Design Optimization of Electromagnetic Devices using an Improved Quantum inspired Particle Swarm Optimizer

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***Abstract*─** Quantum inspired particle swarm optimization (QPSO) is widely used global convergence algorithm for complex design problems. But it may trap into local optima due to premature convergence because of insufficient diversity at the later stage of search process. In this regard, to intensify the QPSO performance in preventing premature convergence to local optima. This work presents a novel QPSO approach using student t probability distribution method with mutation operator on particle with global best position. In addition, a new dynamic control parameter is proposed to tradeoff between the exploration and exploitation searches. The proposed method will intensify the improvement in its convergence behavior and solution quality. The proposed improve QPSO called IQPSO is tested on an electromagnetic design problem namely, the TEAM workshop benchmark problem 22. The experimental results showcase the merit and efficiency of the proposed method.

***Index Terms*─** Electromagnetic design, mutation, particle swarm optimization, quantum mechanics.

I. INTRODUCTION

Most real-world problems in electrical engineering required optimization of multi objective functions with different constraints. However, the deterministic optimization techniques fail to find the global optimum solutions of these types of problems. In last few years, much efforts have been devoted to investigate and developed new stochastic optimal methods such as, genetic algorithm, differential evolution, tabu search method, cross entropy, simulated annealing, ant colony method and particle swarm optimization method etc., have all been successfully applied to electromagnetic design problems. Some latest optimization techniques for engineering application is reported in the following paragraph.

An adaptive null-steering beamformer based on Bat Algorithm (BA) for Uniform Linear Array (ULA) antennas to suppress the interference was proposed in [1]. In [2], for the design and optimization of radome-enclosed antenna arrays, a fast-numerical optimization technique is proposed to compensate the distortion error of radome-enclosed antenna arrays by correcting amplitude and phase of the excitations. A radiation pattern synthesis of non-uniformly excited planar arrays with the lowest relative side lobe level (SLL) was presented in [3]. A time dependent discrete adjoint

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method is applied on electromagnetic problems [4]. A hybrid approach by combining a genetic algorithm (GA) with particle swarm optimization (PSO) is applied to solve electromagnetic problems [5]. An opposition based differential evolution algorithm is used for the optimization of elliptical array antenna [6]. In [7], the comparison of two well-known evolutionary algorithms is presented for the optimization of ships degaussing coil currents.

Though, there is no global optimal algorithm that has been efficient for all engineering design problems. Thus, there is a need to research and develop a global optimization technique for the study of electromagnetic design problems. In this regard, particle swarm optimization method is worthy for further studies.

The particle swarm optimization is an addition to the evolutionary algorithms. It was originated by Kennedy and Eberhart in 1995 [8]. PSO is inspired from the social behavior of bird flocking and school of fishes for hunting their food. PSO is very simple in notion and implementation but it traps into local minima when solving complex optimization problems. This is due to improper balance between exploration and exploitation searches [9]. To address this deficiency in particle swarm optimization, a quantum behaved particle swarm optimization (QPSO) was proposed [10]. Nevertheless, there are still some issues in QPSO that should be solved.

In this context, in this work an improved quantum inspired particle swarm optimization method (IQPSO) has proposed for the study of electromagnetic design problems. In the proposed method, a new mutation strategy with student t probability distribution method is applied on the particle with global best position. In addition, a new parameter updating formulae is proposed to tradeoff between global and local searches.

II. QPSO METHOD

Particle Swarm Optimization (PSO) is a population based stochastic process where individuals are referred to as particles and the population as a swarm. Each particle in a swarm represents a potential solution of the optimization problem. As, the particles move towards the global best point over the multi-dimensional region, the position and velocity are updated according to its own experience and that of its neighbor particles.

Consider a N dimensional design space. The velocity and position of the N^{th} dimension of the i^{th} particle is updated by using the following equations:

$$\begin{aligned} V_i^n &= w \times V_i^n + c_1 \times rand1_i^n \times (pbest_i^n - X_i^n) + \\ & c_2 \times rand2_i^n \times (gbest^n - X_i^n), \end{aligned} \tag{1}$$

$$X_i^n = X_i^n + V_i^n , \tag{2}$$

where, $V_i^n = (V_i^1, V_i^2, ..., V_i^N)$ represents the velocity of the particle *i*. $X_i^n = (X_i^1, X_i^2, ..., X_i^N)$ is the position of the i^{th} particle. $pbest_i = (pbest_i^1, pbest_i^2, ..., pbest_i^N)$ is the personal best position having the best fitness value for the i^{th} particle and $gbest = (gbest^1, gbest^2, ..., gbest^N)$ is the best position found by the entire population. c_1 and c_2 are the two acceleration coefficients, $rand1_i^n$ and $rand2_i^n$ are the two uniform random numbers within the interval [0,1].

The parameter w represents the inertia weight which is used to balance the local and global searches [11]. The value of w is decreasing linearly according to the following equation:

$$w = w_{\max} - t \times (w_{\max} - w_{\min}) / T , \tag{3}$$

where T represents the maximum number of iterations and t is the current iteration.

QPSO was encouraged by analysis of the convergence of the classic PSO and Quantum model. However, unlike PSO, the position and velocity cannot be determined simultaneously in quantum model according to the uncertainty principle. In the quantum time space context, the quantum state of a particle is represented by a wave function $\Psi(x,t)$. It can be absorbed from the probability of the individuals appearing in position x from probability density function $\Psi|(x,t)|^2$, the form of which depends on the field where the particles lie in.

Sun [10] employed Delta potential model with the center on point $p = (p_1, p_2, ..., p_D)$ to constraint the quantum particles in PSO in order that the particles can converge to their local p without explosion. In delta potential well, the wave function is given by:

$$\Psi(x) = \frac{1}{\sqrt{L}} \exp(-|p-x| \,/\, L) , \tag{4}$$

and the probability density function is given by:

$$Q(x) = |\Psi(x)|^2 = \frac{1}{L} \exp(-2|p-x| \,/\, L) . \tag{5}$$

Applying Monte Carlo method, the position of the particle can be measured as:

$$X_i^n(t) = p \pm 0.5 \times L \times \ln(1/u) , \tag{6}$$

where u is a random number with uniform distribution within the range [0, 1] and parameter L as evaluated in [8], is given by the following equation:

$$L(t+1) = 2 \times \beta \times \left| Mbest - X_i^n(t) \right| , \tag{7}$$

where β is a contraction expansion coefficient to control the convergence speed of the algorithm. Generally, it is given by:

$$\beta = 0.5 + (1.0 - 0.5) \times (Maxiter - t) / Maxiter . \tag{8}$$

The global point known as Mean best (*Mbest*) of the swarm is defined as the mean of the personal best and global best positions of all particles, and is given by:

$$Mbest = \frac{1}{M} \sum_{n=1}^{M} pbest_i^n + gbest^n , \tag{9}$$

where M is the size of the population.

Moreover, for the particles to converge to the global best position, the coordinates of each particle are determined by:

$$p = \varphi \times pbest_i^n + (1-\varphi) \times gbest^n , \qquad (10)$$

where φ is a uniform random number within the interval [0, 1].

Thus, the particles will be updated according to the following equation:

$$X_i^n(t+1) = p \pm \alpha \times \left| Mbest - X_i^n(t) \right| \times \ln(1/u) , \qquad (11)$$

III. PROPOSED IQPSO METHOD

To further intensify the QPSO performance in terms of solution quality and convergence speed different approaches such as Gaussian, exponential, Cauchy, beta and other probability distributions methods are used to produced random numbers and improve the position update equation of QPSO. In this work, following the same line of study, new outcomes are presented for the mutation operator in QPSO by using the student t probability distribution method. As, the mutation phenomena have been brought from the evolutionary methods to maintain the diversity. This is because at the early stage of evolution process the diversity of the population is high but later on it reduces quickly. One of the main reason is the improper balance between the local and global searches. Thus, to maintain a good balance between exploration and exploitation searches and to keep the diversity of the population high a new method of mutation is proposed in this work as follows.

A. Mutation strategy

In order to intensify the global searching capability of the proposed IQPSO method, some mutation operation is added to the particle with global best position as follows:

$$Gbest = mut(gbest) , \qquad (12)$$

where *mut* is obtained by the selection of a best fittest value of gbest particle with student t random function.

The *Gbest* is the new global best particle that will further take part in the optimization process to jump from local and achieve a global optimal solution.

The new global best particle *Gbest* will combine with the mutation operator using a modification of parameters c_1 and c_2 of Equation (10) with modifications given by the following equation:

$$p = \frac{st_1 \times pbest_i^n + st_2 \times Gbest^n}{2} , \qquad (13)$$

where st_1 and st_2 are the two random numbers generated with student t probability distribution method.

The generation of random numbers with student t probability distribution function provides a good cooperation between the probability of having a large number of small amplitude around the current point and a small probability holding higher amplitude that will help the particles to escape from local optimum and accomplish the global optimum solution.

B. Updating parameter formulae

Moreover, the contraction expansion coefficient β is the only control parameter for QPSO and is used to tune the algorithm. The β plays an important role to control the convergence behavior of the algorithm. Therefore, different researchers have proposed different strategies to bring a good balance between exploration and exploitation searches to adjust the β parameter [12]. The most common value of β is to initially set to 1 and reduced linearly to 0.5. Also, β plays a vital role to keep balance between the local and global searches of the algorithm. However, improper adjustment of β will make the local and global searches disturb, as a result the algorithm trapped into local minima. Thus, to address this kind of issues, a proper adjustment of the value of β is important so that to jump the algorithm from local optima and achieve a global optimum solution. Thus, in this work, a new dynamic control parameter is proposed that will keep balance between the exploration and exploitation searches and will avoid the algorithm to trap into local minima. The proposed dynamic control parameter is given as:

$$\beta = 0.5 - \cos(rand / 2)(\frac{M_{iter} - t}{M_{iter}}) , \qquad (14)$$

where *rand* is a uniform random number within range [0,1], M_{iter} is the maximum number of iteration and t is the current iteration.

Consequently, on the bases of cosine function values the coefficient expansion β parameter also varies to guarantee a tradeoff between the exploration and exploitation searches.

IV. NUMERICAL APPLICATION

To evaluate the performance of the proposed QPSO method for electromagnetic problems. It is used to solve a well-known benchmark TEAM workshop Problem 22 as stated in [13]-[18]. The TEAM workshop problem is a SMES (superconducting magnetic energy storage system) design optimization as shown in Fig. 1. The system consists of two concentric coils carrying current in the opposite directions. The inner main solenoid and the outer shielding solenoid that is used to minimize the stray field. The optimal design of SMES is to achieve a desired stored energy with minimal stray field. Therefore, the design should fulfil:

(1) The energy stored in the device should be 180 MJ;

(2) The generated magnetic field inside the solenoids must not violate certain physical condition to ensure the superconductivity;

(3) The mean stray field at 22 measurement points along line A and line B at distance of 10 m should be as small as possible.

To guarantee the superconductivity of the superconductors, the constraint equation between the current density of the two solenoids and magnetic flux density should fulfil:

$$J_i \le (-6.4\left|(B_{\max})_i\right| + 54)(A/mm^2) \quad (i=1,2), \quad (15)$$

where J_i and B_{max} are the current density and maximal magnetic flux density in the i^{th} coil.

In the three-parameter optimization problem of SMES design, the inner solenoid is fixed at $r_1 = 2m$, $h_1/2 = 0.8m$, $d_1 = 0.27m$. The dimensions of the outer solenoid are optimized following the constraints as: $2.6m < r_2 < 3.4m$, $0.204m < h_2/2 < 1.1m$, $0.1m < d_2 < 0.4m$. Furthermore, the current densities for the two coils are set to be 22.5 A/mm^2 in opposite directions. Also, for the convenience of numerical implementation, (15) can be simplified to $\left|B_{\max}\right| \le 4.92T$. Under such simplification, the optimization problem is expressed as:

$$\min f = \frac{B_{stray}^2}{B_{norm}^2} + \frac{\left|Energy - E_{ref}\right|}{E_{ref}} \quad \text{subject to}$$

$$\left|B_{\max}\right| \le 4.92T, \quad (16)$$

where $Eref = 180MJ$, $B_{norm} = 3\times10^{-3}T$, $Energy$ is the energy stored in SMES device, B_{max} is the maximum magnetic flux density, B_{stray}^2 is evaluated at 22 equidistance points along line A and line B as shown in Fig. 1, using the following equation:

$$B_{stray}^2 = \sum_{i=1}^{22} B_{stray,i}^2 \Big/ 22. \quad (17)$$

In this case study, the performance parameter as required by Equations (16) and (17) are determined using two-dimensional finite element analysis.

For performance comparison, this case study is solved using the proposed IQPSO method, original QPSO [10], GQPSO [19] and MQPSO [20]. The optimal results of different stochastic approaches for 10 random runs are tabulated in Table 1.

The numerical results in Table 1 and statistical analysis as shown in Fig. 2, demonstrating the superiority of the proposed IQPSO method on other well-designed stochastic approaches. The convergence plot of Fig. 2, also illustrates that the convergence performance of the proposed IQPSO is faster than other tested optimal methods and the proposed IQPSO converges quickly at the initial iterations of the evolution process. Furthermore, it can jump from the local minima to further discover the search space.

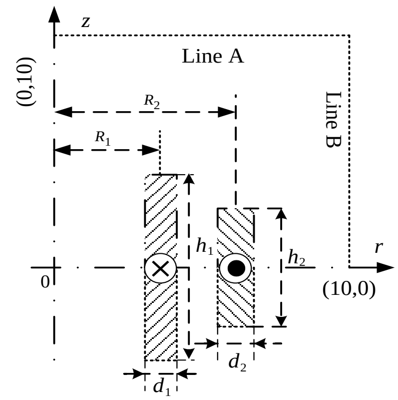

Fig. 1. SMES configuration.

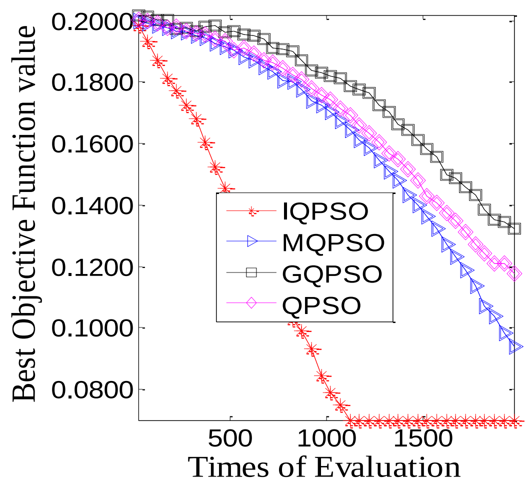

Fig. 2. Convergence comparison of different stochastic methods on Team problem 22.

Table 1: Performance comparison of different stochastic methods on Team workshop problem 22

Optimizer	r_2	$h_2/2$	d_2	Cost Function	Function Calls
GQPSO	3.1723	0.2319	0.3892	0.1222	2000
QPSO	3.0786	0.2414	0.3795	0.1077	2000
MQPSO	3.1198	0.3008	0.3079	0.0903	2000
IQPSO	3.1407	0.3149	0.2886	0.0796	2000

Thus, one can analyze from these numerical outcomes, that the performance of proposed IQPSO is extensively better than other tested stochastic approaches in terms of both solution quality and convergence speed (number of iterations).

V. CONCLUSION

In this paper, a new approach of mutation using student t probability distribution function and updated parameter control formulae is proposed to intensify the performance of QPSO algorithm. The new method has been validated by using an electromagnetic design problem. The experimental outcomes on the case study demonstrates that the proposed method has high global searching capability and used less number of iterations for convergence as compared to other tested optimal methods. Consequently, it showcases the merit and high applicability of the proposed IQPSO method. Moreover, for future work it should be investigated to find other optimal methods for the study of electromagnetic design problems and the proposed method will be applied on other engineering electromagnetic problems.

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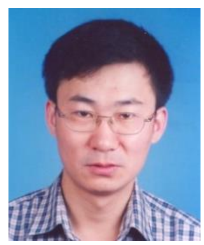

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