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Optimal design of 4KW squirrel cage induction motor using Particle Swarm Optimization (PSO) and Genetic Algorithm (GA)

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Abstract
The optimal design of machines is essential to conserve scarce resources while ensuring standard or improved output. That is why this work seeks to determine the optimal design of a 4-kilowatt (4KW) squirrel cage induction motor through evolutionary algorithms. The paper seeks to minimize mass, cost and losses of production while improving efficiency and torque. Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) are the chosen analytical techniques to determine the optimal design model for a squirrel cage induction motor. Common design parameters were retrieved from existing motors along with relevant constraints to furnish both algorithms. MATLAB R2018a was used to set both algorithms and run analysis. It was discovered after the analysis that both evolutionary algorithms can create superior designs of squirrel cage induction motors while reducing costs, losses and mass. The findings also show that squirrel cage induction motors constructed in line with design parameters from both intelligent algorithms can improve net efficiency and torque. Based on these findings, it is recommended that artificial neural networks should be adopted in building the most efficient models for mechanical parts in industrial manufacturing processes and Computer Aided Design (CAD) should feature in electrical and electronics engineering to increase the probability of solving design problems with greater ease and accuracy.

Keywords: Squirrel cage, induction motor, genetic algorithm, particle swarm optimization, objective function

1. Introduction

Overall designs of induction motors have undergone massive improvement in terms of better power factor, high efficiency and high starting torque. As a result, power factor and efficiency of these motors are quite high. However, few researches have dwelt on comparing multi-objective optimization techniques to ascertain the cost, torque, loss, and efficiency of induction motors. Dwelling on such research will increase the overall functionality of induction motors in general and minimize losses from operations (Abido MA, (2002)) [1].

Designing an induction motor is a complex engineering process that requires significant expertise to achieve the best possible design outcomes. Due to the ongoing gap between energy demand and supply, energy conservation remains a key focus in engineering applications. Efforts to address this challenge include utilizing renewable energy sources and enhancing the efficiency of equipment used in power generation, transmission, and consumption. Induction motors play a crucial role in various industries (Allaoua, B., Abderrahmani A, Gasbaoui B & Nasri A, 2008) [2]. Enhancing the efficiency of squirrel cage induction motors can contribute significantly to energy savings. This can be achieved through optimization techniques and the development of models that assess the performance of existing squirrel cage induction motors in industrial applications.

High running costs, inefficient torque, energy loss, and low operation efficiency are major causes of failure of motors in industry. Many motors that experience any of these faults may fail to exceed or reach their life span (Carrano EG, Takahashi RHC, Caminhas WM and Neto OMA, 2008) [3] Also, industrial operations will be exposed to losses of different forms based if induction motors fail to perform functions as expected. In this study, we are concerned with the optimal design of a 4KW squirrel cage induction motor as this motor belongs to a group of machines that run on electricity that develop faults before completing their expected life span. Since the squirrel cage induction motor may be susceptible to run costly and probably waste useful energy, it is essential to develop an optimal model to ascertain how best these motors can run in industry.

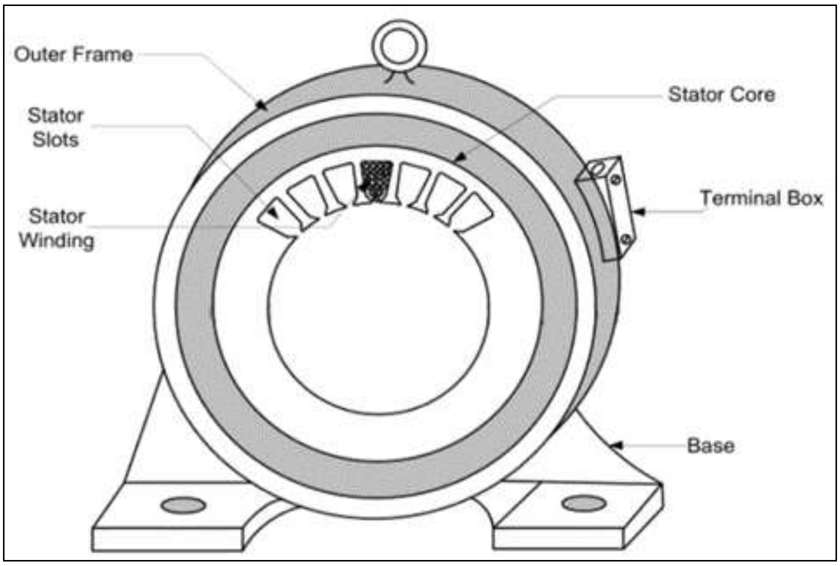

Fig 1: Outer cage and stator of squirrel cage induction motor

The 4KW motor is considered among smaller induction motors and requires stator winding for operation. After completing the single-layer mush winding, the motor was test run to confirm if it is operational. All tests were successful and the motor was found to be in working condition. Also, laboratory tests were carried out on the motor slated for use to determine its performance parameters after obtaining theoretical values.

After taking readings of values for the performance of a 4KW squirrel cage induction motor, no further tests could be carried out due to time constraints for completion of this research (Clerc M & Kennedy J (2002)) [4].

An induction motor can be represented using a steady-state equivalent circuit. The estimation of its parameters is approached as a least-squares optimization problem, where the objective is to minimize the difference between the estimated values and the nameplate data. A more detailed explanation of this formulation is provided below.

The problem formulation relies on manufacturer-provided data, including starting torque, full-load torque, maximum torque, and full-load power factor. The proposed method in this work intends to make a comparative analysis of intelligent algorithms written as MATLAB code. Different objective functions will form the basis of this comparative analysis. The functions are mass, torque, efficiency, loss, and cost (Dorigo M & Stützle T (2004) [5] The same optimization constraints will be used in every case. What this work intends to achieve is to compare the intelligent algorithms to ascertain the acceptance of constraints by both optimization techniques. The work also follows a design focused on discovering the fastness of each algorithm and how close their outputs are.

The Paper centers on the optimal design of 4KW squirrel cage induction motor using Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). The squirrel cage and stator core chosen for this research are in optimal condition and no alterations were made to their basic design (Gupta, VK, Tiwari B & Dewangan B (2015) [6] Tests were conducted to obtain performance values of the chosen induction motor and the analysis to ascertain its optimal design is restricted to both optimization techniques in this body of work.

Genetic algorithm is an optimization technique in computing that finds exact or nearly exact solutions to search problems. It is a global search heuristic. This is a class of evolutionary algorithm technique inspired by evolutional biology like crossover, mutation, inheritance and selection. Genetic algorithm is implemented in simulations where a population of individual's solution to an optimization problem evolves towards better solutions. Typically, binary strings of 0s and 1s represent solutions. The evolution begins with a population of randomly generated individuals and takes place in generations. It begins with no knowledge of the actual solution and depends wholly on environmental and operator responses to achieve the best solution (Kennedy J & Eberhart RC, (1995) [7]. The fitness of each individual in every population across generations is assessed, with multiple individuals stochastically selected based on their fitness. These individuals undergo recombination and random mutation to create a new population, which is then iterated further. The process continues until the maximum number of generations is reached or the population attains a predefined fitness level. Traditionally, a genetic algorithm requires:

a) A genetic representation of the solution domain.
b) A fitness function to evaluate the solution domain.

Genetic Algorithm is based on Charles Darwin's principle of the survival of the fittest, the individual that can survive and live while others die. The principle is ideal for finding fitness values, $f(x)$. The fitness function is an assigned numerical score that indicates how well a particular solution solves the problem. It represents the adaptability capability of the individual to the environment.

Particle Swarm Optimization (PSO) was introduced by James Kennedy and Russell Eberhart in 1995 as an efficient population-based optimization technique and has since been further refined. It is inspired by the collective behavior of bird flocks and fish schools. PSO simulates the interactions within a swarm, where individuals make decisions based on their own experience as well as the experiences of others to enhance the survival of the group.

The algorithm, grounded in the concept of social interaction, searches a solution space by dynamically adjusting the trajectories of particles in a multidimensional space. Each particle is stochastically influenced by its current velocity, its own best past performance, and the best past performance of its neighbors. The search process in PSO involves three key strategies: individual best, local best, and global best.

One of PSO's advantages is its simplicity in implementation, as it does not require gradient information. This makes it applicable to a wide range of optimization problems. Like other optimization techniques such as simulated annealing and ant colony optimization, PSO follows an iterative process based on stochastic decisions. However, unlike Genetic Algorithms and other empirical methods, PSO balances global and local exploration, reducing the risk of premature convergence while improving search efficiency.

PSO has demonstrated superior performance in optimization tasks when compared to composite optimization techniques and the firefly algorithm. It is particularly well-suited for complex optimization problems due to its faster convergence rate and requires fewer tuning parameters than other optimization algorithms.

2. Methodology

The objective of formulating multiple functions is to achieve an optimal design of a 4KW, squirrel cage induction motor by minimizing mass of core metals and copper used, cost of production, and losses from production. Other functions were formulated to maximize the torque and efficiency of a designed squirrel cage induction motor.

2.1 Mass objective function

The required input parameters of a squirrel cage induction motor are necessary for the design to minimize cost, mass, loss while maximizing efficiency and torque in production.

2.2 Loss objective function

Three major losses exist in an induction motor, which are iron (core, mechanical), end ring loss, and (Stator, rotor, etc.) copper losses. According to Masood *et al.*, (2012), these losses across windings can be expressed mathematically to generate accurate values. The iron or core losses comprise of eddy current and hysteresis losses. On the other hand, copper losses are usually aggregated within the primary and secondary windings of an induction motor or transformer. Combining all losses gives a total loss (L_{total}) function. These functions are expressed and combined below;

A. Stator copper loss

(L_{sc}) $L_{sc} = mI_s^2R_s$

Where,

$R_s = \frac{\rho_c l_s}{A_s}$ and $A_s = \frac{I_s}{\delta_s}$

I_s is the stator current (A), R_s is the resistance of stator (Ω), ρ_c is the resistivity of copper(Ω/m), A_s is the cross-sectional area of the stator (m^2), δ_s is the stator current density(A/mm^2), m is the number of phase, l_s is the stator length (m). Hence, L_{sc} becomes, $L_{sc} = mI_s^2\delta_s\rho_c l_s$

B. Rotor bar loss (L_{rb})

$$L_{rb} = I_b^2R_b\mathbf{N}_r$$

Where,

$R_b = \frac{\rho_c l_b}{A_b}$ and $A_b = \frac{I_b}{\delta_b}$

I_b is the rotor bar current (A), R_b is the resistance of rotor bar (Ω), A_b is the Cross sectional area of the rotor (m^2), δ_b is the rotor bar current density(A/mm^2),

N_r, is the armature slots l_b is the rotor length (m). Thus, L_{rb} becomes,

$$L_{rb} = I_b\delta_b\rho_c l_b N_r$$

C. End ring loss (L_{er})

$$L_{er} = 2I_e^2R_e$$

Where,

$R_e = \frac{\rho_c l_e}{A_e}$; $l_e = \pi D_e$; and $A_e = \frac{I_e}{\delta_e}$

I_e is the end ring current (A), R_e is the resistance of end ring (Ω), A_e is the Cross sectional area of the end ring (m^2), δ_e is the end ring current density(A/mm^2), l_e is the end ring length (m), D_e is the diameter of end ring (m).

So, L_{er} becomes,

$$L_{er} = 2I_e\delta_e\rho_c\pi D_e$$

Total loss (L_t) = Stator copper loss (L_{sc}) + Rotor bar loss (L_{rb}) + End ring loss (L_{er}). The total loss equation is expressed as;

$$L_t = mI_s^2\delta_s\rho_c l_s + I_b\delta_b\rho_c l_b N_r + 2I_e\delta_e\rho_c\pi D_e$$

2.3 Efficiency objective function

The efficiency of an induction motor is the ratio of its power output and input percentages.

Efficiency (E or η) = $\frac{kW \text{ X } 1000}{(kW \text{ X } 1000) + total\ loss} \text{ x } 100 - 0.5$

2.4 Cost objective function

Assuming the cost of iron and copper (in Naira per kg) are C_{fe} and C_{cu} respectively, the total cost of materials required for the construction of a squirrel cage induction motor is; $C_t = C_{fe}M_{fe} + C_{cu}M_{cu}$

Substituting expressions for mass of iron and copper respectively gives,

$$C_t = C_{fe}d_{fe}s_f\pi R_c^2((3H+4)(3R_c+T)) + 2C_{cu}d_{cu}h_s\pi(R_pt_p + R_st_s)$$

2.5 Torque objective function

The full load torque of an induction motor must be maximized. The objective function for torque is expressed as;

$$T_m = \frac{60}{2\pi\omega_s} m \frac{V_s^2}{\left(R_1 + \tau_1 \frac{R_2}{s}\right)^2 + (X_1 + \tau_1 X_2)^2} \frac{R_2}{s}$$

ω_s is the synchronous speed in rps, V_s is the voltage applied to the stator, I_2, R_2, X_2 are the rotor current, resistance and reactance referred to stator respectively. R_1, X_1 are the stator resistance and reactance respectively; and τ_1 is the correction factor.

2.6 Genetic Algorithm

Genetic Algorithm (GA)-based optimization is a stochastic search technique that involves randomly generating potential design solutions, systematically evaluating them, and refining them iteratively until a stopping criterion is met. The search process in GA relies on three key operators: selection, crossover, and mutation. The implementation steps of the genetic algorithm are as follows:

1. Define parameters and objective function (Initialization).
2. Generate the initial population randomly.
3. Evaluate the population using the objective function.
4. Check for convergence if the criterion is met, the process stops; otherwise, it continues
5. Perform the reproduction process, including selection, crossover, and mutation.
6. Generate a new population and return to Step 3 for further optimization.

A well-designed genetic algorithm that delivers effective results in many real-world problems consists of three primary operators:

- **Selection:** This process involves choosing individual solutions based on their fitness levels. It is also known as reproduction in some GA applications. The selection probability can be mathematically defined to determine which individuals will be carried forward to the next generation.

$$P_j = F(x_i) \Big/ \sum_{i=1}^{n} F(x_i)$$

Where P_j is the selection probability and $F(x_i)$ is the objective function.

Crossover: This is the most powerful genetic operator. One of commonly used methods for crossover is single-point crossover or uniform crossover. As shown in the following examples, a crossover point is selected between the first and the last bits of the chromosome. Then binary code to the right of the crossover point of chromosome_1 goes to offspring_2 and chromosome_2 passes its code to offspring_1. This operation takes place with a defined probability space P_c that statistically represents the number of individuals involved in the crossover process.

Crossover point Crossover point

Chromosome_1 = 0010010 101

Offspring_1 = 0010010 100

Chromosome_2 = 0101011 100

Offspring_2 = 0101011 101

Mutation: This is a common genetic manipulation operator, and it involves, the random alteration of genes during the process of copying a chromosome from one generation to the next. Raising the ratio of mutations increases the algorithm's freedom to search outside of the current region of parameter space. Mutation changes from a "1" to a "0" or vice versa. It may be illustrated as follows;

110000*0*010 ⟶ 110001*1*010

2.7 Particle Swarm Optimization

The Particle Swarm Optimization (PSO) is a meta-heuristic algorithm inspired by the social behaviour of flocking birds and aims to search for optimal values by updating several generations (iterations) until the global best (g-best) solution is achieved.

It is a computational method that helps find an optimal position by improving candidate solutions. A population of candidate solutions, or particles, are necessary for determining the best position in a certain search space. Every particle in the search space has its local best position, guided towards the most viable solution.

The PSO algorithm is represented mathematically with an i^{th} particle in a swarm of n-dimensional space as;

$$x_i = [x(i,1), x(i,2), x(i,3), \dots, x\ (i,n)]$$

The best previous positions of the i^{th} particle, known as personal best or p-best, is represented by;

$$p_{best} = [p_{best}(i,1), p_{best}(i,2), p_{best}(i,3), \dots, p_{best}\ (i,n)]$$

The index of a swarm's best particle among the whole group is known as global best, or g-best for an i^{th} particle in an n-dimensional space.

Every particle in a swarm must have a velocity while traveling towards the global best point. The velocity (V_i) is described as;

$$v_i = [v(i,1), v(i,2), v(i,3), \dots, v(i,n)]$$

The velocity and distance from the personal best to global best position is defined by;

$$V(i, m^{t+1}) = w * v\ (i, m^t) + c_1^* rand\ (\ ) * (P_{best}(i,m) - X(i,m^t)) + c_2^* rand\ (\ ) * (g_{best}(i,m) - X(i,m^t))$$

and

$$X(i, m_{(t+1)}) = X(i, m_{(t)}) + V(i, m_{(t+1)})$$

For i = 1, 2, 3 … k

m = 1, 2, 3 …, n

k, is the number of particles in the group,

n is the dimension index,

t is the Pointer of iteration,

V(i, m(t)) is the Velocity of particle at iteration i,

W is the Inertia weight factor,

C_1 and C_2 are the acceleration constants, rand () is the random number between 0 and 1,

X (i, m (t)) is the current position of the particle i at iteration,

p_{best} is the best previous position of the i^{th} particle,
g_{best} is the best particle among all the particle in the swarming population

3. Operating characteristics, testing and comparison

3.1 Design variables and input parameters

Table 1: Input parameters of 4kW squirrel cage induction motor

S. No	Input parameters	Values
1	Output Power (kW)	4
2	Rated Voltage (V)	380
3	Winding Connection	δ
4	Number of Poles	4
5	Frequency (Hz)	50
6	Stator Inner Diameter (mm)	105
7	Stator Outer Diameter (mm)	170
8	Rotor Outer Diameter (mm)	104.5
9	Number of Rotor Slots	28
10	Number of Stator Slots	36

Table 2: Upper and lower bounds of design variables

Variables	Description	Lower bound	Upper bound
x_1	Stator turns per phase	50	85
x_2	Stator iron length (m)	0.15	0.30
x_3	End-ring width (m)	0.015	0.030
x_4	Stator interior diameter (m)	0.18	0.25
x_5	Stator slot height (m)	0.018	0.038
x_6	Stator slot width (m)	0.012	0.07
x_7	Air gap (m)	0.004	0.0065
x_8	Rotor slot path (m)	0.0025	0.0035
x_9	Rotor bar diameter (m)	0.006	0.0080
x_{10}	Stator exterior diameter (m)	0.030	0.038

4. Results

Table 3: Squirrel cage induction motor design optimization: mass as an objective function

Variables	Description	Existing Motor	Genetic Algorithm	Particle Swarm Optimization
x_1	Stator iron length (m)	19.6	17	16.8
x_2	End-ring width (m)	25	17.3	15.1
x_3	Stator interior diameter (m)	22	19.1	17.88
x_4	Stator slot height (m)	27	25	24.3
x_5	Stator slot width (m)	10.13	9.62	8.48
x_6	Air gap (m)	0.061	0.057	0.048
x_7	Rotor slot path (m)	10.3	10.17	10.09
x_8	Rotor bar diameter (m)	10.4	10.11	9.87
x_9	Stator exterior diameter (m)	38	34	31

Table 4: Squirrel cage induction motor design optimization: torque as an objective function

Variables	Description	Genetic Algorithm	Particle Swarm Optimization
x_1	Stator iron length (m)	16.64	16.62
x_2	End-ring width (m)	16.64	14.92
x_3	Stator interior diameter (m)	1874	17.7
x_4	Stator slot height (m)	24.64	24.12
x_5	Stator slot width (m)	9.26	8.3
x_6	Air gap (m)	0.035	0.032
x_7	Rotor slot path (m)	9.81	9.91
x_8	Rotor bar diameter (m)	9.75	9.69
x_9	Stator exterior diameter (m)	33.64	30.82

Table 5: Squirrel cage induction motor design optimization: loss as an objective function

Variables	Description	Genetic Algorithm	Particle Swarm Optimization
x_1	Stator iron length (m)	16.44	16.28
x_2	End-ring width (m)	16.58	14.74
x_3	Stator interior diameter (m)	18.38	17.52
x_4	Stator slot height (m)	24.98	24.94
x_5	Stator slot width (m)	8.9	8.12
x_6	Air gap (m)	0.0283	0.032
x_7	Rotor slot path (m)	9.45	9.33
x_8	Rotor bar diameter (m)	9.69	9.51
x_9	Stator exterior diameter (m)	30.64	30.28

Table 6: Squirrel cage induction motor design optimization: cost as an objective function

Variables	Description	Genetic Algorithm	Particle Swarm Optimization
x_1	Stator iron length (cm)	16.1	15.92
x_2	End-ring width (mm)	16.4	16.22
x_3	Stator interior diameter (cm)	18.2	18.02
x_4	Stator slot height (mm)	24.1	23.92
x_5	Stator slot width (mm)	8.72	8.54
x_6	Air gap (cm)	0.043	0.038
x_7	Rotor slot path (cm)	9.27	9.09
x_8	Rotor bar diameter (mm)	9.21	9.03
x_9	Stator exterior diameter (cm)	33.1	32.92

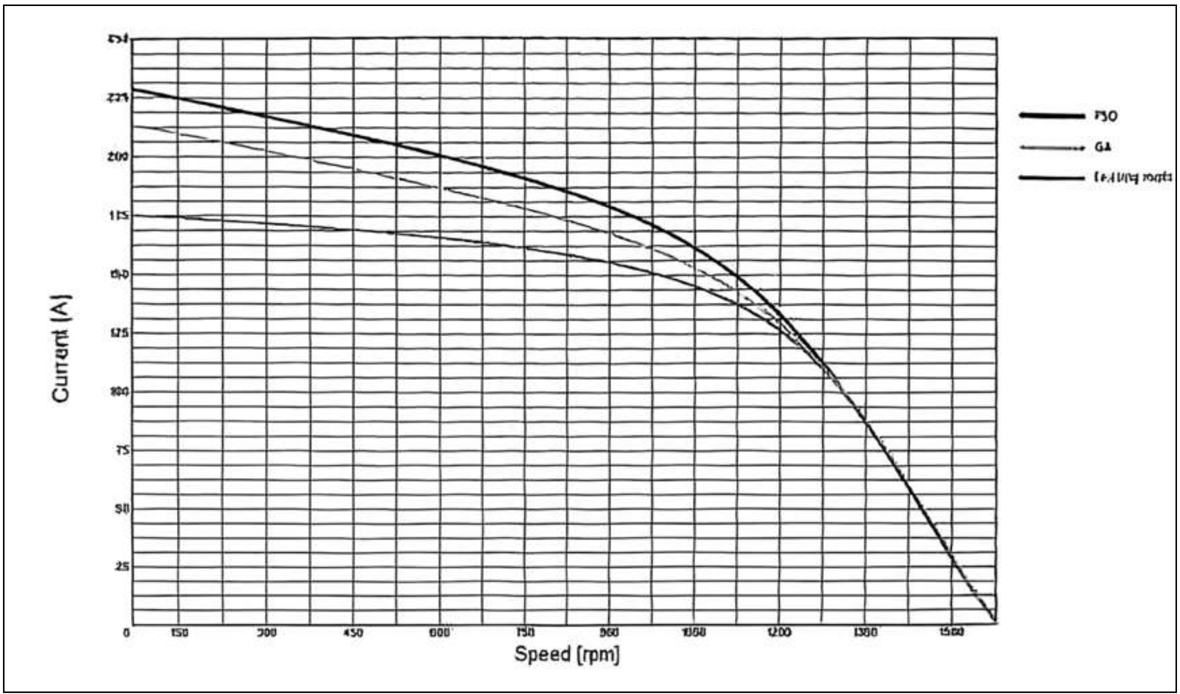

Fig 2: Output Current (A) versus Motor Speed (RPM)

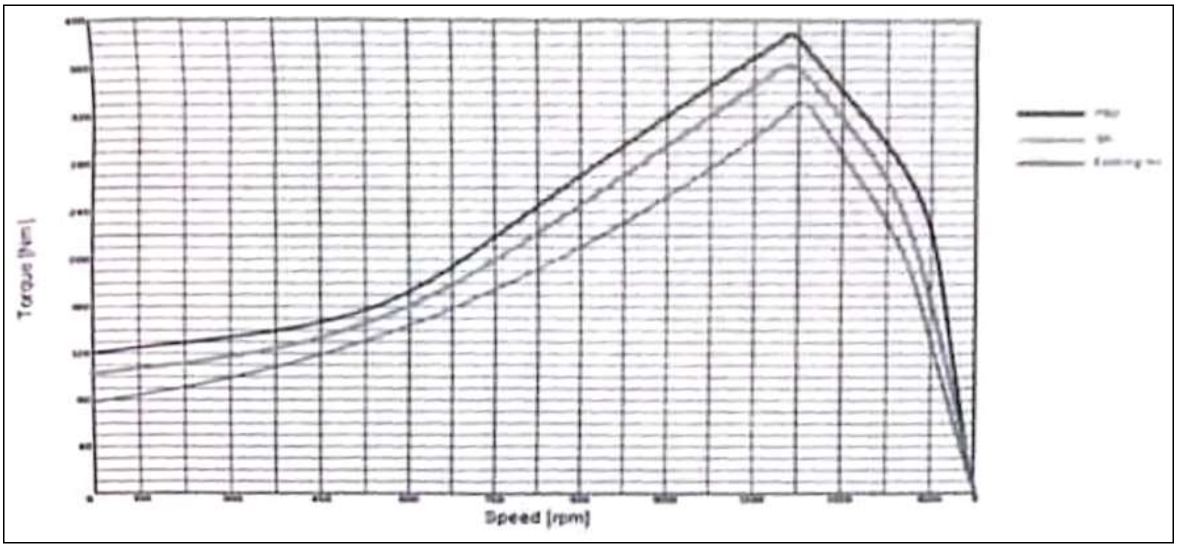

Fig 3: Output Torque (Nm) versus Motor Speed (RPM)

Table 7: Squirrel cage induction motor design optimization: efficiency as an objective function

Variables	Description	Genetic Algorithm	Particle Swarm Optimization
x_1	Stator iron length (cm)	15.74	15.56
x_2	End-ring width (mm)	16.04	15.86
x_3	Stator interior diameter (cm)	17.84	17.66
x_4	Stator slot height (mm)	23.74	23.56
x_5	Stator slot width (mm)	8.36	8.18
x_6	Air gap (cm)	0.043	0.042
x_7	Rotor slot path (cm)	8.91	8.73
x_8	Rotor bar diameter (mm)	8.85	8.67
x_9	Stator exterior diameter (cm)	32.74	32.56

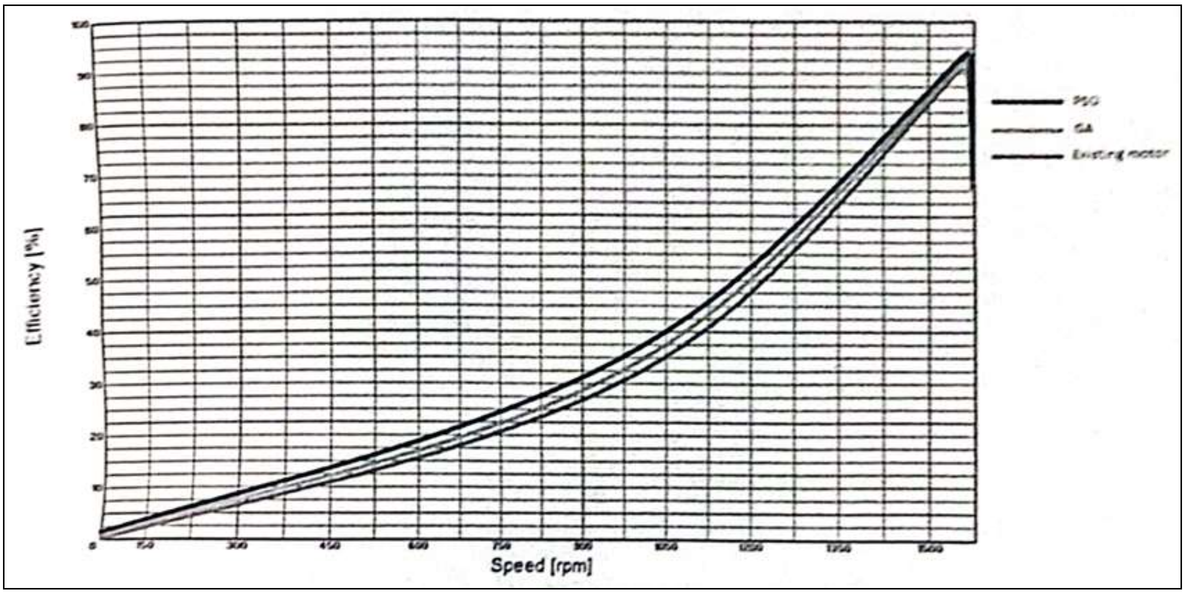

Fig 4: Efficiency (%) versus Motor Speed (RPM)

5. Conclusion

A 4kW, squirrel cage induction motor has been designed using two intelligent algorithms. Five objective functions namely mass, torque, cost, loss and efficiency, and ten constraints were used on the selected algorithms. The induction motor parameters designed for were: stator slot, rotor, and core connector. The expected out parameters are the cost, torque, efficiency, losses, and mass of the induction motor.

This work demonstrates the efficiency of intelligent algorithms and show how their proper use with appropriate objective functions and constraints would produce good results to rival or surpass existing design modules.

6. Recommendations

1. Ingredient mix optimization should be encouraged in building complex machines to help develop efficient production strains with optimal results.
2. Artificial neural networks should be adopted in building the most efficient models for mechanical parts in industrial manufacturing processes.
3. Computer Aided Design (CAD) should feature in electrical and electronics engineering to increase the probability of solving design problems with greater ease and accuracy.

Students should study intelligent algorithms with the ability to support complex design templates for greater insight and easier problem-solving.

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