Received 21 March 2023; revised 19 April 2023; accepted 20 April 2023. Date of publication 27 April 2023; date of current version 23 May 2023.
Digital Object Identifier 10.1109/OJAP.2023.3270970

Planar Array Subarray Division Method in Microwave Wireless Power Transmission Based on PSO&K-Means Algorithm

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This work was supported by the National Natural Science Foundation of China under Grant 61771008.

ABSTRACT For the problem of maximizing beam collection efficiency in microwave wireless power transmission, a clustering algorithm based on a combination of the particle swarm algorithm and the K-means algorithm is proposed for the subarray partitioning of planar arrays. By minimizing the difference between the subarray beam collection efficiency and the reference beam collection efficiency, the subarray partitioning problem is transformed into an excitation matching problem. Then, the optimal subarray configuration is obtained by using a clustering algorithm that combines the particle swarm algorithm and the K-means algorithm. The effectiveness of the proposed method is evaluated by integrating the beam collection efficiency with parameters such as the receiving area and the size of the planar array. The superiority of the proposed method is demonstrated by a comparison with other advanced methods.

INDEX TERMS Microwave wireless power transmission (MWPT), planar array antenna, particle swarm optimization algorithm (PSO), K-means clustering algorithm, beam collection efficiency (BCE).

I. INTRODUCTION

MICROWAVE wireless power transmission (MWPT) is a technology that transmits energy wirelessly from one location to another via microwaves. Currently, MWPT has mature applications, such as wireless charging devices for cell phones, laptops and other electronic devices, as well as wireless charging piles for electric vehicles [1], [2]. In the long-range MWPT application, the space solar power satellite is a research hotspot [3], [4], and MWPT technology plays a key role in the entire satellite system.

MWPT technology can be roughly divided into three categories: inductive wireless power transmission, coupled wireless power transmission, and radiant wireless power transmission [5]. The development of the MWPT system has become an active research field due to the superiority of this mode of transmission technology, and improving the efficiency of the whole system is the research hotspot in this field. Researchers have studied the problem from multiple aspects, such as optimizing the efficiency of the receiving antenna, improving the distance between the receiving antenna and the transmitting antenna, etc [6], [7], [8], [9]. Since the research methods in these aspects are mature, researchers turn their attention to the design and optimization of the transmitting antenna. The efficiency of the entire MWPT system is determined by a variety of factors, including the DC-RF conversion efficiency, the RF rectifier, the efficiency of the RF generator, RF power transmission efficiency in free space, etc. [10]. Among these factors, the power transmission efficiency in free space has the greatest impact on the system, which is defined as the ratio of the energy collected in the receiving area to the total energy transmitted, called beam collection efficiency (BCE). To maximize the BCE to improve the performance of the MWPT system, [11], [12] convert the formula for solving the BCE into a generalized characteristic equation, through which the theoretical maximum beam collection efficiency and the optimal excitation are calculated. However, the emergence of the "quasi-Gaussian" characteristic of the optimal excitation indicates that each element should be equipped with a separate amplifier and phase shifter, and therefore the system becomes large, complex, and expensive to implement. In recent years, researchers have optimized the position of antenna array elements and subarray partitioning in MWPT systems to optimize the transmit antenna synthesis and improve the BCE [18]. For example, the transmitting antenna array element position is optimized by the chaotic particle swarm algorithm (CPSO) in [13], while in [14], a brain storming algorithm (BSO) intelligent optimization algorithm is proposed to change the array element position, and both methods demonstrate good effects on BCE improvement. However, when it comes to traditional large planar arrays, these methods have obvious limitations because large arrays contain numerous elements. Meanwhile, given the aperture size, the method is difficult to implement, and the optimization of the array position needs to deal with too many variables, greatly increasing the optimization time. To address these issues, researchers have applied subarray division technology to MWPT. This technique divides the radiating elements into smaller groups and keeps the excitation of the elements within each group constant, thus reducing the complexity and cost of the antenna system. In 2015, Paolo Rocca's team proposed the continuous partitioning method (CPM) based on the excitation matching technique [15]. The one-dimensional line array was partitioned by CPM, and ideal BCE values were obtained by fewer subarrays. Though the excitation matching technique applied to subarray partitioning shows effectiveness, its computational efficiency is significantly reduced when facing large arrays. In 2019, Li Xun's team applied the K-means clustering algorithm to the subarray partitioning of antenna arrays and calculated the values of BCE under different group numbers [16], different apertures, and different shapes of receiving antennas. Then, the superiority of the proposed method was verified by comparing the results with those of the CPM method. However, the K-means algorithm is vulnerable to the initial clustering center, which may cause locally optimal results.

To overcome the drawbacks of the K-means algorithm, the hybrid PSO&K-means method is applied to the subarray classification of MWPT for the first time in this paper, with the purpose of using the advantage of global adaptive search of PSO algorithm to compensate the shortage of traditional K-means algorithm. The beam collection efficiency is calculated while considering the effects of the array aperture, size, the shape of the receiving area, and the number of subgroups on BCE; also, the method proposed in this paper is compared with the traditional K-means clustering algorithm.

II. PROBLEM DESCRIPTION

Consider a planar array with N radiation cells located in the xoy plane, as shown in Fig. 1, the array factor of this two-dimensional array can be expressed as:

$$AF(u,v)=\sum_{n=1}^{N}\omega_n e^{j\left[k(ux_n+vy_n)\right]} \tag{1}$$

where ω_n and (x_n, y_n) are the excitation coefficient of the nth radiating element and the location of this element, respectively. $k=2\pi/\lambda$ denotes the wave number, and λ is the wavelength. $u=\sin\theta\cos\varphi$, $v=\sin\theta\sin\varphi$, with θ and φ denoting the elevation angle and azimuth angle of the edge of the receiving area under the coordinate origin, respectively.

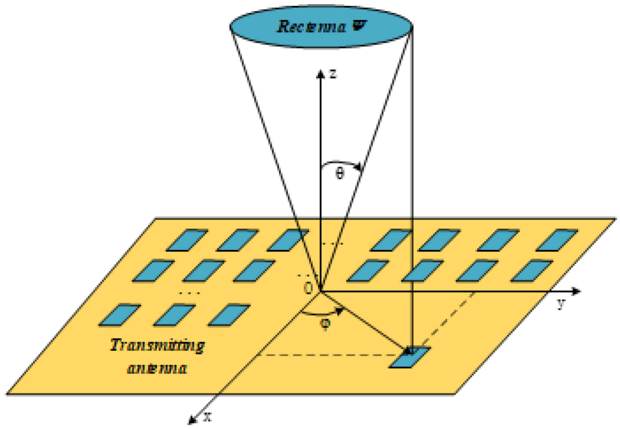

FIGURE 1. 2-D planar array and receiving area.

Based on the definition of beam collection efficiency in [12], the BCE can be expressed as:

$$BCE=\frac{P_\Psi}{P_\Omega}=\frac{\int_\Psi |AF(u,v)|^2 dudv}{\int_\Omega |AF(u,v)|^2 dudv} \tag{2}$$

Let

$$\boldsymbol{\omega}=(\omega_1,\omega_2,\ldots,\omega_N)^H \tag{3}$$

and

$$\boldsymbol{v}(u,v)=\left[e^{-jk(ux_1+vy_1)}, e^{-jk(ux_2+vy_2)},\ldots, e^{-jk(ux_N+vy_N)}\right]^H \tag{4}$$

the superscript "H" denotes conjugate transpose. Then, (1) can be rewritten as:

$$AF(u,v)=\boldsymbol{\omega}^H\boldsymbol{v}(u,v) \tag{5}$$

Substituting equation (5) into equation (2), BCE can be expressed as:

$$BCE=\frac{\boldsymbol{\omega}^H\boldsymbol{A}\boldsymbol{\omega}}{\boldsymbol{\omega}^H\boldsymbol{B}\boldsymbol{\omega}} \tag{6}$$

where $\boldsymbol{A}$ and $\boldsymbol{B}$ are $N\times N$ matrices:

$$\boldsymbol{A}=\int_\Psi \boldsymbol{v}(u,v)\boldsymbol{v}^H(u,v)dudv \tag{7}$$

$$\boldsymbol{B}=\int_\Omega \boldsymbol{v}(u,v)\boldsymbol{v}^H(u,v)dudv \tag{8}$$

Under the condition that the array elements are equally spaced in the array, the theoretical maximum of the beam collection rate can be obtained by the above method. In this way, the calculation of BCE is converted into a generalized characteristic equation problem, the result of the characteristic root represents the theoretically maximum BCE, i.e.,

BCE^{ref}, and the characteristic vector represents the excitation coefficient of the array element corresponding to the theoretically maximum BCE, i.e., ω^{ref}.

When optimizing the transmitting antenna with the subarray technique, the key issues considered are the subarray configuration and the excitation coefficients of each array subarray after subarray division. If the array antenna containing N array elements is divided into K groups, the subarray layout is defined by an $N \times K$ matrix as follows:

$$\boldsymbol{\Delta} = \begin{bmatrix} \delta_{c_1 1} & \delta_{c_1 2} & \cdots & \delta_{c_1 K} \\ \delta_{c_2 1} & \delta_{c_2 2} & \cdots & \delta_{c_2 K} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{c_N 1} & \delta_{c_N 2} & \cdots & \delta_{c_N K} \end{bmatrix} \tag{9}$$

where $\delta_{c_n k}$ in the matrix is defined as the Dirac function:

$$\delta_{c_n k} = \begin{cases} 1, & if\ c_n = k \\ 0, & if\ c_n \neq k \end{cases} \tag{10}$$

and

$$\sum_{k=1}^{K} \delta_{c_n k} = 1, (n = 1, 2, \ldots, N) \tag{11}$$

The integers $\{c_n \in [1, K]; n = 1, 2, \ldots, N\}$ are used to identify the membership of the nth array element with the kth subarray. The subarray excitation coefficients are also represented as a vector of $K \times 1$, i.e., $\boldsymbol{\omega}^{sub} = \{\omega_1^{sub}, \omega_2^{sub}, \ldots, \omega_K^{sub}\}^H$, and the excitation coefficients of each array element after subarray division can be represented by the matrix $\boldsymbol{\Delta}$ and vector $\boldsymbol{\omega}^{sub}$:

$$\tilde{\boldsymbol{\omega}} = \boldsymbol{\Delta} \cdot \boldsymbol{\omega}^{sub} \tag{12}$$

The beam collection efficiency after subarray division can be calculated as BCE^{sub}. Then, the effectiveness of subarray division can be expressed according to the difference between the theoretical BCE and the BCE after subarray division as follows:

$$\begin{aligned} \Delta BCE &= BCE^{sub} - BCE^{ref} \\ &= \frac{\tilde{\boldsymbol{\omega}}^H \boldsymbol{A} \tilde{\boldsymbol{\omega}}}{\tilde{\boldsymbol{\omega}}^H \boldsymbol{B} \tilde{\boldsymbol{\omega}}} = \frac{(\boldsymbol{\omega}^{ref})^H \boldsymbol{A} \boldsymbol{\omega}^{ref}}{(\boldsymbol{\omega}^{ref})^H \boldsymbol{B} \boldsymbol{\omega}^{ref}} \end{aligned} \tag{13}$$

Since the total power emitted by the transmitting antenna is determined, $\tilde{\boldsymbol{\omega}}^H \boldsymbol{B} \tilde{\boldsymbol{\omega}}$ and $(\boldsymbol{\omega}^{ref})^H \boldsymbol{B} \boldsymbol{\omega}^{ref}$ in (13) are equal, then it can be reduced to an optimization problem:

$$\begin{aligned} \min f\left(\boldsymbol{\Delta}, \boldsymbol{\omega}^{sub}\right) = \left(\tilde{\boldsymbol{\omega}} - \boldsymbol{\omega}^{ref}\right)^H \\ \times \boldsymbol{A}\left(\tilde{\boldsymbol{\omega}} - \boldsymbol{\omega}^{ref}\right) \end{aligned} \tag{14}$$

Through the analysis of both rectangular receiving antennas and circular receiving antennas in [16] and the derivation of formulas, the problem of MWPT subarray division can be approximated as an excitation matching problem, and the minimization of the matching error can be formulated as:

$$\begin{aligned} \min\ f\left(\boldsymbol{\Delta}, \boldsymbol{\omega}^{sub}\right) &= \left|\tilde{\boldsymbol{\omega}} - \boldsymbol{\omega}^{ref}\right|^2 \\ &= \sum_{n=1}^{N} \left| \omega^{ref} - \sum_{k=1}^{K} \delta_{c_n k} \omega_k^{sub} \right|^2 \end{aligned} \tag{15}$$

According to [17], the excitation of each subarray in the vector $\boldsymbol{\omega}^{sub}$ is defined as:

$$\begin{aligned} \omega_k^{sub} &= \frac{\sum_{n=1}^{N} \sum_{k=1}^{K} \delta_{c_n k} \omega_n}{\sum_{n=1}^{N} \sum_{k=1}^{K} \delta_{c_n k}}, \\ k &= v1, 2, \ldots, K \end{aligned} \tag{16}$$

III. PSO&K-MEANS ALGORITHM

The PSO&K-means algorithm is a clustering algorithm that combines the particle swarm algorithm and the K-means algorithm. Although the K-means algorithm takes a short time to converge when performing subarray partitioning [19], the randomness of selecting the initial clustering centers may lead to clustering results with no solution or a local optimal solution. Therefore, the advantage of global adaptive search of the PSO algorithm is exploited to combine the two methods [20], [21], [22]. The fundamental principle is to optimize the results generated by the randomly selected initial clustering centers using the PSO algorithm to find the best clustering center so that the sum of the distances from all data to the clustering center to which they belong is minimized. In this way, the accuracy of the clustering results is improved, and the K-means algorithm also runs faster [23], [24].

The process of the algorithm is briefly described as follows.

A. PRE-PROCESSING OF DATA

Before initialization, Q data are randomly selected among all data as the initial clustering centers, and the adjacency law is defined as follows:

If X_n, q satisfies

$$\begin{aligned} \left\|X_n - Z_q\right\| &= \min\|X_n - Z_k\|, \\ k &= 1, 2, \ldots, Q \end{aligned} \tag{17}$$

The X_n belongs to the qth class. After performing the initial clustering division, the center of the clusters after the division, i.e., the arithmetic mean of the same group of data, is calculated:

$$Z_q = \frac{\sum_{m=1}^{M} X_m}{M} \tag{18}$$

where M denotes the number of elements in the qth group.

B. INITIALIZATION OF THE POPULATION

Q cluster centers will be randomly selected as the position encoding of the initial particle, while the corresponding fitness is calculated and initialized for the particle's velocity and other parameters. Here, the fitness is defined as the sum of the distances between each element and the cluster centers of its group, i.e.,

$$J = \sum_{q=1}^{Q} \sum_{m=1}^{M} dis\left(X_{qm}, Z_q\right) \tag{19}$$

where q denotes the group in which the data X_{qm} is located, M is the amount of data in the qth group, and $dis(\cdot)$ denotes the distance between the data and the cluster center. The above steps are repeated K times to obtain K initial particle clusters. Based on the fitness value, the current optimal solution of a single particle is defined as p_{best}, and the current optimal solution of the whole population is defined as g_{best}.

C. UPDATE THE VELOCITY AND POSITION OF THE PARTICLE

$$v_i^d = \omega v_i^{d-1} + c_1 * r_1 * \left(p_{best} - x_i^d\right) + c_2 * r_2 * \left(g_{best} - x_i^d\right) \tag{20}$$

$$x_i^{d+1} = x_i^d + v_i^d \tag{21}$$

The velocity and position of the particle can be updated according to (20) and (21), where c_1 and c_2 denote the individual learning factor and social learning factor of the particle, respectively;r_1 and r_2 denote random numbers between (0,1); ω denotes the inertia weight of the velocity; v_i^d denotes the velocity of the ith particle at the dth iteration; x_i^d denotes the position of the ith particle at the dth iteration.

D. UPDATE INDIVIDUAL, GROUP ADAPTATION

After the velocity and position of particles are updated, the individual particle optimal solution p_{best} and the population optimal solution g_{best} are updated by the following process: If the fitness value of the current position is less than the previously obtained best value p_{best}, this value is updated; otherwise, p_{best} is kept unchanged.

Then, the updated p_{best} is compared with the previously obtained fitness g_{best} of the best position passed by the population. If the updated p_{best} of this particle is less than g_{best}, then the value of updated p_{best} is given to g_{best}; otherwise, g_{best} is kept unchanged.

E. K-MEANS CLUSTERING OF NEW PARTICLES

The new particles obtained are substituted into the K-means algorithm for clustering, and according to the updated particles, they are used as clustering centers, The final clustering results are obtained by dividing the data with the adjacency rule.

Specifically, the PSO&K-means algorithm is implemented as follows:

Step 1: Select K data as the initial clustering centers randomly.

Step 2: Calculate the fitness according to (19).

Step 3: Initialize PSO-related parameters and particle velocity.

Step 4: Update the individual and group fitness.

Step 5: Update the velocity and position of the particles according to (20) and (21).

Step 6: Repeat Step 4 and Step 5 until the maximum number of iterations is reached.

TABLE 1. The square receiving area, the relationship between BCE, and the number of groups.

	K=3	K=4	K=5	K=6
K-means	94.39%	95.74%	98.12%	98.34%
PSO&K-means	94.47%	96.12%	98.46%	98.47%

Step 7: Use the optimal particles obtained through PSO as the clustering centers in the K-means algorithm.

Step 8: Substitute the data into (17) to group the data and calculate the new clustering centers according to (18).

IV. NUMERICAL RESULTS

In this section, to verify the effectiveness of the PSO&K-means method proposed in this paper, the number of transmit antenna array elements, the number of groups, and the shape and size of the receiving antenna are considered; meanwhile, the results of the PSO&K-means method are compared with those of the traditional K-means method and the theoretical values of the generalized eigenvalue equation to verify the effectiveness of the proposed method. The transmit antenna is considered as an $N = n \times n$ two-dimensional square array with a spacing of $dx = dy = \lambda/2$ along both *the* x-axis and y-axis, as shown in Fig. 1. The square receiving antenna area is $\Psi = \{(u, v) : -u_0 \leq u \leq u_0, -v_0 \leq v \leq v_0\}$, and the circular receiving area is set as$\Psi = \{(u, v) : u^2 + v^2 \leq r_0\}$, where u_0, v_0 denote the side lengths of the rectangular receiving antenna, and r_0 denote the radius of the circular receiving antenna.

Firstly, consider the case that the receiving antenna is a square area, the number of array elements is $N = 10\times 10$, the receiving area Ψ is $\Psi = \{(u, v) : -0.5 \leq u \leq 0.5, -0.5 \leq v \leq 0.5\}$, and the whole planar array is divided into 3, 4, 5, and 6 groups respectively. Fig. 2 shows the layout of the subarray and the subarray excitation after dividing the array into five groups under the above conditions. Since the distribution is centrosymmetric, only the first quadrant needs to be considered. Table 1 presents the variation of the beam collection efficiency with the number of groups K derived from the PSO&K-means algorithm and the K-means algorithm under the same conditions. It can be observed that as the number of groups K increases, the BCE obtained by both methods also increases and becomes closer to the theoretical reference value $BCE^{ref} = 99.02\%$. This is because when the number of groups increases, the feed network of the transmitting antenna becomes more complex and closer to the feed network distribution in the theoretical case. Additionally, by comparing the data of the two methods, the superiority of the PSO&K-means algorithm is illustrated. When $K = 5$, only five control units are needed for the entire transmitting antenna, which is 95% reduction compared to the previous design where 100 array elements were individually equipped with control units. This greatly reducing the antenna cost and simplifying the feed network.

Fig. 3 and Table 2 show the relationship between the number of array elements and BCE, and the following information can be derived from the line graph in Fig. 3.

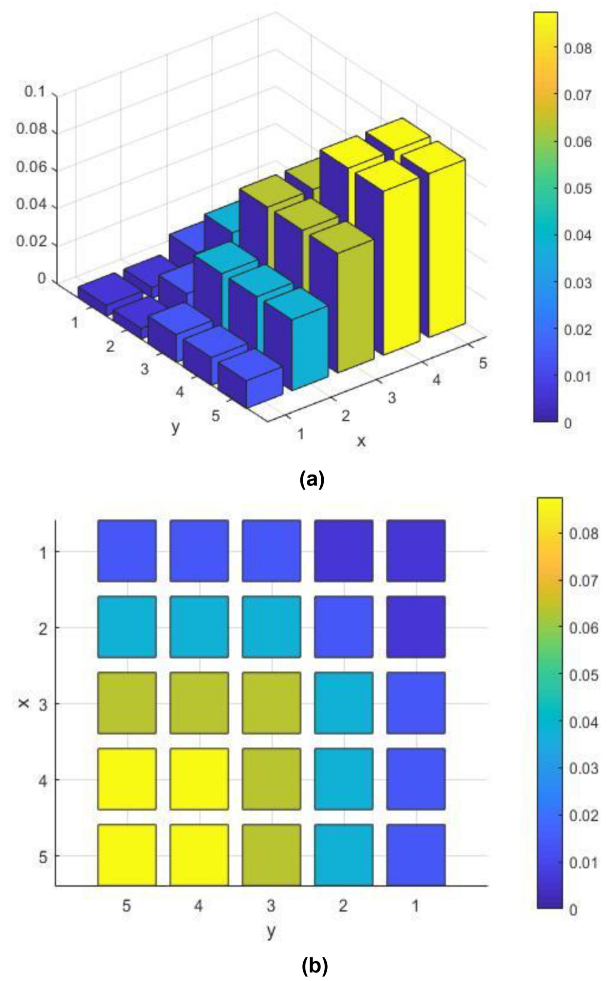

FIGURE 2. The excitation distribution of the array elements after the subarray division.

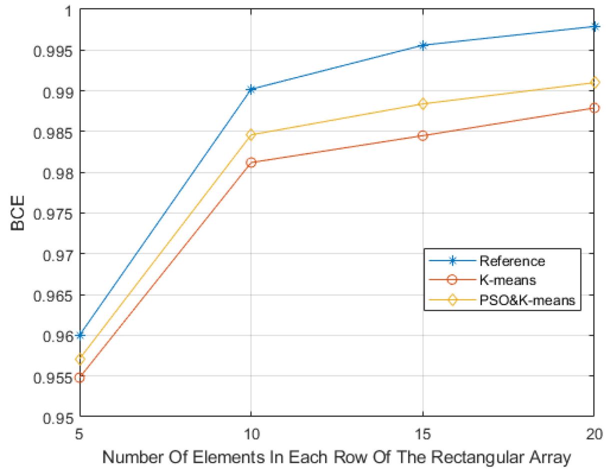

FIGURE 3. The relationship between BCE and the number of array elements.

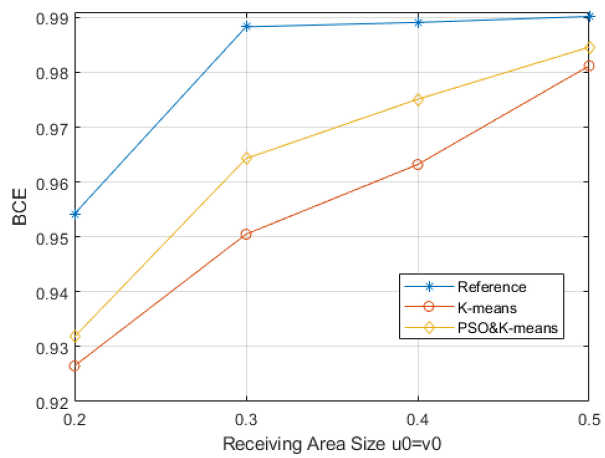

FIGURE 4. The relationship between BCE and the reception area.

TABLE 2. The square receiving area, the relationship between BCE, and the number of array elements.

	$N=5\times5$	$N=10\times10$	$N=15\times15$	$N=20\times20$
BCE^{ref}	96.00%	99.02%	99.56%	99.79%
K-means	95.48%	98.12%	98.45%	98.79%
PSO&K-means	95.71%	98.46%	98.84%	99.10%

TABLE 3. The square receiving area and the relationship between BCE and the reception area.

	$u_0=0.2$	$u_0=0.3$	$u_0=0.4$	$u_0=0.5$
BCE^{ref}	95.42%	98.83%	98.91%	99.02%
K-means	92.65%	95.05%	96.32%	98.12%
PSO&K-means	93.18%	96.34%	97.51%	98.46%

When changing the number of array elements N and keeping the number of groups $K = 5$ and the size $\Psi = \{(u, v) : -0.5 \leq u \leq 0.5, -0.5 \leq v \leq 0.5\}$ of the receiving area unchanged, considering $N = 5 \times 5$, $N = 10 \times 10$, $N = 15 \times 15$, and $N = 20 \times 20$, it can be seen that the clustering effect of the PSO&K-means algorithm is closer to the theoretical reference value; also, it can be calculated from the data in Table 2 that the BCE obtained by PSO&K-means is only about 0.6% different from BCE^{ref}.

Further experiments were conducted to study the relationship between the size of the receiving area and the BCE. When the number of fixed array elements $N = 15 \times 15$ and the array was divided into three groups, as the receiving area expanded, the corresponding BCE value increased. This is because a larger receiving area can receive more energy into free space, leading to higher efficiency. Fig. 4 and Table 3 suggest that the PSO&K-means algorithm achieves better results than the K-means algorithm in terms of theoretical reference values. When the receiving area u_0, v_0 is expanded from 0.2 to 0.3, the BCE value increases significantly by about 3%. However, when the receiving area is expanded to 0.4 and 0.5, the increase of BCE is not significant. Thus, at $N = 15 \times 15$, the best receiving area is selected as $u_0 = v_0 = 0.3$.

To investigate whether the combination of the particle swarm algorithm with the K-means algorithm has an impact

TABLE 4. Comparison of the number of iterations and time for different optimization methods.

	Number of iterations	Time (s)
K-means	3	0.16
PSO&K-means	12	1.25

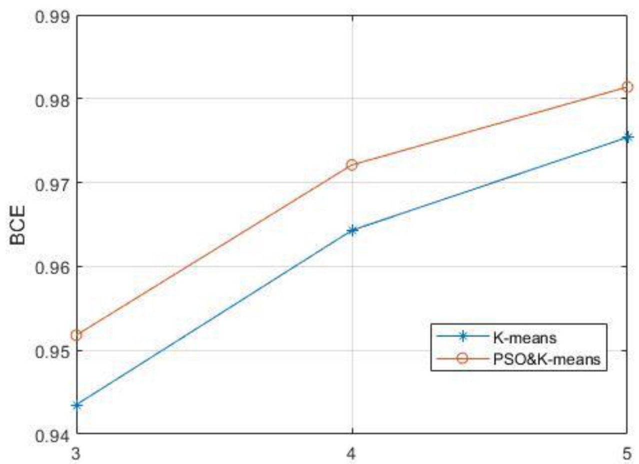

FIGURE 5. The circular reception area and the relationship between BCE and the number of groups.

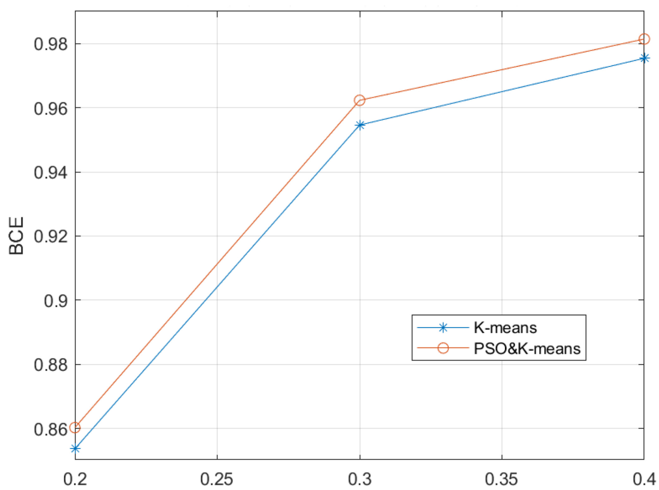

FIGURE 6. The circular receiving area and the relationship between BCE and the reception area.

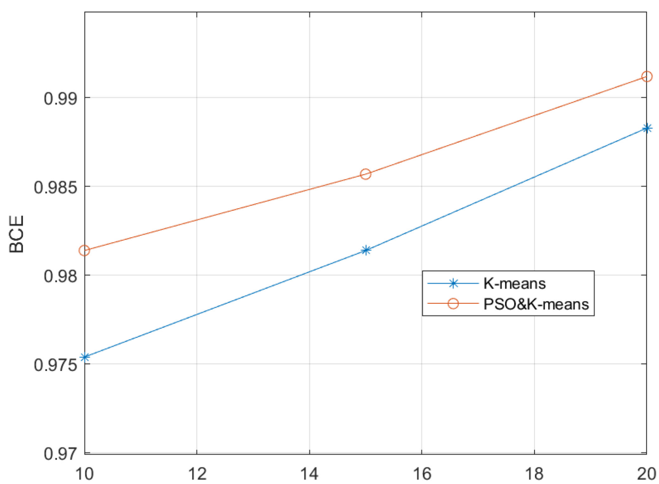

FIGURE 7. The circular reception area and the relationship between BCE and the number of array elements.

on the time required for clustering, the time required to complete clustering and the number of iterations of the whole process between PSO&K-means and K-means were compared. It can be observed from Table 4 that the time to complete clustering and the number of iterations of PSO&K-means are slightly larger than those of the K-means algorithm, but the difference between the two is not significant, and the difference between the completion time is about 1s, which is within a tolerable range.

The above experiments were conducted in a square receiving area. To investigate the influence of the shape of the receiving area on the experimental results, the shape of the receiving antenna was changed to a circle, and the effect of the same three aspects, i.e., the number of groups, the number of array elements, and the size of the receiving area, were studied. The corresponding experimental results under different conditions are shown in Figs. 5, 6, and 7. As the shape of the receiving area is changed and the area of the receiving area is reduced, there is a small decrease in the overall beam collection efficiency compared with the square receiving area. However, the PSO&K-means method has some advantages compared with the K-means method.

Fig. 5 shows the relationship between the beam collection efficiency and the number of groups in the circular receiving area. The number of elements of the transmitting array is $N = 10 \times 10$, and the size of the circular receiving area is $r_0 = 0.4$. Then, the transmitting array is divided into 3, 4, and 5 groups, respectively. As the number of groups increases, the BCE also increases, and the BCE obtained by the proposed PSO&K-means algorithm is better than that of the traditional K-means algorithm throughout the whole process.

Fig. 6 shows the relationship between the beam collection efficiency value and the size of the receiving area in a circular receiving area. The number of transmitting array elements $N = 10 \times 10$, and the number of groups $K = 5$. As the radius of the circular receiving area increases, the corresponding BCE also increases, and the advantages of the PSO&K-means algorithm can still be observed.

Fig. 7 shows the relationship between the beam collection efficiency and the number of transmitting array elements in the circular receiving area. The fixed packet number $K = 5$, and the radius of the circular receiving area $r_0 = 0.4$. Three cases of the number of array elements $N = 10 \times 10$, $N = 15 \times 15$, and $N = 20 \times 20$ are considered, respectively. The more array elements, the larger the BCE value, and the advantages of the PSO&K-means algorithm remain unchanged.

V. CONCLUSION AND DISCUSSION

This paper investigates the problem of maximizing the beam collection efficiency for the MWPT system based on the subarray division method. By deriving an expression for the subarray BCE, the problem is transformed into an excitation matching problem, which is then tackled using the PSO&K-means algorithm. Typical examples are explored from several aspects, such as the number of groups, the number of array elements and receiving antennas, to obtain the BCE in different states. The results are compared with the theoretical maximum to verify the effectiveness of the method. Meanwhile, the results are compared with those obtained by the K-means algorithm and the related literature. It is concluded that the PSO&K-means algorithm has significantly improved the value of BCE, which reflects the superiority of the proposed method. Further work will start from the shortcomings of the PSO algorithm and conduct an in-depth study by introducing the quantum particle swarm method.

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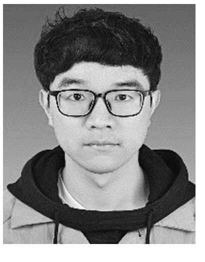

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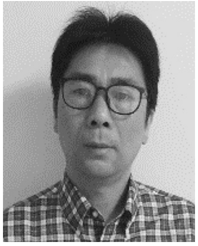

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