number of turns per phase

d_{fe} = Density of iron

I = Stator current

J_s = Current density of stator conductor

m = Number of phase

L_{mt} = Mean turn length of stator winding

k_{cu} = Copper cost factor

k_{fe} = Iron cost factor

A_b = Area of rotor bar

L_b = Length of bar

S_r = Number of rotor slots

A_e = Area of end ring

D_e = Diameter of end ring

S_s = Number of stator slots

D = Stator bore diameter

L = Axial length

D_{sc} = Depth of stator core

D_{ss} = Depth of stator slot

W_{st} = Stator tooth width

D. Constraints

During the course of optimization when variables undergo incrementing or decrementing, they should also be constrained to be within practical ranges [14]. The optimization can be subjected to both equality and inequality constraints. The following constraints were imposed on the induction motor design optimization.

1. Peripheral speed V_s ; $V_s \leq 30 \text{ m/s}$
2. Slot pitch S_p ; $15 \leq S_p \leq 25 \text{ mm}$
3. Flux density, B_{av} ; $B_{av} \leq 0.45 \text{ Wb/m}^2$
4. Specific electric loading Q ; $Q \geq 22000 \text{ AT/m}$
5. Stator tooth width W_{st} ; $W_{st} \geq \frac{\phi P}{1.7 \times S_s \times L_i} \text{ m}$
 ϕ = flux per pole
 L_i = effective axial length
6. Length of air gap L_g ; $L_g \leq 0.2 + 2\sqrt{DL} \text{ mm}$

E. Bound limits for the design variables

The design variables can be restricted to certain limits by specifying the lower limit and upper limit. The bound limits set for the design variables are shown in Table 1.

TABLE 1. BOUND LIMITS FOR THE DESIGN VARIABLES

Design variable	Description	Lower limit	Upper limit
-----------------	-------------	-------------	-------------

D	Stator bore diameter	0.1600	0.1750
L	Axial length	0.1300	0.1450
Dss	Depth of stator slot	0.0255	0.0265
Dsc	Depth of Stator core	0.0254	0.0264
Lmt	Mean turn length	0.8000	0.8300
Wst	Stator tooth width	0.0045	0.0055
Lg	Length of air gap	0.0004	0.0006

IV. RESULTS AND DISCUSSION

The results obtained using five AI techniques to optimize the IM design with material cost as the objective function are presented in Tables 2 to 6

TABLE 2. OPTIMIZATION OF MATERIAL COST USING GA

Optimized variable	Value	Other design parameters	
		Quantity	Value
D	0.1601m	Φ	0.0074Wb
L	0.1301m	Nph	266
Dss	0.0255m	Lb	0.1701m
Dsc	0.0254m	Do	0.2619m
Lmt	0.8004m	Ae	104.36mm
Wst	0.0046m	Ab	39.75mm
Lg	0.0004m	De	0.1193m
Material cost	N83,300		

TABLE 3. OPTIMIZATION OF MATERIAL COST USING ABC

Optimized variable	Value	Other design parameters	
		Quantity	Value
D	0.1687m	Φ	0.0079Wb
L	0.1322m	Nph	248
Dss	0.0260m	Lb	0.1722m
Dsc	0.0273m	Do	0.2753m
Lmt	0.8081m	Ae	97.29mm
Wst	0.0048m	Ab	37.06mm
Lg	0.0006m	De	0.1275m
Material cost	N85,414		

TABLE 4. OPTIMIZATION OF MATERIAL COST USING BA

Optimized variable	Value	Other design parameters	
		Quantity	Value
D	0.1750m	Φ	0.0090Wb
L	0.1450m	Nph	218
Dss	0.0265m	Lb	0.1850m
Dsc	0.0264m	Do	0.2808m
Lmt	0.8300	Ae	85.52mm
Wst	0.0055	Ab	32.58mm
Lg	0.0006	De	0.1338m
Material cost	N88,528		

TABLE 5. OPTIMIZATION OF MATERIAL COST USING CSO

Optimized variable	Value	Other design parameters	
		Quantity	Value
D	0.1606m	Φ	0.0074Wb
L	0.1302m	Nph	264
Dss	0.0255m	Lb	0.1702m
Dsc	0.0254m	Do	0.2624m
Lmt	0.8009m	Ae	103.57mm
Wst	0.0055m	Ab	39.95mm
Lg	0.0006m	De	0.1194m
Material cost	₹83,763		

TABLE 6. OPTIMIZATION OF MATERIAL COST USING CSA

Optimized variable	Value	Other design parameters	
		Quantity	Value
D	0.1616m	Φ	0.0075Wb
L	0.1317m	Nph	262
Dss	0.0255m	Lb	0.1717m
Dsc	0.0257m	Do	0.2640m
Lmt	0.8000m	Ae	102.78mm
Wst	0.0045m	Ab	39.15mm
Lg	0.0006m	De	0.1204m
Material cost	₹84,375		

Tables 2 to 6 present the results obtained from the use of five different AI techniques for material cost optimization of an induction motor design. It can be observed that the results from all the techniques are within the bound limits set. It can also be observed that the results from the techniques differ from one another, an indication that these techniques are not efficiently the same. As the optimized variables vary, so also is the value of the objective function (material cost). The values of the other design parameters in the tables such as flux per pole Φ , number of turns per phase Nph, stator outer diameter Do, length of rotor bar Lb, area of end ring Ae, and diameter of end ring De are also required in order to validate the result of the optimization obtained.

TABLE 7. COMPARISON OF RESULTS FROM THE AI TECHNIQUES

Design variable	AI Technique				
	GA	ABC	BA	CSO	CSA
D(m)	0.1601	0.1687	0.1750	0.1606	0.1616
L(m)	0.1301	0.1322	0.1450	0.1302	0.1317
Dss(m)	0.0255	0.0260	0.0265	0.0255	0.0255
Dsc(m)	0.0254	0.0273	0.0264	0.0254	0.0257
Lmt(m)	0.8004	0.8081	0.8300	0.8009	0.8000
Wst(m)	0.0046	0.0048	0.0055	0.0055	0.0045
Lg(m)	0.0004	0.0006	0.0006	0.0006	0.0006
Material cost (₹)	83,300	85,414	88,528	83,763	84,375

Table 7 presents a comparison of the results obtained from material cost optimization of a squirrel cage induction motor design using five AI techniques. The best optimized material cost of N83, 300 was achieved with the GA technique. ABC, BA, CSO and CSA gave N85,414, N88,528, N83,763 and N84,375 respectively. The results show noticeable variations in the output given by each technique. Comparisons of these results indicate a difference of N5, 228 between Genetic Algorithm which gives the best cost and Bat Algorithm which performed the least.

V. VALIDATION

The results obtained from using the AI techniques require validation to ensure that they are practically feasible. Full load slip and peripheral speed are parameters used to validate these results. These parameters have permissible ranges. For a good and practicable optimized result, these permissible limits must not be violated. The values of these parameters for each AI technique were calculated.

A. Peripheral speed

Peripheral speed, $V_s \leq 30\text{m/s}$

$$V_s = \pi D n_s \quad (5)$$

$$\text{synchronous speed, } n_s = \frac{2 \times f}{P} \quad (6)$$

frequency, $f = 50\text{Hz}$ and number of poles, $P = 4$

$$n_s = \frac{2 \times 50}{4} = 25 \text{ r.p.s}$$

The values of bore diameter, D obtained as contained in TABLES 2 to 6 for each technique was substituted into equation (5) and the peripheral speed obtained as shown in TABLE 8

TABLE 8. VALIDATION OF MATERIAL COST OPTIMIZATION BASED ON PERIPHERAL SPEED

Technique	GA	ABC	BA	CSO	CSA
Peripheral speed (m/s)	12.5	13.3	13.8	12.6	12.7

From table 8, it can be observed that the values of the peripheral speed obtained for all the AI techniques are within the allowable limits. Hence, the optimization passes the validation test based on peripheral speed.

B. Full load slip

Full load slip, $s \leq 0.05$

$$\text{slip} = \frac{P_{\text{rcu}}}{P_{\text{rcu}} + P_{\text{out}} + P_{\text{fw}}} \quad (7)$$

Where,

p_{rcu} = rotor copper loss

p_{out} = Output power

p_{fw} = friction and windage losses

$$p_{\text{rcu}} = 4m p_{\text{cu}} N_{\text{ph}}^2 K_w^2 I_{\text{ph}}^2 \left(\frac{L_b}{S_r A_b} + \frac{2D_e}{A_e \pi P^2} \right) \quad (8)$$

$$p_{\text{out}} = 7.46\text{kW} = 7460 \text{ W}$$

$$p_{\text{fw}} = 2\% \text{ of } p_{\text{out}} = 0.02 \times P_{\text{out}}$$

$$p_{\text{fw}} = 149.2\text{W}$$

Design values obtained as contained in TABLES 2 to 6 for each technique were substituted into equation (8) and (7) and the full load slip obtained as shown in TABLE 9

TABLE 9. VALIDATION OF MATERIAL COST OPTIMIZATION BASED ON FULL LOAD SLIP

Technique	GA	ABC	BA	CSO	CSA
Slip (%)	1.96	1.89	1.86	1.94	1.96

From table 9, it can be observed that the values of the full load slip obtained for all the AI techniques are within the allowable limit. Hence, the optimization passes the validation test based on its full load slip

VI. CONCLUSION

A 10HP, 415V, 3-phase squirrel cage induction motor has been optimized successfully using five different artificial intelligence techniques with seven geometric design variables and material cost as the objective function. The optimal values of these design variables and their respective material cost was obtained for each AI techniques with GA taking the lead. With the use of GA for material cost optimization, induction motor designers and manufacturers would be provided with an opportunity to roll out cheaper products and make more profit.

REFERENCES

- [1] Branko, B. (2010) "New Trends in Efficiency Optimization of Induction Motor Drives, New Trends in Technologies: Devices, Computer, Communication and Industrial Systems" InTech.
- [2] Miralem H., Tine M., Bojan Š. & Ivan Z. (2011) "Winding type influence on efficiency of an induction motor" Electrical Review
- [3] Adhirai S., Mahapatra R. P. & Paramjit S. (2018) "The Whale Optimization Algorithm and Its Implementation in MATLAB" World Academy of Science, Engineering and Technology International Journal of Computer and Information Engineering, Vol:12, No:10
- [4] <http://www.tutorialspoint.com>
- [5] Raghuram A. & Shashikala V. (2013) "Design and Optimization of Three Phase Induction Motor using Genetic Algorithm" International Journal of Advances in Computer Science and Technology, vol. 2. No. 6.
- [6] Satyajit S., Surojit S., Subhro P., Sujay S., Gautam K. P. & Pradip K. S. (2013) "Using Genetic Algorithm Minimizing Length of Air-Gap and Losses along with Maximizing Efficiency for Optimization of Three Phase Induction Motor"
- [7] Asaju L. B., Ahamad T. K., Mohammed A. A. & Mohammed A. A. (2013) "Artificial bee Colony Algorithm, its Variants and Applications: A Survey" journal of theoretical and applied information technology, vol. 47 No.2.
- [8] Adis A. Milan T. "Framework for Bat Algorithm Optimization Metaheuristic" Recent Researches in Medicine, Biology and Bioscience
- [9] Siew M. L. & Kuan Y. L. (2018) "A Brief Survey on Intelligent Swarm-Based Algorithms Solving Optimization Problems"
- [10] Rafiul A., Zheng D., Al Shayokh M., Muhammad I. Z. "Implementation of Chicken Swarm Optimization (CSO) with Partial Transmit Sequences for the Reduction of PAPR in OFDM System"
- [11] Nursyiva I., Aris T. & Dian E. W. (2017) "Chicken Swarm as a Multi Step Algorithm for Global Optimization" International Journal of Engineering Science Vol. 6 Issue 1.
- [12] Ghania K., Belhadri M., Abdellah C. & Bernard M. (2016) "Comparison Of Cuckoo Search, Tabu Search And Ts-Simplex Algorithms For Unconstrained Global Optimization" Computer Modelling & New Technologies
- [13] Sangita R. & Sheli S. C. (2013) "Cuckoo Search Algorithm using Lévy Flight: A Review" I.J. Modern Education and Computer Science.
- [14] John C. N. (2011) "Design of Wind Turbine Tower and Foundation Systems: , Optimization Approach" Theses and Dissertations, Iowa Research Online, University of Iowa .