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Machine Learning Perspective Gene Optimization for Efficient Induction Machine Design

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Abstract – In this paper, induction machine operation efficiency and torque is improved using Machine Learning based Gene Optimization (ML-GO) Technique is introduced. Optimized Genetic Algorithm (OGA) is used to select the optimal induction machine data. In OGA, selection, crossover and mutation process is carried out to find the optimal electrical machine data for induction machine design. Initially, many number of induction machine data are given as input for OGA. Then, fitness value is calculated for all induction machine data to find whether the criterion is satisfied or not through fitness function (i.e., objective function such as starting to full load torque ratio, rotor current, power factor and maximum flux density of stator and rotor teeth). When the criterion is not satisfied, annealed selection approach in OGA is used to move the selection criteria from exploration to exploitation to attain the optimal solution (i.e., efficient machine data). After the selection process, two point crossovers is carried out to select two crossover points within a chromosomes (i.e., design variables) and then swaps two parent's chromosomes for producing two new offspring. Finally, Adaptive Levy Mutation is used in OGA to select any value in random manner and gets mutated to obtain the optimal value. This process gets iterated till finding the optimal value for induction machine design. Experimental evaluation of ML-GO technique is carried out with performance metrics such as torque, rotor current, induction machine operation efficiency and rotor power factor compared to the state-of-the-art works.

Keywords: Induction motor, annealed selection, Adaptive Levy Mutation, two point crossovers, fitness function, optimized genetic algorithm.

1. Introduction

An induction motor is an ac electric motor where the electric current in rotor produces torque by electromagnetic induction from magnetic field of stator winding. The multi-objective design optimization was introduced in [1] with Non-dominated Sorting Genetic Algorithm (NSGA-II) for three phase induction motors. For attaining the Pareto optimal solutions, ranking method was introduced. However, the optimal solution failed to increase the efficiency of induction machine. Two fuzzy logic inputs with speed error, speed variation derivative and fuzzy output, motor reference torque (Te*) were calculated. The genetic optimization algorithm was designed in [2] with higher efficiency and minimal losses. Though the efficiency of induction machine was improved, the torque value was not increased.

Induction machines with external rotor were used in industrial fans with fixed load for increasing the efficiency by redesigning the machine to attain the objective function. The optimal design of induction machine with external rotor was introduced in [3] using Genetic Algorithm (GA). But, the stator and rotor copper loss were not reduced.

The hybrid control of induction motor depending on combination of direct torque control (DTC) and the back stepping one were optimized by Genetic Algorithm (GA) in [4]. DTC was described where torque and stator flux were managed by non linear hysteresis controllers that are large ripple in motor torque at steady state operation. Though the torque level was improved, the efficiency remained unaddressed.

A control plan was introduced in [5] for energy efficiency enhancement of three-phase induction motors (TIM). The control was depending on indirect field oriented approach. A loss model-based controller minimized the copper and iron losses of TIM for many load values. A nonlinear equation depended on quadrature currents and attained suboptimal flux reference in steady-state conditions. Though the copper and iron losses were reduced, the power factor value was not improved. A new method was introduced in [6] for optimization of inverter-driven Induction Motor (IM) by modified Particle Swarm Optimization (PSO). The maximum efficiency of motor was attained through identifying the optimal output frequency and voltage of drive at any operating point. The optimal amplitude and frequency of excitation voltage were identified by modified PSO algorithm. But, the

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efficiency was not improved beyond the certain level.

The magnetic wedges usages in induction motors with semi-closed slots were studied in [7]. The strategy minimized the copper as well as core losses and improved the motor efficiency. The study examined the low power motors based on different permeabilities and geometries for magnetic wedges. Though the motor efficiency was improved by reducing the copper and core losses, the rotor current value was not reduced. A complete theory and analysis method for analytical calculation of induction motors efficiency with combined star-delta windings was introduced in [8]. A new hybrid model was introduced in [9] for optimization of induction motor drives (IMD). Search control technique was employed in steady condition of drive and loss model in transient processes. A new hybrid model for efficiency optimization of the direct vector-controlled induction motor drives was introduced in [10]. The efficiency enhancement approach changed the rotor flux with load torque to minimize the total losses in induction machine. But, the losses were not reduced beyond certain level to increase the efficiency.

The main contribution of the work is as follows: Machine Learning based Gene Optimization (ML-GO) Technique is introduced with Optimized Genetic Algorithm (OGA) to select the optimal induction machine data. Initially in OGA, many number of induction machine data are given as input for OGA. Then, fitness value is calculated for all induction machine data to find whether the criterion is satisfied or not through fitness function. When the criterion is not satisfied, annealed selection approach in OGA is used to move the selection criteria from exploration to exploitation to attain optimal solution. After the selection process, two point crossovers is carried out to select two crossover points within a chromosomes and then swaps two parent's chromosomes for producing two new offspring. Finally, Adaptive Levy Mutation is used in OGA to select any of value in random manner and gets mutated to obtain the optimal value.

The paper is outlined as follows. Section 2 portrays the review of related work of induction machine operation in brief manner, Section 3 describes Machine Learning based Gene Optimization (ML-GO) Technique with neat flow diagram and algorithmic process. In Section 4, the empirical results are discussed in Section 4 with detailed discussions provided in Section 5. Finally, section 6 summarizes the conclusions of the paper.

2. Related Works

The induction motor design by Genetic algorithm was introduced in [11] for increasing the efficiency. Though the efficiency was improved, the computational cost remained unaddressed. A genetic algorithm based self-tuned Neuro fuzzy controller (NFC) for speed control of induction motor drive (IMD) was introduced in [12]. Though the induction motor speed was controlled using Neuro fuzzy controller (NFC), the efficiency remained unaddressed. In NFC system, Fuzzy logic and Artificial Neural Network (ANN) structure with Genetic Algorithm scheme was employed. A new and efficient method with Improved Big Bang-Big Crunch (I-BB-BC) Algorithm was introduced in [13] for efficiency estimation in induction motors. For calculating the induction motor efficiency, current value, power factor and input power were used and suitable objective function was introduced. However, the torque value was not improved using Improved Big Bang-Big Crunch (I-BB-BC) Algorithm.

For nonintrusive efficiency evaluation of inverter-fed induction motors, quantification of additional losses was computed for harmonic equivalent circuits. Recommended methods were designed in [14] for efficiency estimation of highlighted inverter-fed induction motors. Full-load and partial-load efficiency were calculated through dynamometer. But, the rotor current was not improved using recommended methods. A new technique was designed in [15] for calculating the refurbished induction motor's full-load and partial-load efficiencies. An air-gap torque (AGT)-based method was introduced in [16] for efficiency estimation of induction motors. A new stator resistance was estimated through particle swarm optimization approach depending on stator flux equations and reduction of torque error at rated operation point. Though the torque error was reduced, the induction machine efficiency was not improved using air-gap torque (AGT)-based method.

A bacterial foraging algorithm was employed in [17] as an economic, exact and low-invasive tool to work in field conditions, output power, losses and efficiency of induction motors with unbalanced voltages. A multi-objective optimization method was introduced in [18] depending on Genetic Algorithm to improve the efficiency as well as power factor and to reduce motor weight. A cost efficient off-line method was designed in [19] for circuit parameter evaluation of induction motor through genetic algorithm and particle swarm optimization (HGAPSO). Multi-objective fuzzy genetic algorithm (MFGA) was introduced in [20] for optimal design of induction motors. But, the above mentioned techniques failed to reduce the computational complexity. In order to overcome the above mentioned issues, Machine Learning based Gene Optimization (ML-GO) technique is introduced for designing induction machines. In ML-GO technique, OGA is employed to select the optimal machine data to reduce the computational complexity for designing induction machine which is explained in next section.

3. Machine Learning Based Gene Optimization (Ml-Go) Technique

Induction motors are used in many applications due to its low cost maintenance and robustness. However at light loads, no balance in between copper and iron losses leads to reduction in efficiency of induction machine. The efficiency and power factor performances are enhanced through performing the motor excitation adjustment based on load and speed. To increase the efficiency performance of induction machine, Machine Learning based Gene Optimization (ML-GO) technique is designed. In ML-GO technique, Optimized Genetic Algorithm (OGA) is used to attain the best optimal induction machine data for designing the induction machine with higher efficiency.

ML-GO technique finds the optimal induction machine data using Optimized Genetic Algorithm for designing the induction machine. The optimal induction machine data is selected for calculating the fitness function with multiple constraints. When the fitness function satisfies the threshold criteria, the induction machine data is selected for induction machine design with higher efficiency. When the criteria are not satisfied, selection, crossover and mutation process is carried out to select the global optimal solution using optimized genetic algorithm by satisfying all criteria. Through selecting the optimal machine data for induction machine design, the efficiency of IM gets increased. The detailed explanation of Machine Learning and Optimized Genetic Algorithm is explained in Section 3.1 and 3.2.

3.1 Machine learning

Machine learning in ML-GO technique is the subfield of computer science where the computer has ability to learn without any clear programming. Machine learning is used for designing the algorithms for making the predictions on data. Machine learning is used in the range of computing tasks where the designing and programming algorithms with better performance is not infeasible. Optimized Genetic Algorithm (OGA) is the one of the machine learning algorithms. An optimized genetic algorithm is a search heuristic method that uses the selection, crossover and mutation to create new genotype for finding the optimal solution.

3.2 Optimized Genetic Algorithm (OGA)

In OGA, optimum design of induction motor is a non-linear multi dimension issue while optimal control is single or two dimension issues. Then, optimization technique is used in design of IM to obtain global optimal solution.

3.2.1 Population initialization

In ML-GO technique, population initialization is carried out for generating many individuals (i.e., induction machine data) in random manner. It is an iterative process where the population in iteration called as a generation. The generation initiates with the iteration count '0' to address the optimization problem with optimal solutions. Each individual has set of properties (i.e., chromosomes) that are mutated and varied. After that, fitness function is calculated.

3.2.2 Fitness function

The fitness is the value of objective function where the optimization issues are solved. Fitness value of induction machine data is calculated based on four objective functions, namely

$$\begin{aligned} x_1 &= \textit{starting to full load torque ratio} \\ x_2 &= \textit{rotor current} \\ x_3 &= \textit{power factor} \\ x_4 &= \text{maximum } \textit{flux density of stator and rotor teeth} \end{aligned}$$

The total objective function is the sum of all the objective function. Total objective function is formulated as,

$$x = x_1 + x_2 + x_3 + x_4 \tag{1}$$

From (1), the total objective function is calculated. The total objective function and its constraints are given by,

$$A_j(x) \le 0 \leftrightarrow \left\{ \begin{array}{c} \textit{starting to full load torque ratio} \ge 1.5 \\ \textit{Rotor current} \le 6.5 \\ \textit{Rotor power factor} \ge 0.7 \\ \text{maximum flux density of stator and rotor teeth} \le 2 \end{array} \right\} \tag{2}$$

From (2), the primary design variables of induction machine are given with its constraints. Based on the design variables, the induction machine efficiency are to be calculated. The induction machine efficiency is formulated as,

$$B(x) = \textit{Induction} \text{ machine efficiency} = \frac{\textit{Output Power}}{\textit{Output Power} + P_{TL}} \tag{3}$$

From (3), the induction machine efficiency is given by the ratio of the output power to the sum of output power and total power loss. The total power loss in induction machine design is the sum of stator copper loss 'SCL', rotor copper loss 'RCL'and Stator Iron Loss 'SIL'. The total power loss 'P_{TL}' is given by,

$$P_{TL} = SCL + RCL + SIL \tag{4}$$

From (4), the total power loss is calculated. Copper loss is the heat produced by electrical currents in electrical devices. Copper losses are undesirable transfer of energy that results from induced currents in adjacent components. The stator copper loss is calculated by the product of square of current and resistance. Stator copper loss is given by,

$$SCL = I^2 R_s \tag{5}$$

From (5), 'I' denotes the current in amps and 'R_s' represents the stator resistance in ohms. The rotor copper loss is given by,

$$RCL = SI_b R_b \left(L_r + \frac{2D_e}{p} \right) \tag{6}$$

From (6), 'S' represents the number of rotor slots, 'R_b' denotes the resistance of each bar in the rotor, 'I_b' symbolizes the rotor bar current, 'L_r' represents length of the core, 'D_e' denotes the mean end ring diameter and 'p' symbolizes the number of poles. The stator iron loss is calculated based on the weight and losses in stator teeth as well as in stator core. The stator iron loss '*SIL*' is formulated as,

$$\mathrm{SIL} = \left(W_{st} * W_{lst} \right) + \left(W_{sc} * W_{lsc} \right) \tag{7}$$

From (7), 'W_{st}' symbolizes the weight of stator teeth, 'W_{lst}' represents the losses in stator tooth, 'W_{sc}' denotes the weight of stator core and 'W_{lsc}' symbolizes the losses in stator core. After calculating the loss value, the induction machine efficiency is calculated. Then in ML-GO technique, the fitness function of each induction machine data is calculated. The fitness function is mathematically formulated as,

$$\textit{Fitness}\ \text{Function} = \frac{\mathrm{B}(\mathrm{x})}{\sum_{j=1}^{N} A_j(x)} \tag{8}$$

From (8), '$\mathrm{B}(\mathrm{x})$' denotes the induction machine efficiency and '$A_j(x)$' represents the objective function and its constraints. The algorithmic process of fitness function calculation was given below,

Algorithm 1: Fitness Function Calculation Algorithm
Step 1 : **Begin**
Step 2 : Initialize Gene Population
Step 3 : Set Generation (i.e., Iteration count i=0)
Step 4 : Define objective function with its constraints using (2)
Step 5 : For each individuals 'j'
Step 6 : Calculate objective function
Step 7 : Calculate the Induction Machine efficiency using (3)
Step 8 : Compute Fitness Function using (8)
Step 9 : end for
Step 10 : End

From algorithm 1, the fitness function calculation for all induction machine data are made. The annealed selection approach is discussed in next sub-section.

3.2.3 Annealed selection approach

Annealed Selection approach in ML-GO technique is used to move the selection criteria from exploration to exploitation to attain perfect solution. For Annealed Selection approach, fitness value of each individual are calculated. Selection probability of each individual is calculated based on 'j^{th}' individual on 'i^{th}' generation represented as '$X_{i,j}$'. When the generation of population varies, fitness value and selection probability of each individual also gets varied. The blended selection operator calculates fitness value of individual based on current number of generation. Selection probability of 'j^{th}' individual 'PX_j' is calculated by,

$$PX_j = \frac{FX_j}{\sum_{j=1}^{N} FX_j} \tag{9}$$

From (9), 'FX_j' denotes the Average Fitness of the population in j^{th} individual in Annealed Selection approach and 'N' denotes the total number of individuals. The algorithmic process for Annealed Selection Approach is given in below figure,

Algorithm 2: Annealed Selection Algorithm
Begin
Step 1: Initialize Gene Population
Step 2: Set Generation (i.e., Iteration count i=0)
Step 3: For each individuals 'j'
Step 3: Calculate Fitness function using (8)
Step 4: Select the individual using Annealed Selection Approach using (9)
Step 5: **end for**
End

From Algorithm 2, annealed selection is carried out in OGA. After the selection process, the two point crossover operation is carried out. The brief discussion of two point crossover is discussed in next sub-selection.

3.2.4 Two point crossover

In ML-GO technique, two point crossover is a genetic operator for changing the chromosomes from one generation to the next generation. Crossover process takes more than one parent chromosomes and produces offspring for them. Two point crossovers choose the two crossover points inside the chromosomes and then swap the two parent's chromosomes between points for producing two new offspring.

3.2.5 Adaptive levy mutation

In ML-GO technique, Adaptive Levy Mutation is carried out to balance the Classical Evolutionary Programming (CEP) for local search with Fast Evolutionary Programming (FEP). Adaptive Levy Mutation changes one or more design variable values in chromosome from their initial state. In Adaptive Levy Mutation, the solution has the possibility of changing entirely from the previous solution. Mutation takes place in evolution depending on Levy probability distribution function. Adaptive Levy Mutation is carried out by generating two mutated offspring from each parent with help of Levy probability distributions and choosing the most suitable one for rest of the population. The Levy probability density function is given by,

$$f_{levy(\alpha,\gamma)}\left(x\right)=\frac{1}{\pi}\int_{0}^{\infty}e^{-\gamma q^{\alpha}}\cos\left(qx\right)dq \tag{10}$$

From (10), 'α' and 'γ' are parameters used for characterizing the distribution '$0<\alpha<2$' and '$\gamma>0$'. In mutation, a gene value is chosen from the chromosome attained in past generation and gene value is varied for creating the new offspring.

Randomly chosen value

Original sequence <110011101>
Mutated Sequence <110011001> (11)

From (11), the mutation sequence is obtained after using Levy probability density function in the original sequence. The orange color indicates the randomly chosen value for mutation in ML-GO technique. The Levy mutation operation comes from local optimal solution and search for the global optimal solution. The process gets repeated and the best global optimal value is selected for induction machine design with higher efficiency. The algorithmic description of Optimized Genetic Algorithm in ML-GO technique is explained below,

Algorithm 3: Optimized Genetic Algorithm
Input: No. of individuals (N),
Output: Improves Efficiency of Induction Machine Design
Step 1: Begin
Step 2: Generate an initial population
Step 3: Compute the fitness of each individual
Step 4: if criterian satisfied then
Step 5: Select the individual as an optimal one
Step 6: else
Step7: Perform Annealed Selection using (9)
Step 8: Perform Two point Crossover
Step 9: Perform Adaptive Levy Mutation using (10)
Step 10: Goto **Step 3**
Step 8: End if
Step 9: End

As shown in Algorithm 3, initially population is generated. Then, the fitness function of each individual are calculated based on the objective function. After calculating the fitness function, it checks whether the fitness function satisfies the criterion. When the criterion is satisfied, it is said to be optimal solution. Otherwise, selection, crossover and mutation process is carried out in Optimized Genetic Algorithm till finding the optimal solution (i.e., induction machine data). With help of that data, induction machine gets designed. This in turn helps to improve induction machine operation efficiency in efficient way.

4. Simulation Settings

The proposed ML-GO technique is implemented with MATLAB 2015b with 3.4 GHz Intel Core i3 processor, 4GB RAM, and windows 7 platform. The proposed ML-GO technique and two existing Non-dominated Sorting Genetic Algorithm (NSGA-II) and Genetic Optimization Algorithm are used to obtain the optimal design of three IMs. The parameter and values of induction machine 1, 2 and 3 are explained in Table 1.

For induction machine 1, induction machine 2 and induction machine 3, the number of poles taken is 4. The supply voltage and the input power of the induction machine 1 are 400V and 6kW respectively. For induction machine 2, the voltage and the input power of induction machine is given as 400V and 7.5kW respectively. For induction machine 3, the supply voltage and the input power of induction machine 3 is given as 400V and 2.2kW respectively.

By using proposed ML-GO technique the optimal values is chosen to design the induction machines is shown in above Table 2.

Table 1. Parameters and values of Induction Machine 1,2 &3

Parameter	IM 1	IM 2	IM 3
Number of Poles	4	4	4
Supply Voltage	400V	400V	415V
Power	6 kW	2.2 kW	7.5 kW
Frequency	50 Hz	50 Hz	50 Hz
Maximum Speed	1500 rpm	1500 rpm	1440 rpm

Table 2. Optimal values of Induction Machine 1,2 &3

Description	Optimal design using ML-GO		
	IM 1	IM 2	IM 3
Starting to full load torque ratio	1.526	1.416	1.636
Rotor current A/mm^2	4.81	4.03	5.83
Rotor power factor (P.F)	0.762	0.69	0.808
Maximum flux density stator and rot or teeth wb/m^2	1.632	1.567	1.736

5. Result Analysis

The efficiency of ML-GO technique is compared against with the two existing methods namely Non-dominated

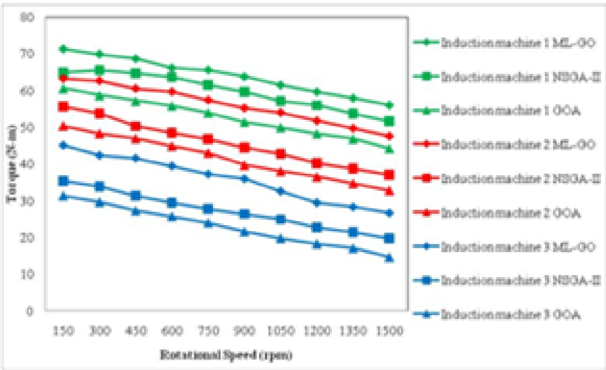

Fig. 1. Measurement of torque

Sorting Genetic Algorithm (NSGA-II) [1] and Genetic Optimization Algorithm [2]. The performance of ML-GO Scheme is evaluated along with the metrics such as torque, rotor power factor, rotor current and induction machine operation efficiency.

5.1 Measurement of torque

Torque (T) is defined as the ratio of power to the rotational speed. Torque is measured in terms of Newton meter (N-m). Torque is mathematically formulated as,

$$T = \frac{Power}{2 * \pi * N} \tag{12}$$

From (12), 'T' represents torque and 'N' symbolizes rotational speed in rpm. When the torque level is higher, the technique is said to be more efficient.

The impact of torque versus different speed range using three methods is described in Fig. 1. As explained in figure, ML-GO technique provides maximum torque when compared to other existing methods namely Non-dominated Sorting Genetic Algorithm (NSGA-II) [1] and Genetic Optimization Algorithm [2]. When the rotational speed increases, torque values get reduced in all three methods. ML-GO technique produces higher torque value than other techniques. This is due to the application of optimized genetic algorithm that select the induction machine data with higher efficiency. Consequently in induction machine 1, the ML-GO technique increases the torque value by 7.0% as compared to NSGA-II [1] and 21.7% as compared to Genetic Optimization Algorithm [2] respectively. In induction machine 2, the torque value gets increased by 23% as compared to NSGA-II [1] and 36.5% as compared to Genetic Optimization Algorithm [2] respectively. For induction machine 3, torque value gets increased by 32% as compared to NSGA-II [1] and 5.9% as compared to Genetic Optimization Algorithm [2] respectively.

The Machine Learning based Gene Optimization for Induction motor 1, Induction motor 2 and Induction motor 3 are described in Fig. 2 with three parameters namely,

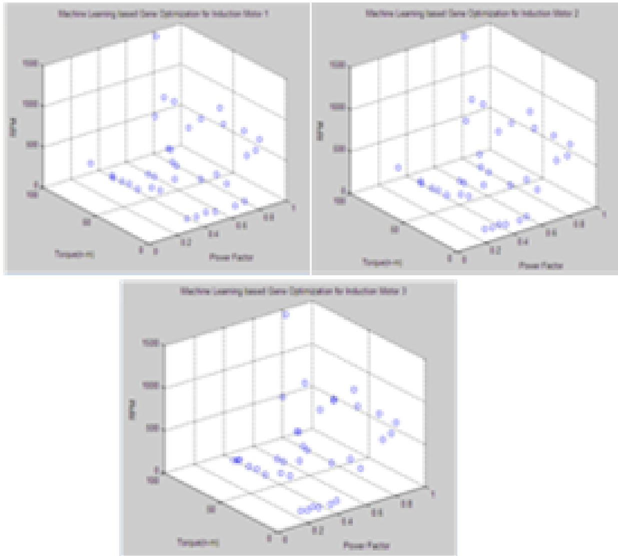

Fig. 2. ML-GO of rotational speed (RPM), torque and power factor for Induction motor 1, Induction motor 2 and Induction motor 3

rotational speed (RPM), torque and power factor. The bubble graph is explained for three induction motor to achieve the higher induction machine efficiency. The figure describes three parameter performance evaluations in one bubble graph. Through satisfying the criterion function, the efficiency of all induction machines gets increased.

5.2 Measurement of rotor power factor

Rotor Power factor is defined as the ratio of real power of the rotor to the apparent power of rotor. The rotor power factor of induction motor is formulated as,

$$\begin{aligned} \textit{Rotor}\ \text{Power Factor} &= \frac{\text{Real Power}}{\textit{Apparent}\ \text{Power}} \\ &= \frac{R_r}{\sqrt{R_r^2 + \left(\left(\frac{N - N_s}{N_s}\right) X_r\right)^2}} \end{aligned} \tag{13}$$

From (13), 'R_r' denotes resistance of rotor, 'X_r' denotes the reactance of rotor, 'N' symbolizes rotational speed and 'N_s' denotes the synchronous speed of induction motor. When the rotor power factor is high, the technique is more efficient.

The rotor power factor using proposed ML-GO technique is higher when compared to other existing methods [1] and [2]. The rotor power factor of induction machine 1 is comparatively higher than other two machines. The graphical analysis of the rotor power factor is shown in Fig. 3.

The impact of rotor power factor versus different speed range using three methods is explained in Fig. 3. As

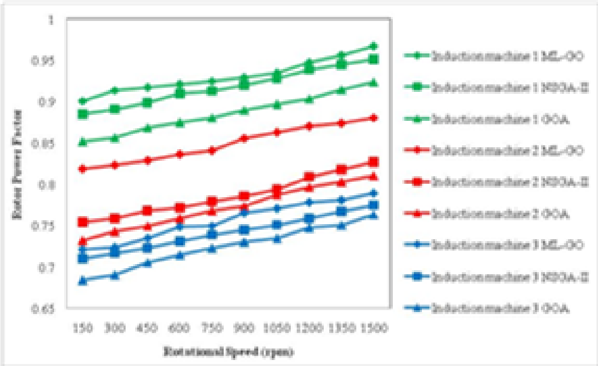

Fig.3. Measurement of rotor power factor

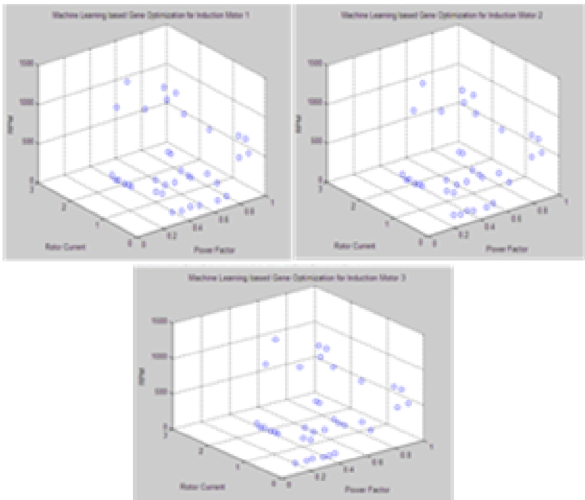

Fig. 4. ML-GO of rotational speed (RPM), rotor current and power factor parameter for Induction motor 1, Induction motor 2 and Induction motor 3

described in figure, ML-GO technique provides higher rotor power factor value when compared to other existing methods namely Non-dominated Sorting Genetic Algorithm (NSGA-II) [1] and Genetic Optimization Algorithm [2]. When the rotational speed gets increases, rotor power factor value gets increased in all three methods. ML-GO technique produces higher rotor power factor value than other techniques. This is due to the application of optimized genetic algorithm that select the induction machine data by Annealed Selection approach using probability density function with higher efficiency. Consequently in induction machine 1, the ML-GO technique increases the rotor power factor value by 1.4% as compared to NSGA-II [1] and 5.0% as compared to Genetic Optimization Algorithm [2] respectively. In induction machine 2, the rotor power factor value gets increased by 7.9% as compared to NSGA-II [1] and 9.9% as compared to Genetic Optimization Algorithm [2] respectively. For induction machine 3, rotor power factor value gets increased by 1.9% as compared to NSGA-II [1] and 4.3% as compared to Genetic Optimization Algorithm [2] respectively.

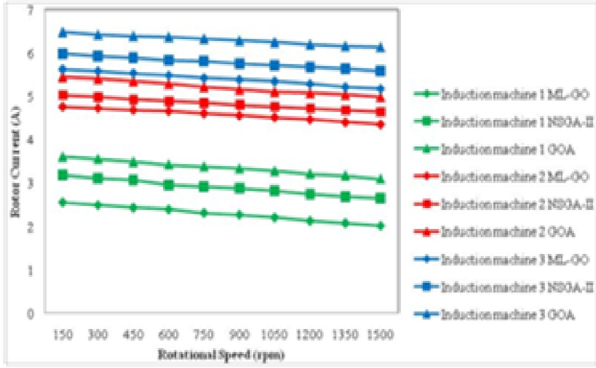

Fig. 5. Measurement of rotor current

The Machine Learning based Gene Optimization for Induction motor 1, Induction motor 2 and Induction motor 3 are portrayed in Fig. 4 with three parameters namely, rotational speed (RPM), rotor current and power factor. The bubble graph is discussed for three induction motor to attain higher induction machine efficiency. The figure describes three parameter performance simulations in one bubble graph. The efficiency of all induction machines gets increased only when it satisfies the criterion function.

5.3 Measurement of rotor current

Rotor current is the ratio of product of slip and emf induced by the rotor to the impedance of rotor. It is measured in ampere (A).

$$I_r = \frac{\left(\frac{N - N_s}{N_s}\right) E_r}{Z_r} \tag{14}$$

From (14), ‘ N_s ’ denotes the synchronous speed, ‘N’ represents the rotational speed of rotor, ‘E_r’ represents emf induced in rotor and ‘Z_r’ symbolizes the rotor impedance. Rotor current is lesser, more efficient the technique is said to be.

The rotor current using proposed ML-GO technique is lesser when compared to other existing methods [1] and [2]. The rotor current of induction machine 1 is comparatively lesser than other two machines. The graphical analysis of the rotor current is shown in Fig. 5.

Fig. 5 explained the impact of rotor current versus different speed range using three methods. As described in Fig. 5, ML-GO technique provides lesser rotor current value when compared to other existing methods namely Non-dominated Sorting Genetic Algorithm (NSGA-II) [1] and Genetic Optimization Algorithm [2]. When the rotational speed gets increased, rotor current value gets reduced in all three methods. ML-GO technique produces lesser rotor current value than other techniques. This is due to the application of optimized genetic algorithm that selects the induction machine data by performing the two-point crossover with higher efficiency. As a result in induction machine 1, the ML-GO technique reduces the rotor current value by 21.3% as compared to NSGA-II [1] and 31.9% as compared to Genetic Optimization Algorithm [2] respectively. In induction machine 2, the rotor current value gets reduced by 5.2% as compared to NSGA-II [1] and 12.1% as compared to Genetic Optimization Algorithm [2] respectively. For induction machine 3, rotor power factor value gets reduced by 6.4% as compared to NSGA-II [1] and 14.2% as compared to Genetic Optimization Algorithm [2] respectively.

5.4 Measurement of induction machine operating efficiency

Induction Machine Operating Efficiency is defined as the ratio of output power to the sum of output power and total power losses. It is measured in terms of percentage (%).

$$\textit{Induction}\text{ machine efficiency} = \frac{\text{Output Power}}{\text{Output Power} + \text{Total Power Loss}} \tag{15}$$

From (15), the induction machine operating efficiency is calculated. When the induction machine operating efficiency is higher, the technique is more efficient.

The induction machine operating efficiency using proposed ML-GO technique is higher when compared to other existing methods. The induction machine operating efficiency of induction machine 1 is higher than that of two machines. The graphical analysis of the induction machine operating efficiency is shown in Fig. 6.

Fig. 6 describes the induction machine operation efficiency with respect to rotational speed. From Fig. 6, ML-GO technique provides higher induction machine operation efficiency value when compared to other existing methods namely Non-dominated Sorting Genetic Algorithm (NSGA-II) [1] and Genetic Optimization Algorithm [2]. When the rotational speed gets increases, induction machine

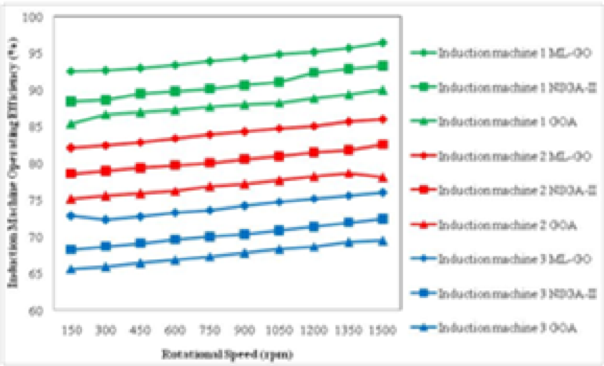

Fig. 6. Measurement of induction machine operating efficiency

operation efficiency gets increased in all three methods. ML-GO technique produces higher induction machine operation efficiency than other techniques. This is due to the application of optimized genetic algorithm that selects the induction machine data by performing the two-point crossover and Adaptive Levy Mutation. Consequently in induction machine 1, the ML-GO technique increases induction machine operation efficiency value by 3.9% as compared to NSGA-II [1] and 7.2% as compared to Genetic Optimization Algorithm [2] respectively. In induction machine 2, the induction machine operation efficiency value gets increased by 4.5% as compared to NSGA-II [1] and 9.2% as compared to Genetic Optimization Algorithm [2] respectively. For induction machine 3, induction machine operation efficiency value gets increased by 5.4% as compared to NSGA-II [1] and 9.6% as compared to Genetic Optimization Algorithm [2] respectively.

6. Conclusion

In this paper, Machine Learning based Gene Optimization (ML-GO) Technique is introduced to select the optimal solution for designing the induction machine with higher efficiency. Optimized Genetic Algorithm (OGA) is used to select the optimal induction machine data. In OGA, selection, crossover and mutation process is carried out to find the optimal electrical machine data for machine design. Fitness value is calculated for all induction machine data to find whether the criterion is satisfied or not through fitness function. When the criterion is not satisfied, annealed selection approach in OGA is used to move the selection criteria from exploration to exploitation to attain optimal solution. Then, two point crossovers are used for producing two new offspring. Finally, Adaptive Levy Mutation in OGA selects any of value in random manner and gets mutated to obtain the global optimal value. This in turn helps to increase the induction machine operation efficiency. The simulation of experiments are conducted to test the metrics such as torque, rotor power factor, rotor current and induction machine operation efficiency with respect to rotational speed. The simulation results explains that ML-GO technique presents better results with minimum rotor current and higher induction machine efficiency by 5.5%, 6.8% and 7.5% in induction machine 1, induction machine 2 and induction machine 3 respectively as compared to state-of-the-art works.

7. Conclusion

Even though a conclusion may review the main results or contributions of the paper, do not duplicate the abstract or the introduction. For a conclusion, you might elaborate on the importance of the work or suggest the potential applications and extensions.

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