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A Modified Particle Swarm Optimization With a Smart Particle for Inverse Problems in Electromagnetic Devices

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ABSTRACT Particle swarm optimization (PSO) is a swarm intelligence-based metaheuristic algorithm inspired by the natural behavior of birds flocking or fish schooling. The PSO's main advantages are its ease of implementation and a small number of fine-tuning parameters. However, the major drawbacks of an existing PSO are its premature convergence and the lack of a balance of exploration and exploitation searches in the search space. To address the aforementioned problems, a new concept known as a smart particle swarm optimization (SPSO) process is introduced and implemented. The smart particle that leads the swarm in the proposed concept has eidetic memory behavior. The smart particle mainly works under the principles of a convergence factor (CF) technique, which integrates the memorization of particles positions, comparison, and leader declaration for the best optimal solution. Additionally, CF uses a particle position vector instead of a particle fitness or mutation to increase the exploration capability in the search space. The TEAM Workshop Problem 22, a super conducting magnetic energy storage (SMES) system; and some well-known benchmark optimization test functions are numerically solved to verify the efficacy of the proposed SPSO. The SPSO finds a better optimal solution than the other tested algorithms, particularly in the initial computational evaluation of the generation according to numerical experiments and case study analysis.

INDEX TERMS Smart particle, position vectors of particles, electromagnetic device, particle swarm optimization, global optimization.

I. INTRODUCTION

Inverse problems are frequently encountered in the design of electromagnetic devices and are expressed mathematically as a constrained mathematical programming of a multimodal cost function. Since deterministic algorithms are inefficient in achieving the global optimal solution for such problems, several researchers have focused on stochastic and heuristic algorithms in the last two decades. In this regard, metaheuristic optimization algorithms provide more advantages than the previously employed approaches.

Metaheuristic optimization algorithms have a strong global search capability, do not require gradient information, and provide precise solutions early in the evolutionary process [1]. There are several metaheuristic algorithms being available to find the global best solution, including swarm intelligence algorithms, human-based algorithms, physics-based algorithms, including simulated annealing algorithm, particle swarm optimization (PSO), glowworm swarm optimization, cuckoo search algorithm, genetic algorithm, ant colony optimization, artificial bee colony, and differential evolution algorithms. Swarm intelligence (SI) algorithms have been introduced, using some searching mechanisms inspired by the cooperative actions of regionalized and self-organized structures such as insects and animals [2]. Self-planned is defined as a system's ability to progress its representatives or gears into a logical form in the absence of external support. SI algorithms with a strong global search ability have thus been applied successfully to solve different engineering design problems. Nonetheless, no metaheuristic algorithm, which can provide a universal solution to all engineering design problems, exists.

The PSO is also based on swarm intelligence principles, which simulates the societal behaviors of fish schooling

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or bird flocking. The algorithm was first introduced [3] in 1995 by James Kennedy and Russell C. Eberhart. It is a well-known algorithm that is extremely useful in many fields of engineering and science. In a PSO, each particle adjusts its drifting speed energetically based on its and its colleagues' flying practices. Each particle adjusts its position based on its current position, velocity, and the distances between its current position and the personal best position (*Pb*) and the current position distance from the global best position (*Gb*) attained by the global best particle. The concept of neighborhood in PSO differs from that of other optimization algorithms in that it is fixed and does not change as frequently as it does in other metaheuristics algorithms [4].

The basic equations for position and velocity updating in a PSO are,

$$V_{id}^{t} = V_{id}^{t} + c_1.r_1.(Pb_{id}^{t} - X_{id}^{t}) + c_2.r_2.(Gb_{id}^{t} - X_{id}^{t}) \quad (1)$$
$$X_{id}^{t} = X_{id}^{t} + V_{id}^{t} \quad (2)$$

where i represents the i^{th} particle, t is the generation index, d is the d^{th} dimension, Pb_i is the best position achieved by particle i, Gb_i is the best position achieved by all particles. V_{id}^{t} is the velocity of the i^{th} particle, X_{id}^{t} is the position of the i^{th} particle. c_1(cognitive) and c_2(social) are two learning parameters, c_1 trying to pull the particle towards the *Pb* and c_2 pushing the particles towards *Gb*, r_1 and r_2 are two random numbers lies between 0 and 1.

Obviously, PSO solves problems through social interaction rather than using the ramp of the problem being optimized. It means that, unlike classical optimization techniques, there is no requirement for the problem to be differential in a PSO [5]. A PSO first initializes the population, then calculates the fitness value of each particle, updates *Pb* and *Gb* in the third step, and adjusts the velocity and position of all particles in the fourth step. The second, third, and fourth steps are repeated until a stopping criteria is met [6]–[8]. The PSO has many advantages over other swarm-based intelligence algorithms: it is very simple to implement, has few parameters, and is very effective in global searching. As a result of its ability to search in the entire space for high-dimensional problems, PSO has become one of the most popular and competent optimization algorithms. As a result, the PSO has been recognized as a strong stochastic algorithm based on swarm measurement and aptitude. PSO can be used to optimize the unbalanced problems that remain piercing and change over time [9]–[11]. However, in PSOs, the three parameters (c_1, c_2 and W) should be carefully determined to maintain the stability and robustness of the algorithm. Consequently, it is possible to correct parameter values that are not optimal, preventing the algorithm to prematurely converge in the search space to the local optimal region. It has a propensity to outcome in a fast and early convergence in average optimal facts; it has slow convergence in a sophisticated area of searching [12], [13]. The key issue in the PSO algorithm is its premature convergence, especially when it is used in dealing with complex design problems. To tackle this problem, various modifications are made by researchers in different fields like complex networks clustering [14], artificial neural network [15], power-system [16], signal-processing [17], steel recycling process [18], control-systems [19], antenna design [20], deep-learning [21], EEG signals [22], internet of things [23], error evaluation [24], face recognition systems [25], energy grid [26], and electromagnetics [27]–[29].

In [30], three enhancements have been reported, uniform initialization for avoiding the aggregation of particles at initial stage. Cosine inertia weight is introduced to adopt a multilevel approach to balance the exploration and exploitation in variable-period. A rank-based policy to regulate the inertia weight of each particle to improve the group's proficiencies of exploration and exploitation at the similar period is also presented.

The constriction factor-based particle swarm optimization (CFPSO) algorithm is being used in the study to analyze minimum zone form errors, which including straightness, circularity, flatness, and cylindricity. The addition of the constriction factor contributes in the CFPSO's convergence attribute being accelerated. For each form issue, a simple minimum zone objective function is mathematically formulated and finally optimized using the proposed CFPSO [31]. PSO with moving particles (MP-PSO) has been reported [32], where some particles have the ability to move on a scale-free network and also variate the collaboration form thru the search space. MP-PSO indicates superior a flexibility and a diversity. The arrangement of the particles may well change adaptively for the purpose to balance the exploration and exploitation towards outsized level. By minimizing geometrical dimensioning and to tolerance (GD & T) error, the author proposed a particle swarm optimization (PSO) strategy to maximize the geometrical accuracy of additive manufacturing (AM) parts. Bed temperature, nozzle temperature, infill, and layer thickness are employed as inputs, while circularity and flatness error in the ABS part are used as responses. In terms of process parameters as design factors, a mathematical model for circularity and flatness error is built using regression methodology. Minimization of circularity and flatness are formulated as a multi-objective, multi-variable optimization problem that is optimized using the particle swarm optimization (PSO) algorithm and thus improves the geometrical accuracy of the ABS part for the optimum search of the AM process parameter values [33].

The most prominent deviations in the PSO is the inclusion of an inertia weight W, which is used to balance the contribution rate of the particles. In the case of higher inertia weight, it conveys particle to exploration and a leaser inertia weight particle drives the search towards exploitation was introduced in 1998 by Shi, Yuhui, and Russell Eberhart [4]. The main aim of this work aim is to control the impact of the previous velocity and to control the particle's behavior of exploration as well as exploitation. Introduction of the inertia-weight improves the performance of PSOs in the terms of convergence speeds and superiority in results [31]. After the inclusion of inertia-weight (W), the velocity equation is updated as

$$V_{id}^{t} = W.V_{id}^{t} + c_1.r_1.(Pb_{id}^{t} - X_{id}^{t}) + c_2.r_2.(Gb_{id}^{t} - X_{id}^{t}) \quad (3)$$

In [35], the authors advised that the initial value of W must be higher than 1.0, it should be ultimately decreased till lower than 1. The objective of the work was to encourage exploration at the initial phase and exploitation may occur at the finishing stage. In [36], another factor of K is introduced in directive to grow the speed of convergence and to sidestep particles from sendoff the searching space, and this concept is called constriction expansion mathematically expressed as,

$$V_{id}^{t} = K[V_{id}^{t} + c_1.r_1.(Pb_{id}^{t} - X_{id}^{t}) + c_2.r_2.(Gb_{id}^{t} - X_{id}^{t})] \quad (4)$$

Moreover, for inverse problems in electromagnetic design optimizations, a standard testing electromagnetic analysis benchmark "TEAM workshop problem 22" is used to check the robustness and output of numerous optimization algorithms [37]–[39]. TEAM problem 22 is the optimal design of a superconducting magnetic energy storage (SMES) device, to stock substantial energy in the magnetic field via coil planning [40].

The rest work of this paper has been organized as follows; Section II contributes to the previously related work. Section III presents the novel SPSO. Section IV numerical results and comparisons, section V results and discussion, section VI statistical analysis, where section VII is the conclusion of the paper.

II. THE PREVIOUSLY RELATED WORK

To understand more clearly our proposed approach, we presented a review of the previously published work in the following paragraphs. In [41], authors adopt the multi-level Gaussian mutations with different standard deviations for the promotion of searching capacity in the feasible region to ensure the speed of convergence and to avoid premature convergence. To overcome the premature convergence, the Euclidean distance method has been reported with a dynamic inertia weight for each particle in [42]. In [43], the author describes a new modified particle swarm optimization (MPSO) technique for evaluating geometric properties that define the form and function of planar surfaces. Straightness, flatness, perpendicularity, and parallelism are the four geometric properties of planar surfaces that are split into four components. For each planar surface geometric characteristic, a non-linear minimal zone objective function is mathematically developed. In the APSO, an adaptive method is applied on the inertia weight to resolve the issue of diversity damaging and to control the premature convergence. Discrete optimum aptness rate of a particle which has been selected from swarm randomly is compared with the current particle, the greater one is used to apprise the velocity of the particle to more identify the particles which are dropping into local optimum [44]. Hybrid PSO with a variable neighborhood search optimization technique is recorded in [45] to show the prominent result and the best solution that quickly converge to global minima without being trapped in local optima. The said approach increases the localization precision, as it combines the key features and real abilities of PSO and variable neighborhood search (VNS). Another innovation is that the MPSO method uses a modified search equation to generate new swarm positions and fitness solutions. For the case of contactless laser scanning, this study models the impact of an object's morphology on the accuracy of the scanned data. Two crucial process parameters are defined using the morphology of scanned objects, namely the scanning angle and the distance of the laser beam from the component surface [46]. In [47], a modified-PSO is advised with the mechanism to update robust and introduced chaos base initialization. The inclusion of a damping-factor (α) to a PSO with a cooperation-mechanism for finding the global optimum in high dimensional and large-scale spaces has been reported in [48].

In the global particle swarm optimization (GPSO), the author worked on classical PSO for the purpose to improve the convergence speed [49]. They incorporated a new parameter E_{best} (Experience) and update the velocity formula of classical PSO. The new parameter is able to hold the information of the previous generation and this can be used for searching a global solution to be more accurate. The value of G_{best} for any generation at any variable (dimension) will be selected randomly and will be used for the value of the velocity. Hence this variable is called E_{best}. The value of the new parameter is the average value of c_1 and c_2 in "(6)"

$$V_i^{k+1} = W^{\boldsymbol{k}} V_i^k + c_1.r_{1i}.\left(P_{best-i}^k - X_i^k\right) + c_2.r_{2i}. \times \left(G_{best-i}^k - X_i^k\right) + c_3.r_{3i}.(E_{best}^k - X_i^k) \quad (5)$$

In "(5)", the last term is called the Improvement Factor (IF). This IF is able to help the velocity for the positions of next particles. Thus, GPSO has shown greater performances as compared to existing PSOs, especially when the problem is high dimensional. The Improvement Factor for the current generation is

$$IF^t = c_3.r_{3i}.\left(G_{best-X2}^m - X_i^k\right) \quad (6)$$

where $c_3 = \left[\frac{c_2+c_2}{2}\right]$.

RMPSO with the application of a gene regulatory network has been reported in [50]. In the said work, the fitness value of each particle has been calculated by "(2)" and "(3)". When the personal best particle is equal to that of the global best, in such a situation it has been observed from the literature to retain the current personal best individuals and ignore the newly obtained global best particle. In RMPSO, the author said that the current Pb and Gb having equal fitness value but they may be of different compositions. Hence, a repository of solutions having the same value of fitness as like a current Pb and they may be similar repository corresponding to the existing Gb value. RMPSO concept introduced two repositories P_{best_rep} and G_{best_rep} for the purpose of storing the solutions corresponding to Pb and Gb respectively. They updated the repositories in two conditions: "first update the position of the particle as per "(2)" and "(3)", then the value of the fitness will be intended and will be compared with *Pb* and *Gb*. "Secondly after updating the position of the particle by applying each mutation mechanism on the current solution, the value of the fitness will be intended and then will be compared with *Pb* and *Gb*. If the current *Pb* is poorer than the new one in fitness, clear the current *Pb* and add the new one to G_{best_rep}. If new fitness value is the same as that of *Gb*, it needs to increase the size of the repository and to add the new one to G_{best_rep}. The repository comprehends distinctive results having an identical value of fitness and the matching solutions will be castoff. The *Pb* from P_{best_rep} and *Gb* from G_{best_rep} will be randomly selected. In the aforementioned work they did a mutation process as per Figure 1.

Initially ***Gbest*** mutated with Gaussian mechanism

$$\boldsymbol{Gbest_{m1}(d) = Gbest_g(d) + \left(X_{max}(d) - X_{min}(d)\right).Gaussian(o,h)}$$

$$\boldsymbol{h^{t+1} = h^t - \left(\frac{1}{t_{max}}\right)}$$

Gbest mutated with Cauchy mechanism

$$\boldsymbol{Gbest_{m2}(d) = Gbest_g(d) + \left(X_{max}(d) - X_{min}(d)\right).Cauchy(o,s)}$$

$$\boldsymbol{s^{t+1} = s^t - \left(\frac{1}{t_{max}}\right)}$$

Gbest mutated with Opposition based (Dimension wise) mechanism

$$\boldsymbol{Gbest_{m3}(d) = X_{min}(d) - X_{max}(d) - Gbest_g(d)}$$

All ***Gbest*** mutated with Opposition based mechanism

$$\boldsymbol{Gbest_{m4} = X_{min} - X_{max} - Gbest_g}$$

Gbest mutated with DE based, where $\boldsymbol{X_1}$ & $\boldsymbol{X_2}$ having unequal finesses.

$$\boldsymbol{Gbest_{m5}(d) = Gbest_g + F(X_1 - X_2)}$$

FIGURE 1. 5-Successive mutations in ELPSO.

The inclusion of a swarm leader as a new feature to the classic PSO was introduced in [51]. The author included some new mutation techniques with 5-staged successive mutations in the enhanced leader PSO (ELPSO) to overcome the stated problem, due to premature convergence in existing PSO, which is characterized as the convergence of *Pb* in relation to *Gb*. In the said work the swarm leader plays a key role and 5-successive mutation techniques are incorporated and checked on each generation of the swarm. The current *Gb* of the swarm has been replaced by a new one if the new *Gb* coming with better value, thus the leader is enhanced and trying to pull all the particles in the direction of a promising region of the searching. In directive to have fewer exploration aptitudes they applied various mutation strategies such as Gaussian, Cauchy, Opposition-based and DE-based to find the leader with better objective value, and the same process will continue *n* times in the anticipation to bargain better leader, as shown in Figure 1.

In order to solve the real world optimization problems, a novel idea called modified particle swarm optimization with effective guides (MPSOEG) [47] is proposed as a continuation of the leader principle in PSO. An optimal guide creation (OGC) module has been added to implement the proposed idea. The key suggestion of the new mechanism is to maintain a good balance between particle exploration and exploitation searches while avoiding the computational time of traditional PSO. The global best particle plays an important role in leading the swarm to the global optimum solution when the problem is simple and unimodal. When working on multimodal complex problems, PSO has a problem with premature convergence. A new global best particle is created in the OGC module. The novel global best particle acts as a leader for the other particles, sharing knowledge with the learning parameters to boost the evolution process. The proposed module will control particles from local optima, especially those falling into local optima; these particles will be led by the global best leader "global exemplar." The global exemplar is capable of responding to the speed or velocity of particles that are about to stagnate. Furthermore, the population learns or shares knowledge independently to monitor particle scattering positions and inspire candidates to the best solution. The difference between *Pb* and *Gb* is high at the start of the optimization process, as we can see from the velocity modified equation. At the end of the evolution process, the majority of the particles are stagnant, and their velocity which appears to converge to zero, causing the algorithm to converge prematurely. To address the aforementioned issue, the "global exemplar" has been implemented in the OGC module with the goal of balancing the swarm's exploration and exploitation searches and dynamically completing the optimization method based on the spatial location of two adjacent neighbors of the global best particle. To solve the second major flaw in a conventional PSO of reducing diversity at the end of the optimization process, the said work incorporates a local leader "local exemplar" who updates the personal best position of its neighbor's particles and guides the particle through the search space. For all particles stuck in local minima, the local exemplar provides an alternative direction in the search path. The global and local both exemplars are changed sequentially based on the search routine of each particle of the novel idea to better track its search progress. The novel global best leader provides information to the other particles in the neighborhood in order to get out of the local optimal field. During the PSO development phase, the proposed module increases particle velocity and prevents stagnation. The proposed algorithm, which is capable of solving optimization problems with less computational cost and showing more robustness and stability, was compared to other variants of PSO using standard mathematical test functions, and the author showed a wide range of numerical and simulation performance.

To summarize, while a lot of efforts has gone into developing different PSO variants, current PSOs are still unable to solve all engineering design problems. We introduced a novel strategy to track the premature convergence, to make the PSO more robust, and to increase its convergence speed in the current article.

III. SMART PARTICLE SWARM OPTIMIZATION

As explained previously, in recent decades, several novel versions of the PSO have been published in the literature. The majority of them have strong searching abilities, but due to the existence of the static positions of the personal best and global best particles, they are stuck in local minima during the early searching generation. Since the basic parameters in traditional PSO are constant, the algorithm converges to the local optimum region or space. Consequently, the standard PSO algorithm has a premature convergence problem for complex, dynamic, and multimodal problem. The proposed method's core concept is to strike a balance between the particles' global and local search abilities while also increasing the individual diversity at the end of the optimization process. A newly designed algorithm Particle swarm optimization with smart particles, is thus introduced to improve PSO's performance. In the proposed modified algorithm, we devise a new technique known as the convergence factor (CF). The convergence factor has three steps to train the particle to have a smart behavior: memorization, comparison, and leader declaration.

1) Memorization, or eidetic memory behavior, enables particles to remember the last position X_{i-1} of all particles, which is then stored in the memory array for possible use by the entire swarm.

2) Comparison, in the comparison step, the present particle position X_i are compared to the previous position X_{i-1}.

The comparison process mathematically expressed as

$$X_i = \begin{cases} X_i & \textit{if } X_i \textit{ is better than } X_{i-1} \\ X_{i-1} & \textit{otherwise} \end{cases} \tag{7}$$

If the present position X_i towards an optimal solution is better (whose fitness value is smaller/converges quickly), it replaces the previous one; otherwise, it retains the earlier value.

3) Leader declaration, on the basis of the fittest values of the P_{best}, a smart particle is declared as a leader (smart). For all generations, P_{best} particles are placed in the memory array, and the fittest particle is declared to lead the swarm to the global minima.

The main aim of our proposed work is to ensure that the best particle survives in future generations and acts as a leader, guiding all trapped particles through the evolution process. As a consequence, the entire swarm will eventually converge to the global best solution. The CF has improved the PSO's results during the SPSO evolution process. According to this approach, the smart particle acts as a superior leader, capable of improving the search process in the same way that a good leader may improve an organization's or society's efficiency. Furthermore, previous algorithms were unable to generate a satisfactory result in a large population; they typically used a limited population size, but the proposed algorithms have also shown good results in a large population. When compared to previous strategies, the particle following the proposed strategy will reach the global minima faster, especially in the initial generations.

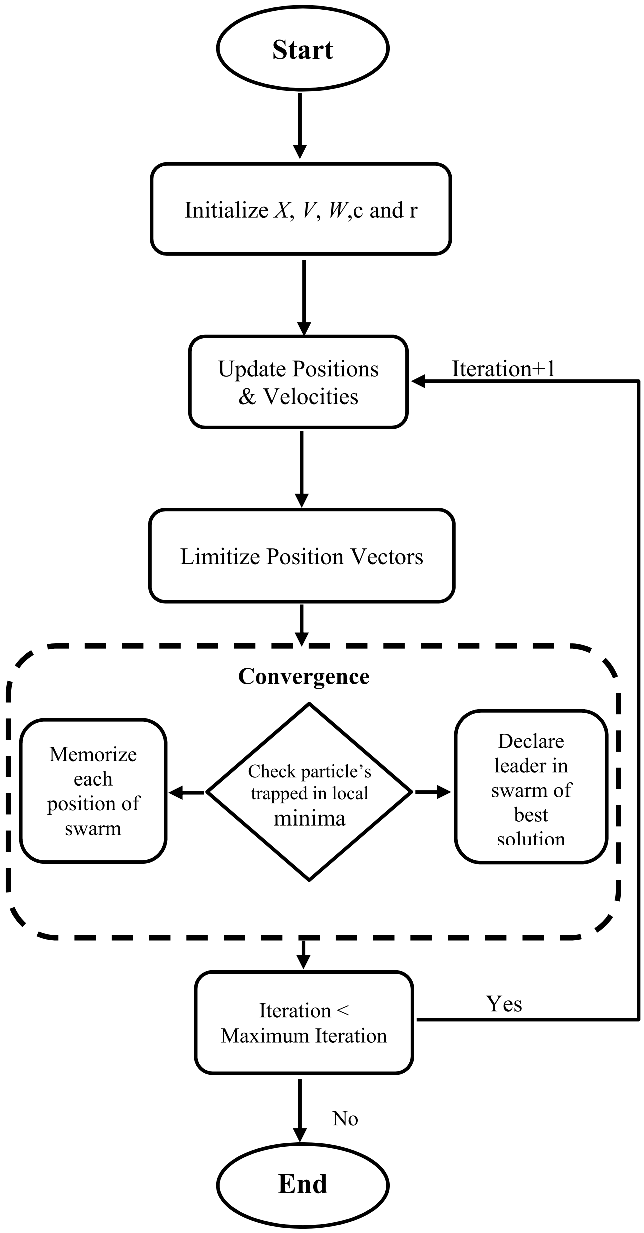

FIGURE 2. Flow-chart of SPSO algorithm.

In comparison to other well-known existing approaches and other optimal algorithms, the proposed algorithm is simple to implement and takes less time. As shown in the next segment, SPSO can produce more consistent results across all 100-runs. This is evident from the objective function values, which show that the values of the objective obtained

TABLE 1. High dimensional classical benchmark functions.

Function's Name	Mathematical Definition	Range
Rastrigin	$f_1(x)=\sum_{i=1}^{n} x_i^2 - 10\cos(2\pi x_i)+10$	*[-5.12,5.12]*
Sphere	$f_2(x)=\sum_{i=1}^{n} x_i^2$	*[-5.12,5.12]*
Bent Cigar	$f_3(x)=x_1^2+10^6\sum_{i=2}^{n} x_i^2$	*[-100,100]*
Discus	$f_4(x)=10^6 x_1^2\sum_{i=2}^{n} x_i^2$	*[-100,100]*
Zakharov	$f_5(x)=\sum_{i=1}^{n} {X_i}^2+\left(\sum_{i=1}^{n} 0.5iX_i\right)^2+\left(\sum_{i=1}^{n} 0.5iX_i\right)^4$	*[-5,10]*
Dixon-Price	$f_6(x)=-(x_1-1)^2+\sum_{i=0}^{n} i(2x_i^2-x_i-1)^2$	*[-10,10]*
Rosenbrock	$f_7(x)=\sum_{i=1}^{n-1}[100(x_{i+1}-x_i^2)^2+(x_i-1)^2]$	*[-5,10]*
HappyCat	$f_8(x)=\left\lvert\sum_{i=1}^{n} {x_i}^2-n\right\rvert^{\frac{1}{4}}+\frac{(0.5\sum_{i=1}^{n}{x_i}^2+\sum_{i=1}^{n}x_i)}{n}+0.5$	*[-100,100]*
HGBat	$f_9(x)=\left\lvert(\sum_{i=1}^{n} {x_i}^2)^2-(\sum_{i=1}^{n} x_i)^2\right\rvert^{\frac{1}{2}}+\frac{(0.5\sum_{i=1}^{n}{x_i}^2+\sum_{i=1}^{n}x_i)}{n}+0.5$	*[-100,100]*
Ackley	$f_{10}(x)=-20\,exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right)-exp(\frac{1}{D}\sum_{i=1}^{D} cos(2\pi x_i)+20+e$	*[-15,30]*
Schwefel's Problem 1.2	$f_{11}(x)=\sum_{i=1}^{D}(\sum_{i=1}^{n} z_i)^2+f_{bias_1},\ z=x-o \text{ and } f_{bias_1}=-450$	*[-100,100]^D*
Griewank	$f_{12}(x)=\frac{1}{4000}\sum_{i=1}^{n} z_i^2-\prod_{i=1}^{n} cos\left(\frac{z_i}{\sqrt{i}}\right)+1+f_{bias_2}$, $z=x-o \text{ and } f_{bias_2}=-180$	*[-100,100]^D*

by the proposed algorithm are better to those obtained from other PSO variants. The flowchart of the proposed SPSO algorithm's novel strategy is shown in Figure 2.

IV. NUMERICAL RESULT AND COMPARISON

A. BENCHMARK TEST FUNCTION

Twelve well-known benchmark functions are chosen to test the proposed SPSO algorithm's performance, and the results are then compared to those of other PSO variants, i.e., GPSO, RMPSO, ELPSO, and MPSOEG. A list of benchmark test functions is given below in Table 1:

In the computational tests, we used the same parameter values for all variants of PSO algorithms: the maximum generation is set to 100, the swarm size to 60, W to 1, c_1 and c_2 to 2, and the values of r_1 and r_2 to 0.5 each. The maximum (Max), minimum (Min), standard deviation (Std), and mean (Mn) values of the final solution for GPSO, RMPSO, ELPSO, MPSOEG, and SPSO in 100 trial runs are tabulated in Table 2 to checked the performance of all algorithms.

V. RESULTS AND DISCUSSION

Table 2 shows that our proposed method produces good results for the Rastrigin function. The Rastrigin function is a complicated multimodal function with several local minima and a single global optimal solution. Sphere function, which is a complex and unimodal benchmark problem, is similar. We know that our novel approach outperforms other algorithms based on the tabulation results. Also, on the HappyCat benchmark function, our updated algorithm produced the best results. The HappyCat function is a complicated and complex optimization problem that is commonly used for algorithm validation. Also, on the HappyCat benchmark function, our updated algorithm produced the best results. The HappyCat function is a complicated and complex optimization problem that is commonly used for algorithm validation. Other

TABLE 2. Performance comparison of SPSO with GPSO, RMPSO, ELPSO and MPSOEG for 30 dimension.

O. F	SPSO	RMPSO	ELPSO	GPSO	MPSOEG
Rastrigin f_1					
Max	2.8201	2.8201	2.8201	2.8201	2.3491
Min	**-15.0221**	-1.4571	0.0201	-1.1021	-3.3942
Std	4.5774	1.0881	0.8163	0.9848	1.5538
Mn	-9.9923	-0.9567	0.3399	-0.7508	-2.9126
Sphere f_2					
Max	0.5753	2.8771	2.8771	2.8771	-3.3572
Min	**-15.6000**	-7.6185	-5.9769	-3.2970	-11.0012
Std	2.9674	2.7173	3.3405	1.3998	1.4819
Mn	-11.5073	-2.0705	-3.9874	-1.9769	-9.9934
Bent Cigar f_3					
Max	14.3901	14.3908	14.3901	14.3908	5.1593
Min	**2.4193**	3.8943	5.1477	8.2158	2.4000
Std	2.1706	2.7173	2.1617	1.3998	0.9873
Mn	3.1522	9.4423	7.7797	9.5359	3.2485
Discus f_4					
Max	14.9662	14.9662	14.9662	14.9662	6.5141
Min	**-8.6500**	-6.0267	-4.7846	2.6162	-5
Std	5.8837	5.4347	2.7141	2.7996	3.4662
Mn	-5.4742	5.0691	-4.3990	5.2564	-1.0678
Zakharov f_5					
Max	7.6194	23.9658	7.6194	7.6194	6.4553
Min	**-5.0933**	14.0313	0.3163	-1.9803	-4.3966
Std	2.5299	3.0019	1.4000	1.9732	1.6876
Mn	-3.3700	16.4974	1.4661	-0.3291	-4.0438
Dixon & Price f_6					
Max	0.4054	3.7323	0.4054	0.4054	-0.1985
Min	**-6.8447**	-0.9925	-2.0946	-4.3703	-3.9866
Std	2.3591	1.3590	0.7802	1.4876	1.0889
Mn	-4.6430	-0.5673	-0.9069	-3.2716	-2.9988
Rosenbrock f_7					
Max	5.0960	5.0960	5.0960	5.0960	-1.4069
Min	**-6.7171**	1.9018	-0.0986	-1.3932	-4.2300
Std	1.9115	0.8612	0.7443	1.5702	1.2653

TABLE 2. *(Continued.)* Performance comparison of SPSO with GPSO, RMPSO, ELPSO and MPSOEG for 30 dimension.

O. F	SPSO	RMPSO	ELPSO	GPSO	MPSOEG
Mn	-5.5760	2.5224	0.0898	-0.5228	-3.2054
HappyCat f_8					
Max	1.1937	1.1937	1.1937	1.1937	1.1913
Min	**0.2000**	0.5856	0.8922	0.2939	1.1787
Std	0.2071	0.1925	0.1301	0.2496	0.0032
Mn	0.4793	0.7032	0.9770	0.5112	1.1818
HGBat f_9					
Max	0.5382	0.5382	0.5382	0.5382	-0.3886
Min	**-0.6907**	-0.6789	-0.0101	-0.5365	-0.6700
Std	0.1559	0.2936	0.2753	0.1916	0.0508
Mn	-0.6500	-0.3902	0.2749	-0.4104	-0.6586
Ackley's Function f_{10}					
Max	8.3765	8.3765	8.3765	8.3765	2.7983
Min	**-1.3950**	-0.9963	-0.0364	0.1541	0.4637
Std	1.3298	1.7230	1.9830	2.0657	0.4341
Mn	0.2468	0.5508	-0.3174	-0.3697	0.7394
Schwefel's Problem 1.2 f_{11}					
Max	5.6066	5.6066	5.60661	5.6066	6.1075
Min	**0.0629**	4.6359	2.7853	1.2998	1.7500
Std	0.8924	0.7813	1.3546	1.6973	2.3372
Mn	1.0649	4.1199	3.6256	2.1186	2.8389
Griewank complex f_{12}					
Max	5.1871	5.18603	5.1823	5.1823	5.1819
Min	**5.1678**	5.1789	5.1693	5.1803	5.1750
Std	0.0033	0.0015	0.0037	0.0006	1.3672
Mn	5.1689	5.1806	5.1708	5.1808	5.1783

test functions such as the Zakharov, Dixon-Prince, Ackley, Rosenbrock, HGBat, Bent Cigar, and Discus functions can also be observed. The above functions are more challenging and complex, and researchers often use them as benchmark problems for evaluating algorithm results. As a result, the tabulations show that our novel smart PSO outperforms other well-known modified algorithms on the above mathematical optimization problems.

The proposed SPSO converges to the optimal global region faster than the GPSO, RMPSO, ELPSO, and MPSOEG, particularly in the early generations, as shown by the convergence characteristic curves of the test functions. Similarly, the convergence trajectory for other test functions demonstrates the proposed method's superiority compared to other algorithms. In conclusion, the proposed algorithm finds the global best solution for all test functions, showing that the novel algorithm is more efficient. According to these numerical results and the statistical analysis, the proposed SPSO's final solution has a substantially higher quality than GPSO, RMPSO, ELPSO, and MPSOEG. SPSO effectively converges to global minima in the early stages of the search operation, unlike other PSO modifications stuck in local minima.

The convergence characteristics of a typical run for each algorithm are shown in Figures 3–14 for test functions f1 − f12, respectively. We use the objective function's logarithm values for comparison in this article because the objective function values of the test functions in Table 1 are so small in decimal numbers.

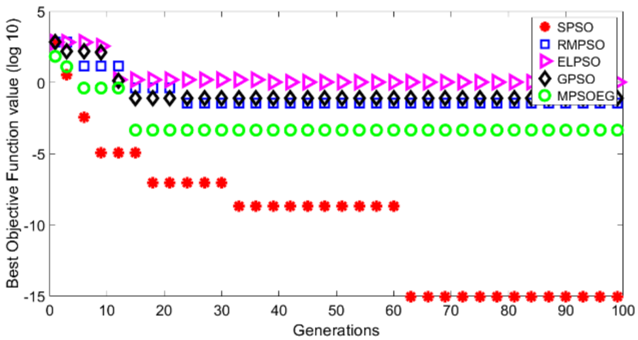

FIGURE 3. Convergence plot of different algorithms on f_1.

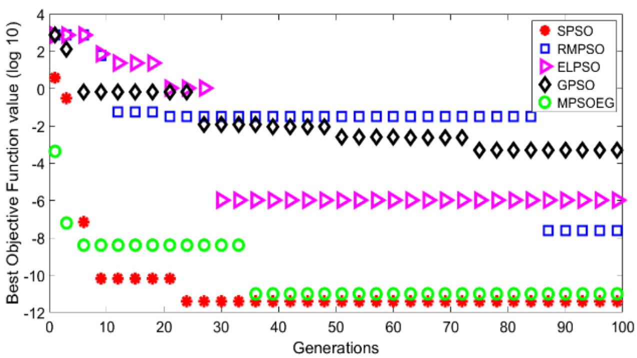

FIGURE 4. Convergence plot of different algorithms on f_2.

A. OPTIMIZATION IN ELECTROMAGNETIC DEVICES

1) TEAM WORKSHOP PROBLEM 2

Using the TEAM workshop problem 22 [40], authors have tested a number of optimization methods for electromagnetic inverse problems. The performance of the proposed SPSO in inverse problems of electromagnetic devices has also been tested using the same problem. For performance comparisons

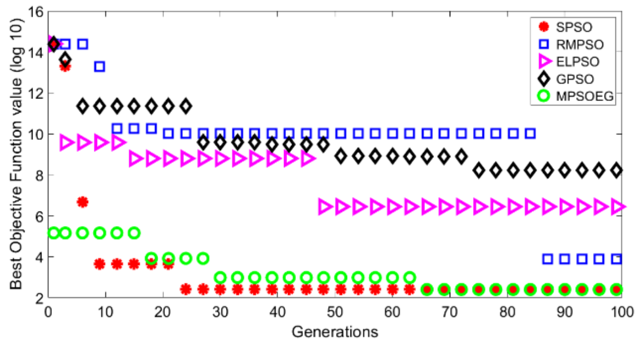

FIGURE 5. Convergence plot of different algorithms on f_3.

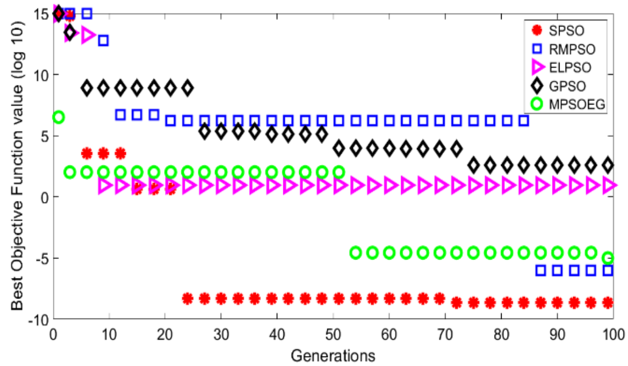

FIGURE 6. Convergence plot of different algorithms on f_4.

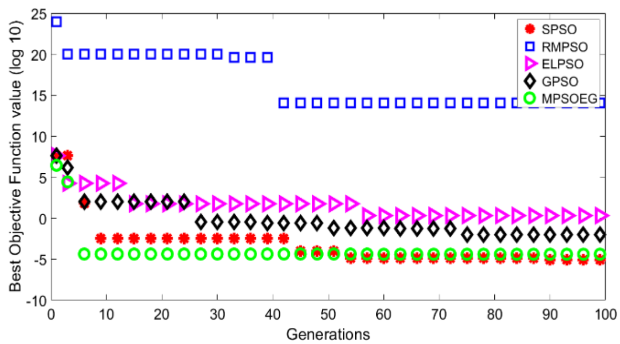

FIGURE 7. Convergence plot of different algorithms on f_5.

with other optimal algorithms, the testing of electromagnetic optimization benchmark function, workshop problem 22 of a SMES, containing three parameters of two concentric coils with currents in opposite directions is used [52], [53].

2) OBJECTIVE FUNCTION

In [40], SMES has a single objective function, but it actually incorporates two objective functions to correlate magnetically stored energy in a couple of coils W_m, $W_{erf} = 180$ M Joule, $B_{norm} = 3$ m Tesla and B_{stray} expressed "(9)" with $N = 22$.

$$OF = \frac{B_{stray}^2}{B_{ref}^2} + \frac{\left\| W_m - W_{m,ref} \right\|}{W_{m,ref}} \tag{8}$$

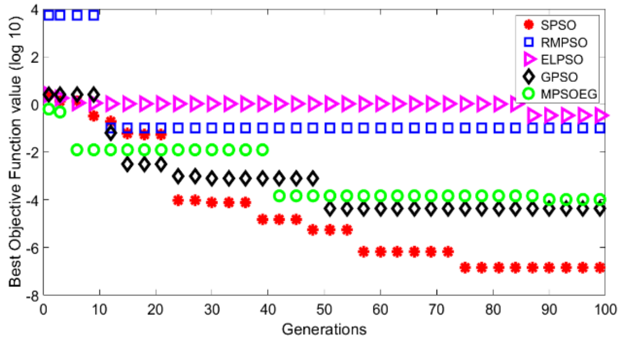

FIGURE 8. Convergence plot of different algorithms on f_6.

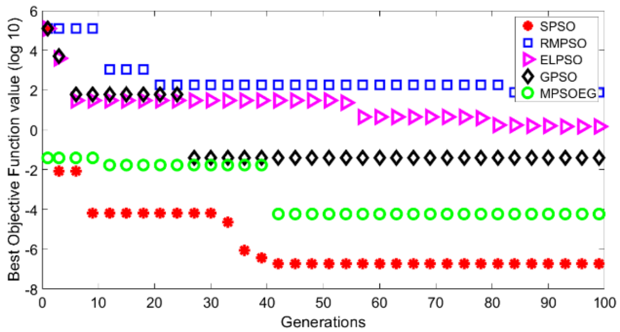

FIGURE 9. Convergence plot of different algorithms on f_7.

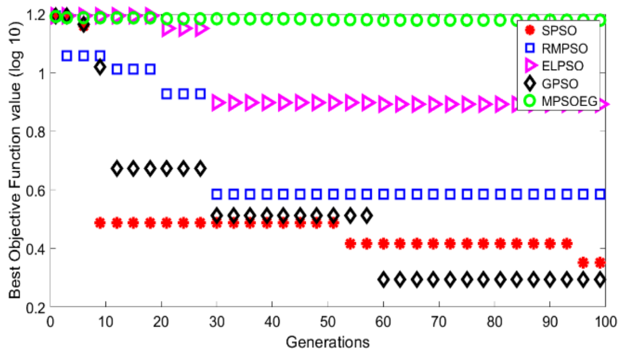

FIGURE 10. Convergence plot of different algorithms on f_8.

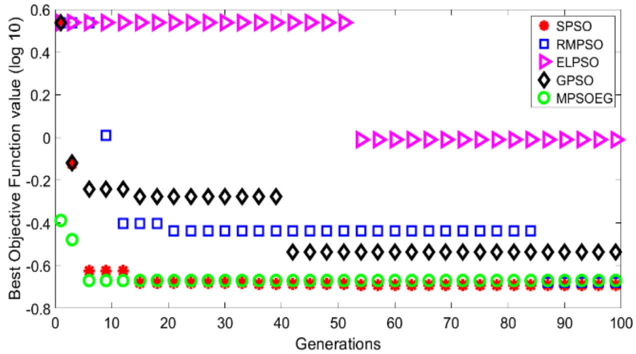

FIGURE 11. Convergence plot of different algorithms on f_9.

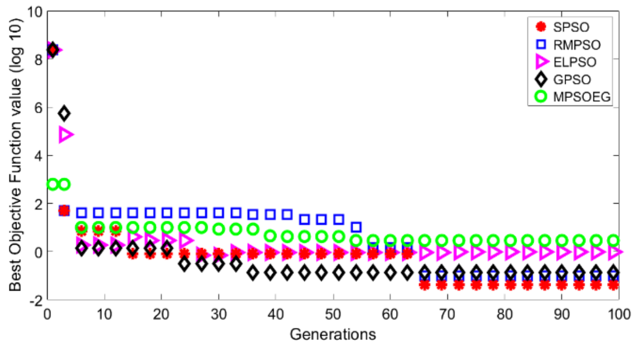

FIGURE 12. Convergence plot of different algorithms on f_{10}.

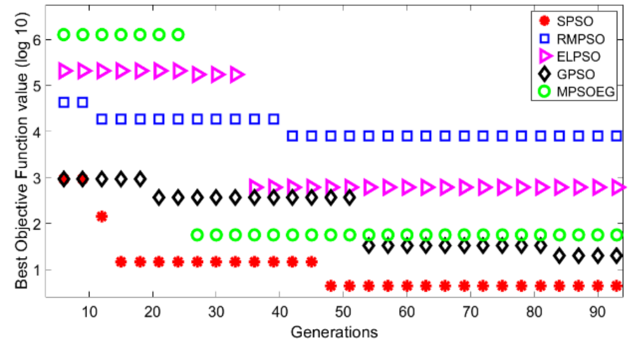

FIGURE 13. Convergence plot of different algorithms on f_{11}.

where, B_{stray} is defined as

$$B_{stray}^2 = \frac{\sum_{i=1}^{N} B_{stray,i}^2}{N} \tag{9}$$

3) QUENCH CONDITION

It is important to maintain the physical condition of coils in order to ensure superconductivity within the solenoids when a magnetic field is produced. Current density is 22.5 A/mm^2, which states that B_{max} should be less than 4.92 Tesla.

$$J_i \leq \left(-6.4\left|(B_{max})_i\right| + 54\right)\left(\frac{A}{mm^2}\right) \tag{10}$$

In "(10)", J_i represents the current density of the coil, B_{max} shows the maximum magnetic flux density of i_{th} coil where i represents the coil number.

4) RESULTS COMPARISONS

In this electromagnetic device optimization of SMES, the inner solenoid is fixed, $r_1 = 2$ m, $d_1 = 0.27$m and $h_{1/2} = 0.8$m, while the outer-solenoid geometrical dimension, $2.6 \leq r_2 \leq 3.4m$ and $0.1 \leq d_2 \leq 0.4m$ are optimized.

For performance comparisons, the case study was solved using the proposed SPSO and other PSO variants, GPSO, RMPSO, ELPSO, and MPSOEG. After compiling for

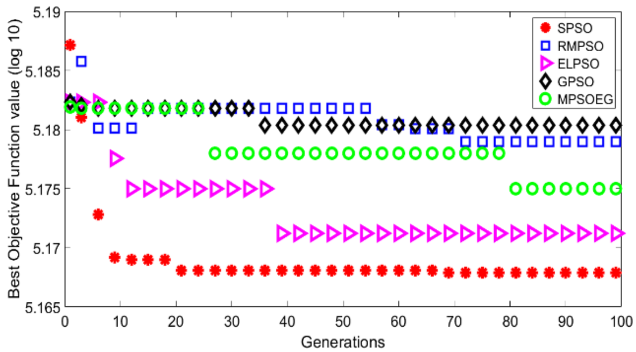

FIGURE 14. Convergence plot of different algorithms on f_{12}.

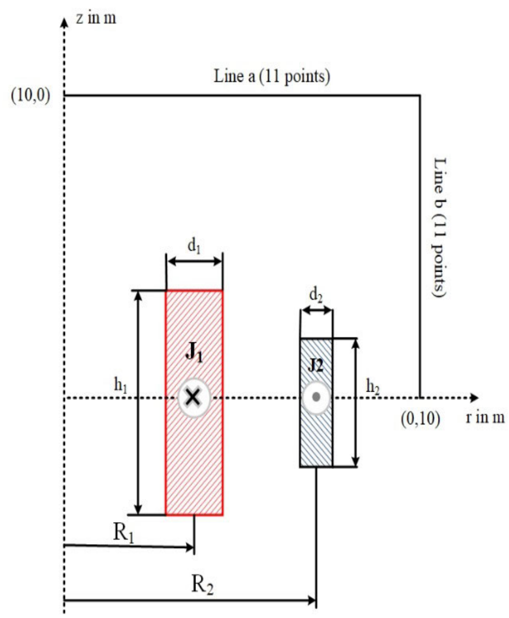

FIGURE 15. Schematic diagram of SMES devic.

TABLE 3. Results comparison of SPSO with RMPSO, ELPSO and GPSO on team workshop problem 22.

Algorithms	r_2	d_2	C.F
GPSO	3.0924	0.3523	0.4243
RMPSO	3.1061	0.3689	0.6115
ELPSO	3.0732	0.3812	0.4247
MPSOEG	3.1103	0.2731	0.0368
SPSO	3.0814	0.2731	**0.0294**

Note: C.F means cost function

20 random runs, the numerical results of all algorithms are recorded in Table 3.

When compared to other tested optimum algorithms, the numerical results show that the proposed SPSO has a strong convergence.

VI. STATISTICAL ANALYSIS

The Wilcoxon signed-ranks test [54] is a non-parametric statistical hypothesis test that analyses the ranks for positive and negative differences in related samples of data sets while

TABLE 4. Statistical results OF paired data sets of SPSO WITH RMPSO, ELPSO, GPSO and MPSOEG.

Function	Measurement	RMPSO	ELPSO	GPSO	MPSOEG
f_1	z	-5.066	-5.066	-5.068	-5.068
	p	.000	.000	.000	.000
f_2	z	-5.133	-5.102	-5.024	-3.901
	p	.000	.000	.000	.000
f_3	z	-5.176	-2.539	-5.030	-2.486
	p	.000	.011	.000	.013
f_4	z	-5.176	-4.446	-4.437	-2.779
	p	.000	.000	.000	.005
f_5	z	-5.169	-4.458	-4.430	-2.606
	p	.000	.000	.000	.009
f_6	z	-4.957	-4.455	-2.985	-1.262
	p	.000	.000	.003	.207
f_7	z	-5.063	-5.047	-5.154	-5.157
	p	.000	.000	.000	.000
f_8	z	-4.139	-5.045	-1.286	-5.020
	p	.000	.000	.198	.000
f_9	z	-5.042	-5.091	-5.089	-2.804
	p	.000	.000	.000	.005
f_{10}	z	-2.394	-2.927	-4.463	-4.442
	p	.017	.003	.000	.000
f_{11}	z	-5.094	-5.084	-4.820	-5.089
	p	.000	.000	.000	.000
f_{12}	z	-5.051	-3.036	-5.057	-5.065
	p	.000	.002	.000	.000
*f_{13}	z	-2.729	-5.141	-2.993	-4.959
	p	.006	.000	.003	.000

* f_{13} represent TEAM problem 22.

ignoring the signs. d_i is the difference between the two data sets on the i^{th} out of data sets ($N = 33$) in "(11)","(12)". The variations are ranked by their absolute values. Let R^+ be the total of rankings for data sets with a positive rank, and R^- be the sum of ranks for data sets with a negative rank. In case of $d_i = 0$ than ignored [55], [56]:

$$R^+ = \sum\nolimits_{d_i>0} rank(d_i) + \frac{1}{2}\sum\nolimits_{d_i=0} rank(d_i) \quad (11)$$

$$R^- = \sum\nolimits_{d_i<0} rank(d_i) + \frac{1}{2}\sum\nolimits_{d_i=0} rank(d_i) \quad (12)$$

$$z = \frac{T - \frac{1}{4}N\,(N+1)}{\sqrt{\frac{1}{24}N\,(N+1)\,(2N+1)}} \quad (13)$$

where T is the lower rank of the sum and is stated mathematically as:

$$T = min(R^+, R^-) \quad (14)$$

For all benchmark test functions in Table 1 and TEAM problem 22, Wilcoxon singed-rank test results were obtained by considering pairs of proposed algorithms SPSO with RMPSO, ELPSO, GPSO, and MPSOEG (SMES). On almost all test functions, SPSO outperformed to RMPSO, ELPSO, GPSO, and MPSOEG, according to the statistical results in table 4. Furthermore, if z is less than -1.96, the significance of $\alpha = 0.05$ is rejected, and the null hypothesis is rejected. The p value indicates the level of significance of the hypothesis test, indicating that SPSO outperforms other PSO variations.

VII. CONCLUSION

The proposed work introduces a new idea into existing PSOs, in which the newly introduced smart particle has an eidetic memory behavior and employs a CF to achieve the best inverse problem solution in electromagnetic devices. The mathematical test functions and SMES of TEAM workshop problem 22 have been used to validate the new PSO algorithm. The SPSO's experimental results show that it obtains a better optimal solution than other PSO variants, particularly at the initial generation in a large population. Furthermore, future research and testing would be needed to solve inverse problems in electromagnetic devices using other optimization techniques to obtain a better optimal solution.

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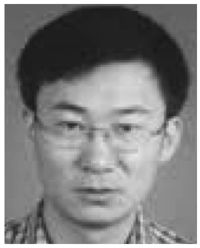

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