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Optimum Design of a High-Temperature Superconducting Induction/Synchronous Motor to Increase Torque Density Using Collective Decision Optimization Algorithm

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ABSTRACT

Today, with the rapid advances in technology and the expansion of industries, electric motors are used extensively and consume a large part of the electrical energy produced by power plants. Therefore, researchers and experts have always been seeking solutions to make electric motors with high reliability and low losses. The machines are made of a high-temperature superconducting motor with high efficiency, came to be called high-temperature superconductor/induction synchronous motor. This paper studies the high-temperature superconducting induction/synchronous motor (HTS-ISM). The torque density and structural dimensions of HTS-ISM are optimized using one of the newest optimization methods, the collective decision optimization algorithm (CDOA). The results show a torque of about 51.75% increase via the optimization process. Also, the particle swarm optimization algorithm (PSO) as a commonly used optimization method is employed to compare the results. The comparison proves the high capability of the CDOA method to optimize the motor design parameters. All algorithms in this paper are run with the MATLAB software package.

Article Info

Keywords:
Collective decision optimization algorithm, High-temperature superconductor, Induction/Synchronous motor, Torque density

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I. INTRODUCTION

Today, with the advancement of technology and the expansion of industries, electric motors are used extensively and consume a large part of the electrical energy produced by power plants [1]. Therefore, researchers have always been trying to make electric motors more reliable with lower losses.

Using superconducting materials, a new electric motor has been designed that has a lot of advantages over the traditional motors, called the high temperature superconductor (HTS) motor.

The HTS motors are used to propel ships, submarines, and aircraft. Several experiments have concluded that the HTS machines have significant advantages, such as smaller size, lighter weight, and higher efficiency. They also consume less energy and fuel to generate power, which reduces carbon dioxide emissions. The HTS generator series, the ability to withstand high centrifugal force and high current flow, also requires a special cooling system for rotary winding and most components need a new design [2].

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In the process of presenting the paper, introduce and investigate HTS-ISM [3] and CDOA algorithm [6], then calculated optimum torque density of HTS-ISM by CDOA algorithm and present the results of the studies. These results indicate that using the superconductor in the HTS motor of the torque engine significantly increases, and the structural dimensions of the motor are reduced.

II. HTS-ISM

These machines are made up of a high-temperature superconducting motor with high efficiency. These machines are called Super-Temperature and Synchronous Inductors (HTS-ISM). The first thing to do in these motors is the rotor winding (secondary)(Fig.1). The rotor and the end ring are made of superconducting material. The advantages of the HTS-ISM are (1) despite the synchronization, it works well in the event of a slipping operation, (2) the motor drive has high efficiency in steady state, (3) against overload, the state of the synchronization resists vibration mode, (4) the torque density is increased by increasing the current through the winding, and (5) autonomy stability against variable speed control with the aid of nonlinear flow mode[3].

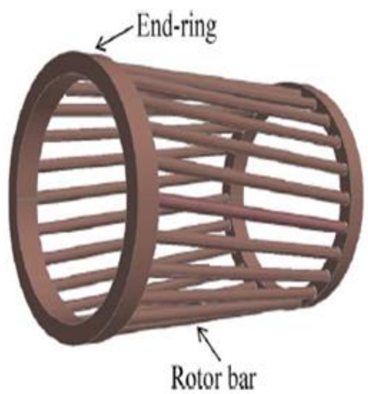


Fig.1. Schematic diagram of rotor (secondary) windings. Rotor bars are located in the rotor core (silicon steel), and then short-circuited by the endrings [4]–[5].

III. PROBLEM DESCRIPTION

Because of high load torque in the industry, the torque of the superconducting induction-synchronous motor like the other motors is one of the most fascinating fields of study.

The paper aim is to optimize the superconducting induction/synchronous dimensions to maximize the output torque using one of the new algorithms.

A. The objective function

The HTS-ISM has a higher torque than the traditional motors. The maximum synchronous torque is based on the nonlinear electrical equivalent circuit that can be calculated by Eq [5].

$$\tau_{sm} = \frac{P_{sm}}{2\omega / p} = \xi \frac{pole}{2} \varphi_s' I_c' \tag{1}$$

where, ξ, p, φ_s, I_c, and ω, denote the phase number, the pole number, the air-gap trapped magnetic flux, the critical current of one phase and the angular frequency, respectively. The superscript ' denotes that the value is converted to the stator primary side. The maximum synchronous power Psm is also expressed in the equations. Further, the value of φ_s is formulated as follows:

$$\varphi_s' = \frac{\sqrt{V_1^2 - [\omega(l_1 + l_2)I_c{}']^2} - r_1 I_c{}'}{\omega} \tag{2}$$

where, V_1, $l_1 + l_2$, and r_1 show the primary phase voltage, the total leakage inductances and the stator resistance, respectively. It should be noted that Ic is determined by the average critical current of the BSCCO[1] tapes.

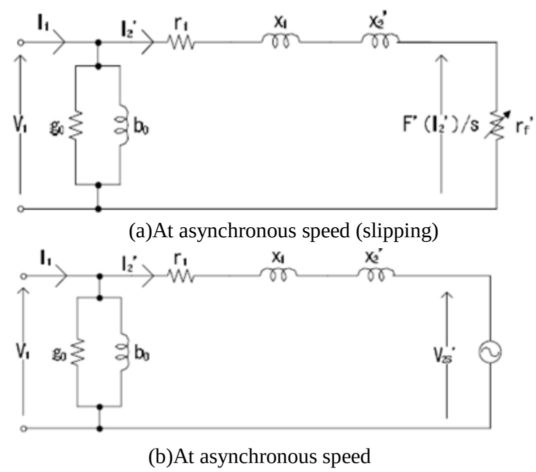


Fig. 2. Equivalent circuits of the HTS induction motor in steady-state [5].

The equivalent electrical circuit is similar to the equivalent circuit, such as the synchronous motor (Fig. 2); because the squirrel-cage winding acts as a permanent magnet due to the persistent current [5].

The following equation is used to calculate the self-inductance of the stator [8]:

$$l_1 = \frac{4\mu_0 l_a (k_a k_{wa} N_{at})^2}{p\pi(1-x^2)^2} D_{1p}(x) \tag{3}$$

[1]Bismuth strontium calcium copper oxide

$$D_{1p}(x)=\begin{cases}\frac{1}{p^2-4}\left\{p-2+4x^{p+2}-(p+2)x^4+2\frac{p-2}{p+2}(1-x^{p+2})^2(\frac{R_{ao}}{R_{si}})^{2p}\right\} & p\neq 2\\ \frac{1}{4}\left\{1-x^4+4x^4\ln(x)+\frac{1}{2}(1-x^4)(\frac{R_{ao}}{R_{si}})^4\right\} & p=2\end{cases} \quad (4)$$

$$x=\frac{R_{ai}}{R_{ao}} \quad (5)$$

$$k_a=\frac{\sin(\frac{\theta_{wae}}{2})}{(\frac{\theta_{wae}}{2})} \quad (6)$$

where p is the number of pair of poles, l_a is the effective stator length, N_{at} is the number turn of the stator, R_{ai} is the stator inner radius, R_{ao} is the stator outer radius, k_{wa} is the stator winding coefficient, and θ_{wae} is the stator electric angle.

The following equation is used to calculate the self-inductance of the rotor [8]:

$$l_2{}' = \frac{4\mu_0 l_f (k_f\ )^2}{N_{at}p\pi(1-y^2)^2}D_{1p}(y) \quad (7)$$

$$D_{1p}(y)=\begin{cases}\frac{1}{p^2-4}\left\{p-2+4y^{p+2}-(p+2)y^4+2\frac{p-2}{p+2}(1-y^{p+2})^2(\frac{R_{fo}}{R_{si}})^{2p}\right\} & p\neq 2\\ \frac{1}{4}\left\{1-y^4+4y^4\ln(y)+\frac{1}{2}(1-y^4)(\frac{R_{fo}}{R_{si}})^4\right\} & p=2\end{cases} \quad (8)$$

$$x=\frac{R_{fi}}{R_{fo}} \quad (9)$$

$$k_f=\frac{\sin(\frac{\theta_{wfe}}{2})}{(\frac{\theta_{wfe}}{2})} \quad (10)$$

where p is the number of pair of poles, l_f is the effective rotor length, R_{fi} is the rotor inner radius, R_{fo} is the rotor outer radius, and θ_{wfe} is the stator electric angle.

B. Collective Decision Optimization algorithm (CDOA)

The researchers have explored a new heuristic algorithm called the collective decision optimization algorithm (CDOA) that can be designed using a new way to generate vectors and combine them with precise information from the search space. In other words, the search space around each member can be sampled by increasing the number of selectable responses based on a specific rule.

This algorithm, like other nature-based approaches, is a population-based search approach that includes a population of candidate and potential responses to achieve Uses the overall optimal response. Each agent, on the basis of different locations, provides a number of possible and improved responses based on a multi-stage location selection plan. These responses refer to a new location generated by the previous move and are defined as the starting point of the next move, which is guided by other special locations. This method, on the one hand, will be beneficial in that the best overall response will change its position abruptly and randomly. This move will act as a local searcher. In some cases, a large number of probabilistic responses are generated randomly and around the overall optimal response. Therefore, it will be beneficial to increase the number of similar responses for each agent in order to sample the search space in a regular way and better search for the optimal overall response. In fact, when faced with an overwhelming problem, we form a group of different people with different abilities so that the best decision can be made to solve the problem. At this meeting, a group of individuals takes a unique decision or takes a particular view whose final result is the selection of the best decision[6].

1) Group generation

In order to simulate the decision behavior clearly, it is assumed that the initial population with N agents is randomly sampled from the feasible solution space [6].

$$X_i(t)=(x_i^1(t),x_i^2(t),...,x_i^D(t)),i=1,2,...N \quad (11)$$

$$x_i^k=LB^k+r\times(UB^k-LB^k),k=1,2,...,D \quad (12)$$

$$Pop(t)=(X_1(t),X_2(t),...,X_N(t)) \quad (13)$$

where N is the population size, D denotes the dimension of optimization problem, t is the current number of generation, r is a random number between 0 and 1, and LB and UB are the lower and upper bounds of variables, respectively.

2) Experience-based phase

In the meeting, for an issue, decider's first reaction is to ponder and develop a preliminary plan based on personal experience accumulated from daily life.

In CDOA, personal experience is determined as the best location of individual (φp) so far. The operator is expressed as follows [6]:

$$newX_{i0} = X_i(t) + \overrightarrow{\tau_0} \times step_{size}(t) \times d_0 \quad (14)$$

$$d_0 = \varphi_0 - X_i(t) \quad (15)$$

where τ_0 is a random vector with each member in the range (0 ,1), *stepsize(t)* denotes the step size of the current iteration, and d_0 is the direction of movement.

3) Others'-based phase

They interact with other members randomly. We know that the decider can take something new if another decider is better than him in discussions and communication. In CDOA model, the individual (*Xj(t)*) is randomly selected from the population, and it is better than the current member (*Xi(t)*) in terms of fitness value. The calculation formula is premeditated as follows [5]:

$$newX_{i1} = X_{i0}(t) + \overrightarrow{\tau_1} \times step_{size}(t) \times d_1 \quad (16)$$

$$d_1 = beta_1 \times d_0 + beta_{11}(X_j(t) - X_i(t)) \quad (17)$$

where *j* defines a random integer in the limited area [1,N]. $\tau 1$ is a random vector with each number uniformly divided in the interval (0, 1), *step size*(t) defines the step size of the current iteration, *d1* is the new direction of motion, and *beta1* and *beta11* are the random numbers in the limited area (-1, 1) and (0, 2), respectively.

4) Group thinking-based phase

In the meeting, everyone can represent their situation voluntarily. Then, the decision of each decider is influenced by the collective thinking process. In the proposed model, for simplicity, it can be assumed that the geometric center (φG) is defined as the group's thinking position. From a statistical point of view, the geometric center is an important digital feature and represents the process of population changes at some levels [6].

$$\varphi_G = \frac{1}{N}(X_1(t), X_2(t), \ldots X_N(t) = \{\frac{1}{N}\sum_{i=1}^{N} x_i^1(t), \frac{1}{N}\sum_{i=1}^{N} x_i^2, \ldots, \frac{1}{N}\sum_{i=1}^{N} x_i^D(t)\} \quad (18)$$

Then, the new position of agent is calculated using the following formula:

$$newX_{i2} = X_{i1}(t) + \overrightarrow{\tau_2} \times step_{size}(t) \times d_2 \quad (19)$$

$$d_2 = beta_2 \times d_1 + beta_{22}(\varphi_G - X_i(t)) \quad (20)$$

where τ_2 is a random vector with each number uniformly generated in the interval (0, 1), *stepsize*(*t*) denotes the step size of the current iteration, d_2 is the new direction of movement, $beta_2$ and $beta_{22}$ are the random numbers in the range (-1, 1) and (0,2), respectively.

5) Leader-based phase

The leader in one of the early deciders that play an important role in overall decision making. It not only immigrates about different impacts for other policymakers, but also determines the path and outcome of the decision. In the proposed model, Leader (φL) is considered the best person (the fittest element) in population [5].

$$newX_{i3} = X_{i2}(t) + \overrightarrow{\tau_3} \times step_{size}(t) \times d_3 \quad (21)$$

$$d_3 = beta_3 \times d_2 + beta_{33}(\varphi_L - X_i(t)) \quad (22)$$

where τ_3 is a random vector with each number uniformly generated in the interval (0, 1), *stepsize(t)* denotes the step size of the current iteration, d_3 is the new direction of movement, and $beta_3$ and $beta_{33}$ are the random numbers in the range (-1, 1) and (0, 2), respectively.

In addition, for convenience, we assume that the thought of the leader or the program can only arbitrarily change itself. In our model, it is better to slightly change its position using a random walk strategy, which works as a local search. In this case, some neighbors can be randomly built around the best solution.

$$newX_q = \varphi_L + \overrightarrow{W}_q, (q = 1,2,3,4,5) \quad (23)$$

where W_q is a random vector with each number in the range (0, 1).

6) Innovation-based phase

It is generally recognized that innovation not only breaks down the bonds of convention, but also expands our horizons. Some researchers believe that this is another effective way to produce good designs in the decision making process. In our model, innovation refers to making small changes among variables. This is equivalent to a one-dimensional mutation operator in the evolutionary methods. This operator can run as follows [6]:

$$r_1 \le MF \quad (24)$$

$$newX_{i4} = newX_{i3} \quad (25)$$

$$newX_{i4}^{p} = LB(p) + r_2 \times (UB(p) - LB(p)) \qquad (26)$$

where p is generated randomly in the range [1, D], $r1$ and $r2$ are two random values distributed in the interval (0, 1), MF is the innovation (mutation) factor, which is a large amount to improve the diversity of the population to avoid early convergence in this study.

Another concern is to update the step size according to the repetition (t). The size of a large search step (step size (t)) can spread the generated vectors widely over the search space and explore the search space effectively in the initial stage of evolution. In other repetitions, a small step size focuses on the range of solutions; and can, thus accelerate convergence. Therefore, this study describes the impact using an adaptive mechanism [6].

$$step_{size}(t) = 2 - 1.7(\frac{t-1}{T-1}) \qquad (27)$$

where T is the maximum number of iteration.

As described above, the main pseudo code of the CDOA algorithm is summarized as follows [6]:

Collective Decision Optimization Algorithm

Initialize a population (*Pop*) and termination criterion(T)
calculate the fitness of each search agent
The personal best location $\longleftarrow$ *Pop*, $t=1$;
while the termination criterion is not satisfied ($t<T$) **do**
Find the global best(φ_L)
compute the step size ($step_{size}(t)$) on Eq.(27)
for $i=1 \longrightarrow N$ do
newpop $\longleftarrow$ []
if φ_L **then**
Calculate the new solutions (*new* X_q) by the Eq.(23)
newpop $\longleftarrow$ *new* X_q
else
Change the location of an agent by Eq.(14)-(21) ,(24)-(26)
newpop $\longleftarrow$ [$newX_{i0}$,$newX_{i1}$,$newX_{i2}$,$newX_{i3}$, $newX_{i4}^{p}$]
end if
Evaluate the fitness of *newpop*
Update $X_i(t)$ and the personal best location using the best on among these resultant positions
end for
t=t+1;
end while
Output the best candidate solution

Also the flowchart for this algorithm is depicted in Fig.3.

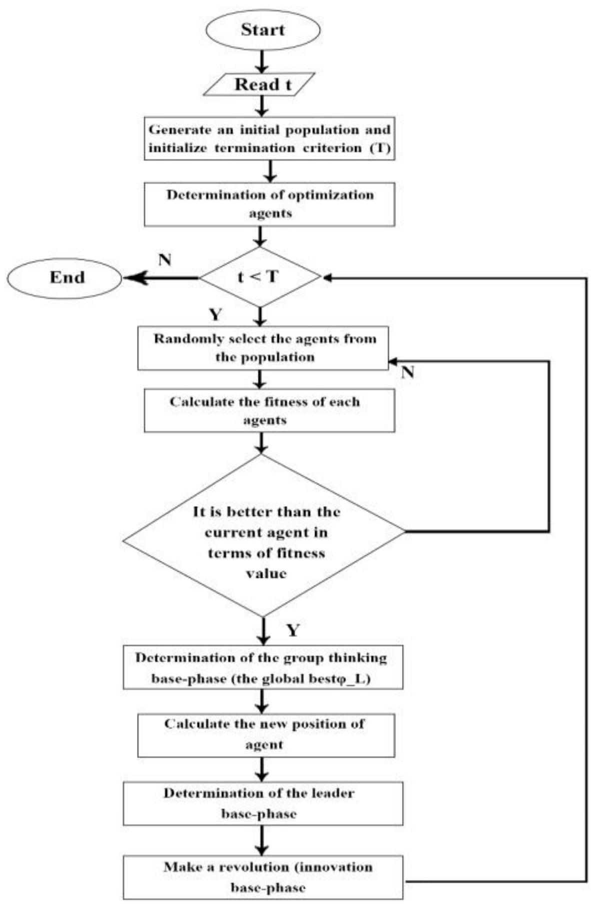


Fig. 3. The flowchart of the CDOA algorithm

C. Parameters setting

The characteristics of HTS-ISM that we need to optimize are shown in Table I.

TABLE I.

SPECIFICATIONS OF HTS-ISM [1]

	Stator	Rotor
Number of pole	8	---
Number of slat	24	38
Inner diameter	160 mm	50 mm
Outer diameter	265 mm	159.4 mm
Core length	200 mm	206 mm
Number of coil turns	30	---
Critical current	30.7 A	2090 A
Material of conductor	DI-BSCCO Type ACT	DI-BSCCO Type H

Optimizing population size (N) and coefficient of revolution (MF) are 50 and 0.8, respectively [6].

The constraints that were considered for the problem are :

-The inner diameter of the stator is in the range of 110 to 160 mm .

-The outer diameter of the stator is in the range of 215 to 265 mm .

-The length of the stator core is in the range of 150 to 200 mm .

-The inner diameter of the rotor is in the range of 0 to 50 mm .

-The outer diameter of the rotor is in the range of 110 to 154.9 mm .

-The length of the rotor core is in the range of 156 to 206 mm .

-The air gap should not exceed 0.6 mm.

IV. SIMULATION

Using the MATLAB software, the CDOA optimization algorithm and PSO optimization algorithm are used to optimize the objective function according to the HTS-ISM specifications and constraints.

A. Simulation results of CDOA

The results of this optimization are displayed in Fig. 4 -6.

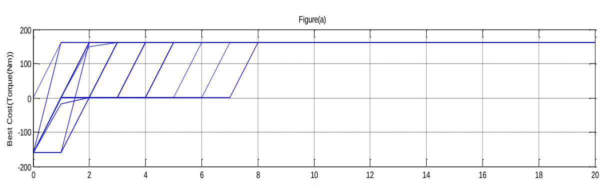
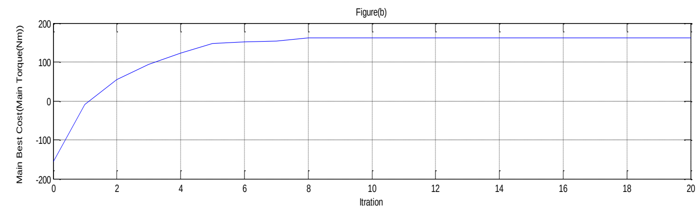


Fig. 4 .(a) The torque curve in 50 consecutive repetitions



(b)The main torque curve

Fig. 4. The optimized torque curve

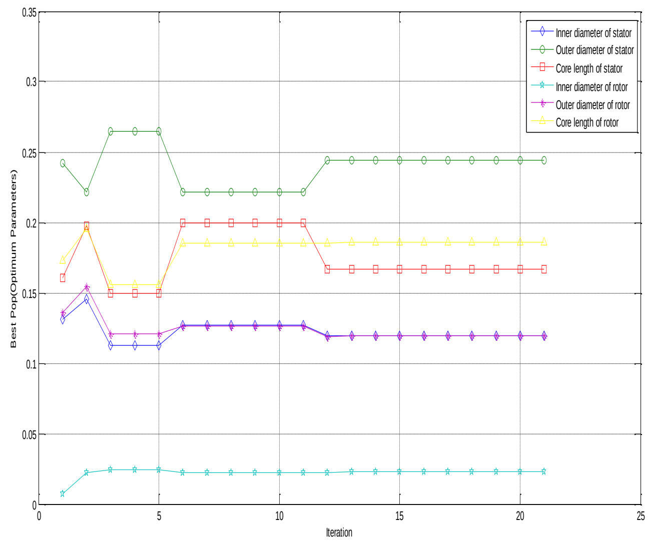


Fig. 5. The optimized parameters curve

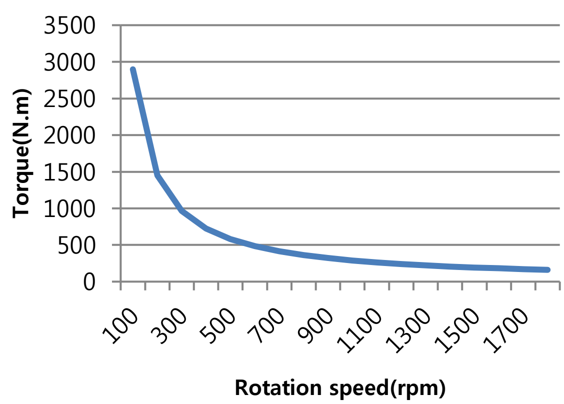


Fig. 6. The speed-torque curve

The HTS-ISM torque is 106.1 Nm [8], which, according to Fig. 4, has an optimized torque when CDOA increases to 160.9705Nm. Regarding Fig.5, the optimized parameters of the HTS-ISM reduce the volume and cost while increasing the torque. Fig.6 shows the torque curve at different speeds with optimized dimensions.

The optimized values for the HTS-ISM dimensions are shown in Table II.

TABLE II.
OPTIMIZED VALUES FOR HTS-ISM DIMENSIONS

Inner diameter of stator	112.7 mm
Outer diameter of stator	239.8mm
Core length of stator	152.9 mm
Inner diameter of rotor	21.7 mm
Outer diameter of rotor	112.6 mm
Core length of rotor	159.3 mm

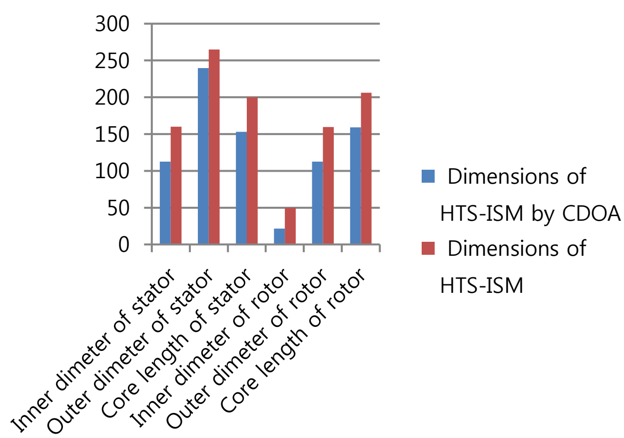


Fig. 7. Dimensions optimized by CDOA algorithm and its results compared with the real results for HTS-ISM.

The dimensions of the optimized HTS-ISM by CDOA are significantly reduced with respect to Fig. 7. The results of this optimization are as follows:

According to the HTS-ISM specifications, which has a torque of 106.1 Nm, the torque optimized by the CDOA method is 160.9705 N.m, with a torque of about 51.75% increase.

-The internal diameter of the stator HTS-ISM is 160 mm, which is optimized by the CDOA method to; 112.7 mm, i.e. 30% lower.

-The outer diameter of the stator HTS-ISM is 265 mm, the internal diameter of the stator, optimized with the CDOA method; is 239.8mm, which is downgraded by 9.5%.

-The length of the core of the HTS-ISM stator is 200mm, the stator core length optimized by the CDOA method is 152.9mm, which is 23.5% lower.

-The internal diameter of the HTS-ISM rotor is 50 mm, the internal diameter of the rotor is 21.7 mm CDOA, which is reduced by 56.6%.

-The outer diameter of the HTS-ISM rotor is 159.4 mm, which is optimized by the CDOA method is 112.6 mm, which to 29.5% lower.

-The length of the core of the HTS-ISM rotor is 206 mm, which is optimized by the CDOA method to; 159.3 mm, which is declined by 29.1%.

B. Simulation results of PSO

For the correctness and comparison of the CDOA optimization method, the optimization problem is optimized using a widely used method, PSO optimization, the objective function and the characteristics of the HTS-ISM that we need to optimize is objective function and the characteristics of the HTS-ISM use in CDOA algorithm. The results of this method are shown in Table III.

TABLE III.
THE OPTIMIZED VALUES OF THE HTS-ISM DIMENSIONS BY PSO METHOD

Inner diameter of stator	129.6 mm
Outer diameter of stator	215.2mm
Core length of stator	197.1 mm
Inner diameter of rotor	42.2 mm
Outer diameter of rotor	129.3mm
Core length of rotor	163 mm

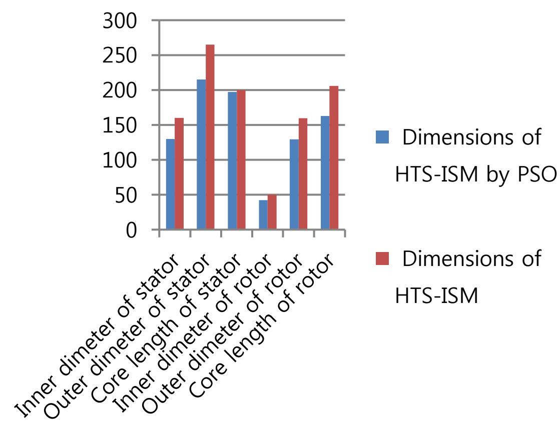


Fig. 8. The dimensions optimized by the PSO algorithm And its results compared with the real results for HTS-ISM.

The dimensions of the HTS-ISM optimized by PSO are significantly reduced with respect to Fig. 8.

The results of this optimization are as follows:

-The internal diameter of the stator HTS-ISM is 160 mm, optimized by the PSO method to, 129.6 mm, which is 19% lower.

-The outer diameter of the stator HTS-ISM is 265 mm, which is optimized with the PSO method to, 215.2 mm, which is downgraded by 18.7%.

-The length of the core of the HTS-ISM stator is 200 mm, which is optimized by the PSO method is 197.1 mm, which is 1.45% lower.

-The internal diameter of the HTS-ISM rotor is 50 mm, reduced by 15.6% to 42.2 mm by PSO.

-The outer diameter of the HTS-ISM rotor is 159.4 mm reduced by 18.8% to 129.3 mm after optimization by the PSO method.

-The length of the core of the HTS-ISM rotor is 206 mm, which is optimized by the PSO method to 163 mm, i.e. 20.8% lower.

C. Results Comparison

The values obtained from the CDOA and PSO methods are compared in Fig. 9.

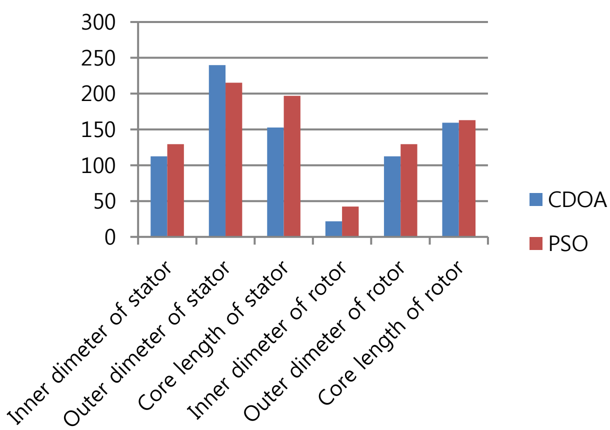


Fig.9. The dimensions optimized by the CDOA algorithm and its results compared with the results for the dimensions optimized by the PSO algorithm for HTS-ISM.

According to Fig.9, the dimensions optimized by the CDOA method have smaller dimensions and higher torque than the PSO method, so the dimensions obtained from the CDOA optimization process are used to compute the dimensions of the motor.

V. CALCULATION OF THE DIMENSIONS OF THE SQUIRREL CAGE ROTOR

The optimal dimensions of the squirrel cage rotor are obtained from the results of the optimization of the rotor and stator dimensions of the HTS-SIM.

A. Calculation of the dimensions of the rotor bar

The following equation is used to calculate the rotor bar dimensions [9].

$$W_b = \left(\frac{\pi}{2S_2}(D_{ro} + D_{ri})(1 - \frac{B_{av}}{B_{t2}}) \right) - C_r \qquad (28)$$

$$d_b = (0.1 + 0.03D_{ro}) - C_r \qquad (29)$$

$$L_b = \sqrt{(D_{ro} - D_{ri})^2 + sk^2} \qquad (30)$$

$$A_b = W_b \times d_b \qquad (31)$$

where W_b is the rotor bar width, S_r is the number slot of rotor, D_{ro} is inner rotor diameter, D_{ro} is the outer rotor diameter, B_{av} is the airgap flux density, B_t is the teeth flux density, d_b is the rotor bar depth, L_b is the rotor bar length, A_b is the rotor bar area, and C_r is the coefficient between 0.01 and 0.015 in[9]. which the dimensions are in inches.

Usually, the value of flux density in radial fluxes is selected to be between 0.32 and 0.56 Tesla [11]. The amount of flux density of the teeth is 1.7 Tesla [11].

Considering the above formulas and optimized dimensions, we have:

$$L_b = 90.97mm$$

$$W_b = 2.13mm$$

$$d_b = 5.55mm$$

$$A_b = 11.82mm^2$$

B. Area of the end ring

The maximum current flow of the end ring is obtained from the product of the average flow of the rod and half the number of rods per pole. Assuming that the flow of the end ring changes sinusically similar to the flow of the bar, the effective value of the end-flow is calculated as follows [11]:

$$I_{er} = \frac{2}{\pi}\sqrt{2}I_b \frac{Sr/2}{P} \times \frac{1}{\sqrt{2}} \qquad (32)$$

rewritten for simplification as follows:

$$I_{er} = \frac{S_r I_b}{\pi P_2} \qquad (33)$$

in which I_{er} in the flow of the end ring and I_b is the flow of the rotor bar.

In general, the ventilation of the end rings is better than the rotor bars and the current density in the end ring can be equal to or slightly higher than the current density in the bar. In most cases, the dimensions of the end rings are chosen in such a way that their contribution to the rotor's winding resistance is minimal.

The cross-section of each ending loop is obtained from the following equation:

$$A_{er} = \frac{I_b S_r}{\pi P_2 J_{er}} \qquad (34)$$

$$A_{er} = \frac{A_b S_r}{\pi P} \frac{J_b}{J_{er}} \qquad (35)$$

A_{er} , J_{er} , J_b is end section of the cross-section, the flow density in the end ring, and the rod flow density, respectively.

Given the equal flow density for the bars and the end ring, the cross-section of the end ring is calculated as follows:

$$A_{er} = \frac{A_b S_r}{\pi P} = 17.88mm^2$$

VI. Conclusion

In this paper, the torque and dimensions of the HTS-ISM were optimized using one of the newest optimization algorithms called collective decision algorithms. By this optimization, the torque of the HTS-ISM is increased. However, its dimensions are decreased. Increasing the torque is very desirable, on the other hand, reducing dimensions in addition to reducing weight and volume, also decreases the costs.The HTS-ISM torque was optimized with the PSO as one of the commonly used optimization methods. The optimized dimensions and torque of HTS-ISM were improved using PSO but CDOA optimization was shown to be better than the CDOA optimized dimensions.

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