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Optimization Design of Sectional Dynamic Power Supply Track Based on Improved CPSO Algorithm

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Abstract: As an important part of smart grid, EVs have many advantages in energy saving and low pollution and become a research hotspot. Based on the wireless power transfer technology, dynamic power supply technology develops rapidly and can effectively reduce the battery capacity of EVs. This paper the issue on the optimal design of sectional dynamic power supply track has been investigates the optimal design of sectional dynamic power supply track. For the optimal design of sectional tracks, a mathematical model of the minimal average annual comprehensive cost has been set up and a novel Cellular Particle Swarm Optimization (CPSO) based on PSO and CA are proposed to solve the nonlinear optimization problem. The results of numerical simulation show that it is more reliable to obtain the optimal design by CPSO rather than by PSO. Furthermore, the minimal average annual comprehensive cost is 60 thousand Yuan produced by CPSO less than that by PSO.

Keywords: Cellular automata, cellular particle swarm optimization, dynamic power supply, optimal design, sectional track.

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1. INTRODUCTION

As environmental deterioration and energy depletion become increasingly severe, the green EVs have aroused more and more public attentions because of their low carbon dioxide emission high energy efficiency compared to internal combustion engine vehicles (ICEVs), which burn fossil fuels. Compared with the traditional conductive charging mode, wireless charging for EVs, based on the wireless power transfer technology, has many advantages such as making charging more convenient by setting program to charge automatically without man management after parking, and more secure as settling the issues of wire aging and leakage without mechanical friction and exposed cables. It can not only interact with the grid, more efficiently to suppress the fluctuations of the output of renewable energy and reduce the impact on the power grid, but also improve the mileage of EVs with the smaller capacity and size of battery [1]. This technology is in favor of the development and popularization of EVs and has become a hot research issue [2-4].

The electromagnetic coupling-based wireless dynamic power supply technology for EVs is a real-time power supply from the transmitting coil array or track laid under the load to the vehicle battery pack or motor, which has caused wide attention [5-7]. In this system, storage battery could be cut down even canceled with an extended mileage. Stamati T. E. *et al*. analyzed the characteristics of energy efficiency and system stability of several topologies of the wireless dynamic power supply system and put forward the design of sectional dynamic power supply track [8]. From the perspective of economy, for minimizing the system operating cost including the nonrecurring construction cost, maintenance cost and track operation loss cost, it is important to make a reasonable plan for sectional tracks from the layout and capacity, *etc*.

The optimal problem of sectional dynamic power supply track is a nonlinear optimization problem with multiple variables and constraints, and it is difficult for conventional mathematical method to produce the ideal optimization result. Accordingly, intelligent optimization algorithm is usually applied to solve this problem. As of now, most researches adopt the Genetic Algorithm (GA) or Particle Swarm Optimization (PSO) to design the sectional track [9]. However, there are some problems remained in these algorithms, such as slow convergence speed, low accuracy and premature convergence. For avoiding falling into local convergence and balancing the global search and local optimization, this paper proposes a novel Cellular Particle Swarm Optimization (CPSO) based on PSO, which could improve the mechanism of information sharing and inheritance, ameliorate the convergence accuracy and enhance the optimization stability [10,11]. Through four test functions, the performances of the PSO and CPSO are compared. Furthermore, an economic model of sectional track optimal design is presented and these two algorithms are respectively applied to optimize the design. Finally, the results of simulation show that CPSO possesses a stronger search ability to obtain an extreme point with higher accuracy than PSO. And the minimal average annual comprehensive cost of sectional track solved by CPSO is 60 thousand Yuan

(RMB) less than that caused by PSO, namely 3% less of running cost.

2. OPTIMIZATION MODEL OF SECTIONAL SUPPLY POWER TRACK

The design of sectional dynamic power supply track mainly depends on the magnetic coupling power wireless transfer technology, which can transfer power from the power transmitting coil laid under the load to the power pick-up coil installed in the vehicle *via* high-frequency magnetic field. A typical wireless power transfer system is as shown in Fig. (**1**)

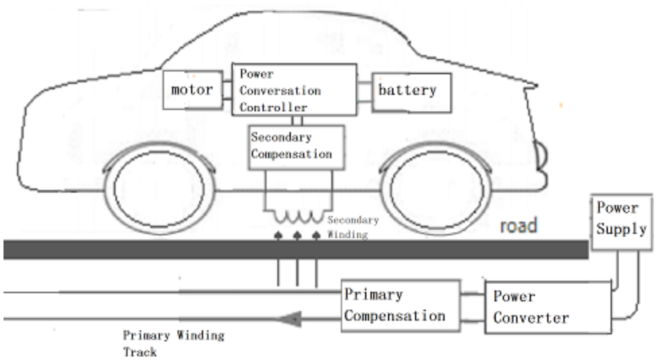

Fig. (1). Typical wireless power transfer system.

In sectional dynamic power supply system, the primary winding track consists of power transmitting coils which are switched to transfer power according to vehicle situation. The cost of this system is enormous and it is necessary to optimize the design of the sectional dynamic power supply track on the economic level.

2.1. Economic Model of Sectional Track Optimal Design

The economic issue of sectional wireless power supply track optimal can be described that under the circumstance that the distribution of load demands of target sections are known, how to determine the length l_k and capacity P_k of each segment and the total number N of segments for the lowest one-time construction cost (including equipment cost and track cost) and average annual operation cost (track operating loss cost, *etc*.). If take the lowest annual cost T_{cst} as purpose, the objective function could be expressed as

$$\min T_{cst}(l_k, P_k, N) = F_{cst} + I_{cst} + L_{cst} \tag{1}$$

where, F_{cst} stands for the corrected annual investment cost of power conversion and control devices, and can be calculated by

$$F_{\mathrm{cst}} = \sum_{k=1}^{\mathrm{N}} \left[f\left(P_k\right) \frac{r_0\left(1+r_0\right)^{m_1}}{\left(1+r_0\right)^{m_1}-1} + u\left(P_k\right) \right] \tag{2}$$

where, $f\left(P_k\right) = 0.01e^{\sqrt{P_k}}$ is the investment cost of the k^{th} segment track; r_0 is the discount rate and m_1 is the period of depreciation; $u(P_{\mathrm{k}})$ is the equipment maintenance cost of the segment track k and can be obtained by

$$u\left(p_k\right) = 0.01\left(\tanh\left(\sqrt{P_k}-4\right)+2\right) \tag{3}$$

I_{cst} is the corrected annual investment cost of tracks and can be calculated by

$$I_{\mathrm{cst}} = \sum_{k=1}^{N} l_k p \left[\frac{r_0\left(1+r_0\right)^{m_2}}{\left(1+r_0\right)^{m_2}-1} \right] \tag{4}$$

where, p represents the investment cost of unit length track, varied with the voltage level, current level and protection grade of the track; m_2 is the period of depreciation of the track.

L_{cst} is the corrected annual operating loss cost of the tracks and can be calculated by

$$L_{\mathrm{cst}} = \sum_{k=1}^{N} \left(a_1 b_{k1} + a_2 b_{k2}\right) \times l_k R I_k^2 \tag{5}$$

where, a_1 and a_2 represent the daytime and nighttime electricity price respectively. b_{k1} and b_{k2} are respectively the annual daytime and nighttime running time of the segment track k. I_k is the current flowing through the segment track k, and R is the resistance of per unit length track.

2.2. Constraints

In the optimal design of sectional tracks, the total number N of tracks, the length l_k and capacity P_k of each segment will be affected by many factors. There are some constraints on each variable were discussed as following.

1) Device capacity constraint

If W_{a} stands for the load demand forecast of load node a (EV); η_k is the efficiency of the k^{th} segment track; J_k is the set of load nodes supplied by the segment track k; J is the set of total load node, then the capacity P_k of each segment should meet

$$\mathrm{P}_k \geq \frac{\sum_{a \in J_k} W_a + l_k R I_k{}^2}{\eta_k \left(\sum_{a \in J_k} W_a \right)} \left(k = 1, 2, \cdots, N; J_1 \cup J_2 \cup \cdots \cup J_N = J\right) \tag{6}$$

Meanwhile, the capacity P_k should be not less than the maximum power demand $P_{s\mathrm{Max}}$ of a single load node

$$P_k \geq P_{s\mathrm{Max}} / \eta_k \tag{7}$$

2) Length constraint of segment track

By switching frequency limit, the length l_{k} of each segment track should not be less than the distance yielded by an electric vehicle with a top speed $V_{\max}$ in one switching period $T_{\min}$. Based on the Equation (6), it is easily deduced as

$$T_{\min} V_{\max} \leq l_k \leq \frac{(P_k - \sum_{a \in J_k} W_a)}{R I_k^2} \tag{8}$$

3) Total length constraint of track

The total length is constrained by the top speed $V_{\max}$ of EVs and the shortest time $t_{\min}$ for EV getting enough electricity supply

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$$\sum_{k=1}^{\mathrm{N}} l_k \geq V_{\max} t_{\min} \tag{9}$$

4) Position constraint of EV

At any time, each EV is above one track, it could be expressed as

$$\sum_{k=1}^{N} g_{ka} = 1\left(\mathrm{g}_{ka} \in \{0,1\}\right) \tag{10}$$

where, g_{ka} is a sign of whether the EV a is powered by the segment track k or not. “1” and “0” stand for "Yes" and "no" respectively.

3 PARTICLE SWARM OPTIMIZATION BASED ON CELLULAR AUTOMATA

3.1. Standard PSO

In standard PSO, particle is the fundamental unit and the position of each particle represents the candidate solution of solution space. If solution space is a D-dimensional space, which means that the candidate solution is made up of d variables, then the position and the velocity of i^{th} particle can be expressed as $X_i=(x_{i1},x_{i2},\ldots,x_{i\mathrm{D}})^{\mathrm{T}}$ and $V_i=(v_{i1},v_{i2},\ldots,v_{i\mathrm{D}})^{\mathrm{T}}$ respectively. The speed and position of particle is updated according to

$$V_{id}^{t+1} = \omega V_{id}^{t} + c_1 r_1 (P_{id}^{t} - X_{id}^{t}) + c_2 r_2 (g_d^{t} - X_{id}^{t}) \tag{11}$$

$$X_{id}^{t+1} = X_{id}^{t} + r V_{id}^{t+1} \tag{12}$$

where, V_{id}^{t} , X_{id}^{t} and P_{id}^{t} stand for respectively the d^{th} dimension components of speed, position and extremum of the i^{th} particle in the t^{th} iterate; g_d^{t} is the d^{th} dimension component of global extremum in the t^{th} iterate; c_1 and c_2 are cognitive factors, which are usually set to 2; r_1 and r_2 are two random numbers varied in range of 0~1; ω is the inertia weight with the range of 0.4~0.9, which can usually be obtained by

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{t_{\max}} \times t \tag{13}$$

The moving speed of particles in each dimension cannot be larger than the maximum speed of $V_{\max}$. Merits of the particle position is decided by the fitness values of its own, and the better the fitness value, the more optimal the position of the particle.

3.2. Improved CPSO

For standard PSO, there are some disadvantages in premature convergence and searching precision. And it is unfit for the multiple objectives, constraints and uncertainty optimization problems. As a result, adjusting parameters, redefining or modifying updating strategy of PSO and combining other algorithms are the main ideas to improve PSO. Two key factors, namely population structure of the communication and information exchange mechanism of the integration and diffusion, are important to effect on the searching performance of PSO, which can affect the cooperation of population and adaptive adjustment of individual.

Therefore, based on the standard PSO, this paper proposes an improved Cellular Particle Swarm Optimization algorithm (CPSO) by introducing the idea of cellular automata and designing the neighborhood model of particles. In CPSO, each particle just only exchanges information with the neighbors determined by the neighbor function. This mechanism can make the information disseminate slowly in population, which contributes to maintain the diversity of the population and fully mine local information of each particle. CPSO can better balance the depth and breadth of search capability.

In CPSO, each particle is defined as a cell and it is obvious that the number of cells is equal to the size of population. Moore-neighbor topology is adopted and as shown in Fig. (**2**).

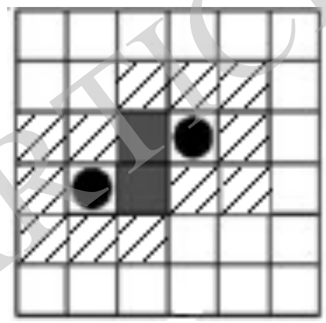

Fig. (2). Moore-neighbor topology.

In Fig. (**2**), black dots represent cells, and each individual cell has 8 neighbors with the stripes. The gray grids stand for the shared neighborhood part of two cells, which provide the way that two particles exchange information. The overlapping structure between two neighbors provides a hidden mechanism for the algorithm to promote the optimal individual to spread gently in the whole population, which can reduce the selection pressure and improve the diversity of algorithm. According to the population scale, randomly generate particles and load them without repeatedly into the grids with the same number of particles. Throughout the iteration process, the particles keep the same relative position in the grid structure.

In CPSO, the cellular states S_i^t contain two kinds of information at the time t, which are the optimal position P_i^t and P_n^t of one particle and its neighbor particles, namely $S_i^t = \left[P_i^t, P_n^t\right]$. And these two kinds of information are represented by $S_i^t\left(P_i\right)$ and $S_i^t\left(P_n\right)$ respectively by the transfer rules

$$\begin{aligned} S_i^{t+1} &= f\left(S_i^t, S_{i+\zeta_1}^t, \ldots, S_{i+\zeta_k}^t\right) \\ &= \min(\mathit{fitness}(S_i^t), \mathit{fitness}(S_{i+\zeta_1}^t), \ldots, \mathit{fitness}(S_{i+\zeta_k}^t)) \end{aligned} \tag{14}$$

Equation (14) shows that the optimal position update of one cell’s neighbor is based on the identification of best location of its all neighbors. To better guide particle to move, we can replace the particle's own previous best location P_i^t

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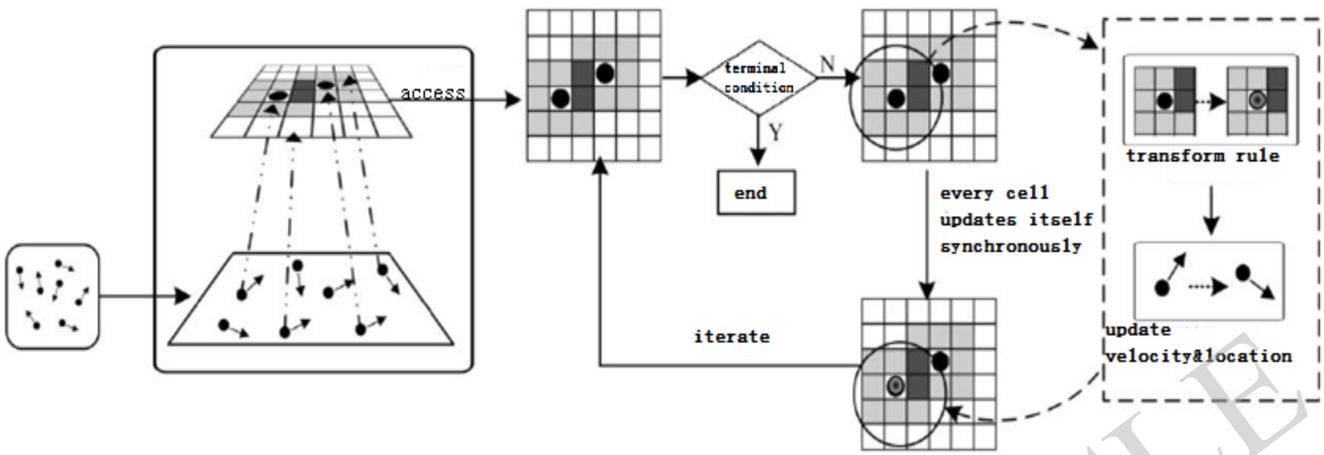

Fig. (3). Process of CPSO.

with its neighbor optimal location P_n^t, and the speed update function is shown as follows

$$V_i^{t+1} = \omega V_i^t + c_1 r_1 \left(P_n^t - X_i^t\right) + c_2 r_2 \left(g_d^t - X_i^t\right) \tag{15}$$

Fig. (**3**) describes the process of CPSO.

4. THE OPTIMAL DESIGN OF SECTIONAL DYNAMIC POWER SUPPLY TRACK

4.1. Design of CPSO

For the design of track, each cell object is defined as each generation of particle population, and the location of particle can be seen as potential solution for the optimization problem. The dimension D of solution space is the same as the number of variables of optimization function. The location of the i^{th} particle can be represented as $X_i=(x_{i1},x_{i2},\ldots,x_{iD})^T$. And the cellular state is defined as $S_i^t = [p_i^t, nbest_i^t]$, where p_i^t and $nbest_i^t$ stand for the optimal location of the i^{th} particle and its neighbor in the t^{th} iterate.

The encoding form of particles is the key of the algorithm, which will improve the global search ability and reduce the risk of getting into local optimum. Moore-neighbor topology is adopted to construct the neighbor function. Table **1** shows the encoding scheme.

In this scheme, each particle is set to a $\sqrt{N}\times\sqrt{N}$ (N is the size of population) mesh topology sequentially and non-repetitively, and each cell has the same number of neighbors. The process of CPSO is as follows.

Step 1: Initialize algorithm parameters: number of population N, dimensionality D, the maximum number of iterations $T_{\max}$, the learning factors c_1 and c_2, the maximum and minimum weight coefficient $\omega_{\max}$ and $\omega_{\min}$. Then calculate the inertia weight factor ω according to the Equation (13).

Step 2: Initialized population: generate position X_i and velocity V_i of each particle randomly.

Step 3: Encode particles, construct neighbor function and distribute particles into Moore-neighbor topology.

Step 4: Calculate the fitness of each individual to seek out the optimal value p_i, assess the neighbors of each particle and determine the optimum value $nbest_i^0$ of initial neighborhood structure and the global optimal value g_d^0 for determining the initial cellular states $S_i^0 = [p_i^0, nbest_i^0]$.

Step 5: Local search in the neighbor structure based on the initial solution defined as each particle in the current population, and find out the optimal location $nbest$. Then update the cellular states and the speed and location of

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Table 1. Encoding scheme for particles.

$V_1=(v_{1,1},v_{1,2},\ldots,v_{1,d})$	$V_2=(v_{2,1},v_{2,2},\ldots,v_{2,d})$	…	$V_{\sqrt{N}}=(v_{\sqrt{N},1},v_{\sqrt{N},2},\ldots,v_{\sqrt{N},d})$
$V_{\sqrt{N}+1}=(v_{\sqrt{N}+1,1},v_{\sqrt{N}+1,2},\ldots,v_{\sqrt{N}+1,d})$	$V_{\sqrt{N}+2}=(v_{\sqrt{N}+2,1},v_{\sqrt{N}+2,2},\ldots,v_{\sqrt{N}+2,d})$	…	$V_{2\sqrt{N}}=(v_{2\sqrt{N},1},v_{2\sqrt{N},2},\ldots,v_{2\sqrt{N},d})$
$V_{2\sqrt{N}+1}=(v_{2\sqrt{N}+1,1},v_{2\sqrt{N}+1,2},\ldots,v_{2\sqrt{N}+1,d})$	$V_{2\sqrt{N}+2}=(v_{2\sqrt{N}+2,1},v_{2\sqrt{N}+2,2},\ldots,v_{2\sqrt{N}+2,d})$	…	$V_{3\sqrt{N}}=(v_{3\sqrt{N},1},v_{3\sqrt{N},2},\ldots,v_{3\sqrt{N},d})$
⋮	⋮	…	⋮
$V_{\sqrt{N-1}\cdot\sqrt{N}+1}=(v_{\sqrt{N-1}\cdot\sqrt{N}+1},v_{\sqrt{N-1}\cdot\sqrt{N}+1},\ldots,v_{\sqrt{N-1}\cdot\sqrt{N}+1})$	$V_{\sqrt{N-1}\cdot\sqrt{N}+2}=(v_{\sqrt{N-1}\cdot\sqrt{N}+2},v_{\sqrt{N-1}\cdot\sqrt{N}+2},\ldots,v_{\sqrt{N-1}\cdot\sqrt{N}+2})$	…	$V_N=(v_{N,1},v_{N,2},\ldots,v_{N,d})$

particle according to Equation (15).

Step 6: Carry out disturbance to the generated particle swarm with a certain probability, then reappraise the new particle swarm and update the g_d.

Step 7: If the termination condition is met, output g_{best}, otherwise, return to step 4.

4.2. Numerical Simulation And Analysis

To illustrate the feasibility of CPSO, a numerical simulation of the optimal design for the sectional power supply tracks has been carried out. The main parameters are shown in Tables **2** and **3**.

Table 2. Parameter of CPSO.

Parameter	N	D	T_{max}	c_1	c_2	ω_{max}	ω_{min}
Value	100	3	200	1.4692	1.4692	0.9	0.4

Table 3. Parameter of numerical simulation.

Parameter	Value	Parameter	Value
t_{min} (minute)	12	a_1 (Yuan/kmh)	0.6
V_{max} (km/h)	50	a_2 (Yuan/kmh)	0.4
m_1 (year)	20	b_1 (h)	1400
m_2 (year)	20	b_2 (h)	1400
r_0 (%)	15		

Considering 30 EVs, CPSO and PSO are adopted to solve the fitness function for 50 times respectively, and the optimal solution is taken as the final plan. The results are shown in Table **4**.

In Table **4**, under the condition of meeting the demand of power supply, 60 thousand Yuan (RMB) can be saved annual by CPSO rather than by PSO, which decreases the operating cost 3%. Furthermore, Fig. (**4**) shows the stability of two algorithms.

Table 4. Results of simulation of CPSO and PSO.

Algorithm	CPSO	PSO
Length of single track (m)	135	117
Device capacity (kW)	24	24
Number of track	74	86
Annual investment cost (Ten Thousand Yuan)	152.1	158.1

In Fig. (**4**), it is clear that the optimal fitness with CPSO is rather smooth without any major mutations. Instead, the curve with PSO fluctuates greatly in 50 times searches. This result suggests that success rate of improved algorithm-CPSO is significantly higher than that of the standard PSO in solving objective function.

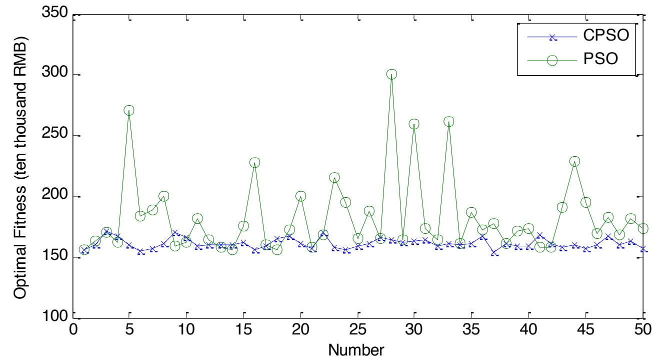

Fig. (4). Stability performance of PSO and CPSO.

CONCLUSION

In this paper, the issue on the optimal design of sectional dynamic power supply track has been investigated. For the purpose of minimizing the average annual comprehensive cost, an optimal mathematical model has been proposed. In order to avoid the risk of local optimization and improve the reliability of optimization, this paper combines the idea of CA, introduces an effective neighbor structure and makes it better for better local search. Finally, the optimal design of sectional tracks is carried out and the result shows that the minimal average annual comprehensive cost is 60 thousand Yuan produced by CPSO less than that by PSO. Furthermore, the result of 50 optimal researches shows that the stability of CPSO is also significantly higher than that of PSO.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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