Segmented Tracks Planning of Roadway-Powered System for Electric Vehicles using Improved Particle Swarm Optimization

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Abstract: As a kind of prospective green vehicles, electric vehicles have not been welcomed by potential customers due to drawbacks such as the high price, short driving range and long charging time. The Roadway-powered Electric Vehicles (RPEVs) using an Inductive Power Transfer (IPT) is considered as an effective solution to resolve these drawbacks. In the segmented RPEVs system, efficiency and annual cost are affected by many factors, such as the track distance, tracks interval, number of tracks and installed capacity of each track. According to such problem, the Nonlinear Programming (NLP) model for segmented tracks planning of RPEVs system is proposed in this paper. An Improved Particle Swarm Optimization (IPSO) algorithm is adopted to solve the proposed NLP model to minimize the annual cost. A case for segmented tracks planning is designed to test the rationality of the proposed NLP model and the performance of the IPSO algorithm. Simulation results show that the IPSO algorithm is more accurate, consistent and effective than the classical PSO algorithm.

Key words: Roadway-powered electric vehicles, inductive power transfer, segmented tracks, particle swarm optimization

INTRODUCTION

Electric vehicle, which is considered as one of the most prospective green vehicles, has become a hot research area because of the fossil fuel shortage and environmental deterioration. However, it is not yet welcomed into the markets by potential customers due to drawbacks such as its high price, heaviness and the large space required by its battery pack. Other factors are limited lithium resources, a driving range shorter than that of a normally fueled car, a long charging time and the frequent charging requirements.

In an effort to resolve these problems, a new Roadway-powered Electric Vehicles (RPEVs) using an Inductive Power Transfer (IPT) has been developed (Covic et al., 2007; Huh et al., 2011, 2012; Tian et al., 2012). If a long distance track is used in this system, both the coupling factor and transmission efficiency will be very low due to large leakage flux between track and pickup (Budhia et al., 2010). If the segmented tracks mode is employed, each track can be powered on and off individually and as a result, the track loss can be reduced and the efficiency can be improved because the track loss without load can be canceled. However, construction and maintenance costs must be taken into consideration because of increasing equipment needs. So, the study on optimization of segmented tracks is very important to minimize the total cost.

The Particle Swarm Optimization (PSO) is a heuristic optimization technique that inspired by the swarm intelligences of animals such as bird flocking and fish schooling (Zhu et al., 2012). Compared with other optimization algorithms such as Simulated Annealing (SA), Ant Colony Optimization (ACO), Evolutionary Algorithm (EA) and Genetic Algorithm (GA), PSO is easy to implement and compute efficiency (Gao et al., 2011). PSO has gained much attention in recent years and it has been successfully applied to various optimization problems such as economic dispatch (Dieu et al., 2011), siting and sizing of distributed generation planning (Liu et al., 2008, 2009), path optimization and positioning (Huang et al., 2012), system identification and parameter tuning (Yang et al., 2009; Zhu et al., 2012) and reactive power and voltage control (Mandal et al., 2013).

In this study, an improved PSO algorithm is proposed to solve the segmented tracks optimization of roadway-powered system for electric vehicles.

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ROADWAY-POWERED SYSTEM FOR ELECTRIC VEHICLES

The roadway-powered system for electric vehicles mainly employs inductive coupling, magnetic resonance and microwave, replacing wires and connectors to transmit electric energy from power supply to load. Figure 1 shows the fundamental structure of such roadway-powered system using the IPT technique. Grid power is transformed into high frequency current and injected in the primary sub-track. And then high frequency magnetic field is formed around the sub-track. Part of the field will across the onboard pick-up(s) in which high frequency current is induced. Finally, the induced current is conditioned by the onboard converter and controller to supply suitable power to the battery pack or motor.

Efficiency analysis: Compensation capacitor is used to realize maximum power transmission and lower volt-ampere rating of power source in IPT system. On the basis of different connection between the windings and the compensation capacitors, there are four basic resonant topologies labeled as SS, SP, PS and PP. The first letter presents the primary connection and the second one shows the secondary connection. S or P indicates that the compensation capacitor is connected with the winding in series or in parallel. SS topology is widely used for RPEVs application due to the series-compensated primary is more advantageous for high-power transfer and the series-compensated secondary reflects no reactance at the resonant frequency (Sallan et al., 2009). The equivalent circuit of basic SS topology is shown in Fig. 2, where \( C_p, L_s, \) and \( R_s \) are the primary compensation capacitor, track inductance and internal resistance of track, respectively; \( C_m, L_m, \) and \( R_m \) are the secondary compensation capacitor, secondary winding inductance and internal resistance of secondary winding respectively; \( L_m \) is the leakage flux, \( R_l \) is the load resistance and \( Z_o \) is the impedance looking from the primary side.

The impedance \( Z_o \) is given by:

\[
Z_o = \frac{j\omega L_o}{j\omega L_o + \frac{1}{j\omega C_o} + R_s + R_l} \\
= \frac{j\omega L_o}{j\omega L_o + R_s + R_l} \\
= R_o + j\omega L_o
\]  

(1)

where, \( \omega \) is the angular frequency of system; the value of \( R_o \) is \( \omega^2 M^2/(R_c + R_o) \).

In high frequency application, litz wire is usually used and its resistance consists of the direct-current part and the alternating-current part, which are given by Sinha et al. (2010):

\[
R_w = \frac{4\rho l_s}{n_s d_s^2} 
\]

(2)

\[
R_w = R_w + \frac{\left(\frac{\rho_{\text{metal}} \times 10^7}{\rho_{\text{air}}}ight) l_{\text{w}}}{(8\pi k_{\text{metal}} \times 10^{-7}) + R_o}
\]

(3)

where, \( \rho \) is the resistivity of conductor (for copper wire, the value is \( 17.24 \times 10^{-9} \) \( \Omega \)m under 20°C); \( n_s \) is the total number of strands; \( d_s \) is the diameter of a strand and \( l_{\text{w}} \) is the total length of litz wire.

Fig. 1: Fundamental structure of RPEVs system

Fig. 2: Equivalent circuit of basic SS topology
The total internal resistance is therefore, given as:

\[ R_i = R_p + R_m \]  \hspace{1cm} (4)

Because \( R_p \) is series-connected with \( R_m \), the primary efficiency can be expressed as:

\[ \eta_p = \frac{R_p}{R_p + R_m} \]  \hspace{1cm} (5)

In a similar way, the secondary efficiency can be expressed as follows:

\[ \eta_s = \frac{R_s}{R_s + R_l} \]  \hspace{1cm} (6)

Based on Eq. 5 and 6, the total efficiency can be calculated as follows:

\[ \eta = \eta_p \eta_s = \frac{R_s}{R_s + R_l} \frac{1}{1 + \frac{R_s(R_p + R_m)}{\sigma^2M}} \]  \hspace{1cm} (7)

Assuming parameters of system as following:

- Operating frequency \( f \): 40 kHz
- Diameter of a single strand \( d_p \): 0.1 mm
- Total number of strands \( n_p \): 1000
- Size of pick-up: 1 x 1 m
- Turns of pickup: 20
- Size of track: 1 m x \( l_r \)
- Turns of track: 4
- Load \( R_s \): 25 Ω
- Mutual inductance: 62 μH

Thus, from Eq. 7, the numerical relation between \( \eta \) and \( l_r \) can be given by:

\[ \eta = \frac{9052 + 536 l_r + 268 l_r^2}{9245 + 597 l_r + 275 l_r^2 + l_r^3} \]  \hspace{1cm} (8)

Figure 3 shows the effect on the efficiency of system when the track length is varied. It indicates that the efficiency decreases sharply when the track length is increased. The efficiency even will be lower than 60% when the track length exceeded 200 m. Consequently, the track length must be limited to keep a receivable efficiency rate and then the segmented track structure shown in Fig. 4 is a good choice. In such system, each track can be powered on and off individually and as a result, the efficiency can be improved because the loss of these no-load tracks can be canceled. However, construction and maintenance costs must be taken into consideration because of increasing equipment needs. Hence to minimize the total cost, the study on optimization of segmented tracks is very necessary.

**NONLINEAR PROGRAMMING MODEL OF SEGMENTED TRACKS**

The segmented tracks optimization problem of roadway-powered system for electric vehicles can be described as: on condition that the power demand of loads has been determined, finding out the optimal
distance of each track (marked as \( l_1 \)), the interval of the adjacent two tracks (marked as \( l_2 \)), the number of tracks (marked as \( N \)) and the installed capacity of each single track (marked as \( P_i \)) to minimize the annual total cost. Mathematically, the problem is formulated as follows:

\[
\min Z_{at}(l_1, l_2, N) = E_{at} + T_{at} + L_{at}
\]

where, \( E_{at} \), \( T_{at} \) and \( L_{at} \) are annual equipment cost, annual track cost and annual loss cost of tracks, respectively.

\( E_{at} \) can be given by:

\[
E_{at} = \sum_{i=1}^{n} [ f(P_i) \left( \frac{\delta(1+\varepsilon)^p}{(1+\varepsilon)^p - 1} \right) + u(R_i)]
\]

where, \( f(P_i) \) is the equipment cost of track \( b \); \( r_0 \) is the discount rate; \( m_0 \) is the depreciable life of equipment; \( u(R_i) \) is the equipment maintenance cost of track \( b \).

\( T_{at} \) can be given by:

\[
T_{at} = \sum_{i=1}^{n} [ h(R_i) \left( \frac{\delta(1+\varepsilon)^p}{(1+\varepsilon)^p - 1} \right) ]
\]

where, \( p \) is the track cost per unit length; \( m_0 \) is the depreciable life of tracks.

\( L_{at} \) can be given by:

\[
L_{at} = \sum_{i=1}^{n} [ (\alpha_1 R_i + \alpha_2 R_i) (1 - m_0) l_1 R_i]
\]

where, \( \alpha_1 \) and \( \alpha_2 \) are the diurnal price for electricity and nightly price for electricity, respectively; \( R_i, R_i \) are diurnal and nightly running time of system, respectively.

\textbf{Constraints:} The length of each single track must be constrained by the maximum speed of load EVs and the shortest safety cut-off period of switching devices as following:

\[
l_i \geq V_{max} T_{min}
\]

where, \( V_{max} \) is the max speed of operating load EVs and \( T_{min} \) is the shortest safety cut-off period of switching devices.

The installed capacity of each single track must be bigger than the sum of driving power and charging power of all load EVs as following:

\[
\sum_{i=1}^{n} (P_i + nP_i) + l_i R_i E_i \leq \eta_{min} P_i
\]

where, \( J_0 \) is the set of load EVs powered by track \( b \); \( n \) is the charging rate; \( R_b \) is the track resistance per unit length; \( P_i \) is the driving power; \( P_i \) is the charging power and \( \eta_{min} \) is the minimum efficiency.

To supply load EVs with enough energy, the track distance and track interval are asked to meet the following condition:

\[
N(\frac{b}{V_{max}} - \frac{1}{r}) \geq \pi P
\]

where, \( V_{max} \) is the minimum speed of load EVs and \( r \) is the minimum charge ratio.

What's more, the relation among \( N, l_1 \) and \( l_2 \) can be expressed as:

\[
N(l_1 + l_2) = l_{at}
\]

\textbf{Fitness function:} According to the external penalty method, the fitness function \( FT \) can be defined as:

\[
FT = Z_{at} + s \sum_{i=1}^{n} \max (0, g_i(x))^7
\]

where, \( g_i(x) \) stands for \( i \)th constraint; \( n \) stands for the number of constraints and \( s \) is a great positive integer. In this paper, a smaller \( FT \) is considered better.

Equation 17 indicates that the segmented tracks optimization model is nonlinear and non-differential and thus, the gradient information cannot be expressed as explicit formulas. As a result, the conventional gradient-based optimization methods cannot work well. Although this problem can be handled by the direct search algorithm, such as the Nelder-Mead simplex algorithm, however, it relies on good choice of initial points heavily and may fall into the local optimum (Yang et al., 2013). Therefore, the global search algorithm is required for instance, the simulated annealing, ant colony optimization, evolutionary algorithm, genetic algorithm and particle swarm optimization. In this paper, an improved particle swarm optimization is proposed to solve the segmented tracks optimization problem.

\textbf{PARTICLE SWARM OPTIMIZATION}

\textbf{Classical PSO:} Since the first invention in 1995, PSO has become one of the most popular methods applied in various optimization problems due to its simplicity and
ability to find near optimal solutions, especially for complicated problems. In PSO, each candidate solution is called as a particle and a swarm is composed of \( n \) particles. Each single particle is associated with the following two vectors: the position vector \( \mathbf{x}_i = (x_{i1}, x_{i2}, \ldots, x_{id}) \) and the velocity vector \( \mathbf{v}_i = (v_{i1}, v_{i2}, \ldots, v_{id}) \), where \( d \) stands for the dimension of the searching space. Each particle adjusts its own position according to its personal best experienced position (pbest) and the global best experienced position (gbest). Then the velocity and position of \( i \)th particle in the next iteration \((k+1)\) for fitness function evaluation can be updated by:

\[
v_{ik}^{(k+1)} = w v_{ik}^{(k)} + c_{1} r_{1} (p_{best}^{(k)} - x_{ik}^{(k)}) + c_{2} r_{2} (g_{best}^{(k)} - x_{ik}^{(k)})
\]

(18)

\[
x_{ik}^{(k+1)} = x_{ik}^{(k)} + v_{ik}^{(k+1)}
\]

(19)

where, \( w \) is the inertia weight, usually in the range of \([0.4, 0.9]\); \( r_{1} \) and \( r_{2} \) are two random numbers in the range of \([0, 1]\); \( c_{1} \) is the cognitive factor and \( c_{2} \) is the social factor.

Generally, for increased search performance, the inertia weight is decreased linearly, which is defined as:

\[
w = w_{max} - \frac{k}{k_{max}} (w_{min} - w_{max})
\]

(20)

where, \( w_{max} \) and \( w_{min} \) are the maximum and minimum inertia weight and \( k_{max} \) is the maximum number of iterations. Such particle swarm optimization algorithm with a linearly decreased inertia weight is called as Linearly Particle Swarm Optimization (LPSO) for short.

**Improved PSO:** In Eq. 20, the inertia weight is linearly reduced from the maximum value to the minimum one during the iterative process. One of its disadvantages is the weak local search ability, that's to say it is slow convergence in refined search stage. At the beginning of the search process, the velocity of particles is high for quickly moving to optimal solution and it will be sharply slower as number of iterations increased. At the end, the velocity of particles becomes very low so that they are entirely possible converge to a local optimal solution. In this paper, a sigmoid function with a random factor is proposed and given by:

\[
w_{i} = w_{max} - (w_{max} - w_{min}) \frac{1 + \text{tanh}(2ak/k_{max} - s)}{2}
\]

(21)

\[
w_{i} = w_{max} + \text{rand} \times w_{i}
\]

(22)

where, \( s \) is a factor used to adjust the turning position of the sigmoid function, \( \text{rand} \) is a random factor used to help the algorithm to escape local optimum.

Fig. 5: Comparison curves of inertia weights

As comparison, the characteristic curves of inertia weights shown in Eq. 20-22 are presented in Fig. 5. It tells us that at the beginning of the search process, \( w \) expressed by Eq. 22 is changed randomly in a greater range in favour of quick search. However, at the end it is changed randomly in a smaller range, which is conductive to escaping from local optimum.

Moreover, the self-adapting study factors can help to improve the searching performance. At the beginning of the search process, a larger cognitive factor \( c_{1} \) and a smaller social factor \( c_{2} \) are beneficial to make the swarm fly over the whole search space and escape the local optimum. At the end, however, a smaller \( c_{1} \) and a larger \( c_{2} \) are good for searching the global optimum. The self-adapting study factors are given by:

\[
\begin{align*}
|c_{1} &= (c_{1i} - c_{1f})(1 - k/k_{max}) + c_{1f} \\
|c_{2} &= (c_{2i} - c_{2f})(1 - k/k_{max}) + c_{2f}
\end{align*}
\]

(23)

where, \( c_{1i} \) and \( c_{1f} \) are the initial and final values of cognitive factor \( c_{1} \); \( c_{2i} \) and \( c_{2f} \) are the initial and final values of social factor \( c_{2} \).

The detailed steps of the proposed improved PSO for solving the segmented tracks optimization problem of roadway-powered system for electric vehicles are described below.

**Step 1:** Initialize the parameters for IPSO, including number of particles \( N_p \), initial velocity of particles \( v_{i} \), maximum and minimum velocity of particles \( v_{max} \) and \( v_{min} \), initial position of particles \( x_{i} \), maximum and minimum position of particles \( x_{max} \) and \( x_{min} \), personal best experienced position of particles pbest, global best experienced position of particles gbest, values of acceleration coefficients \( c_{ai} \), \( c_{bi} \), \( c_{ci} \) and \( c_{di} \), maximum and minimum values of inertia weight \( w_{max} \) and \( w_{min} \), and maximum number of iterations \( k_{max} \).
Step 2: Calculate the value of inertia weight $w_i$ based on Eq. 21 and 22. Update the value of $c_i$ and $c_j$ using Eq. 23.

Step 3: Update velocity $v_i$ and position $x_i$ for each particle using Eq. 18 and 19, respectively. Note that the obtained velocity and position of particles should not exceed their lower and upper limits set in step 1.

Step 4: Calculate the current fitness $F_t$ for each particle using Eq. 17. Compare it to $F_t^{k-1}_{best}$ to obtain the best fitness function up to the current iteration $F_t^{k-1}_{best}$. Determine the global best value of fitness function using $F_{best} = \min (F_t^{k-1}_{best}, F_t^{best})$. Update personal best experienced position $x_{pbest}$ for each particle and global best experienced position $gbest$ for particle swarm.

Step 5: If $k < k_{max}$, then $k = k+1$ and return to step 2. Otherwise, stop and present the results.

**PLANNING CASE**

In this section, the proposed IPSO will be used to solve and analyze an example of segmented tracks optimization. The optimization example is shown as follows:

- Total length from position A to position B $L_{ab}$: 100 km
- Maximum velocity of load EVs $V_{max}$: 60 km/h
- Minimum velocity of load EVs $V_{min}$: 30 km/h
- Driving power demand of load EV $P_d$: 15 kW
- Charging power demand of load EV $P_s$: 15 kW
- Minimum charge ratio: 50%
- Charging rate: 1
- Minimum efficiency of system $\eta_{min}$: 70%
- Minimum security switching period of switching devices $T_{min}$: 6 sec
- Diurnal price for electricity $\alpha_d$: 0.1 $/kWh
- Nightly price for electricity $\alpha_n$: 0.06 $/kWh
- Diurnal and nightly running time of system $\beta_d$: 1500 h/year
- Nightly running time of system $\beta_n$: 1500 h/year
- Safety distance $d$: 0.05 km
- Track current $I$: 100 A
- Track resistance $R$: 0.48 $\Omega$ km
- Discount rate: 0.1
- Depreciable life of equipment: 10 year
- Depreciable life of tracks: 30 year

Solving the objective function using Linearly Particle Swarm Optimization (LPSO) and IPSO, respectively, the results are shown in Fig. 6-8. In both simulations, the maximum number of iterations is 200, the number of trials is 50 and the number of running times of program is 10. The parameters of these two algorithms are listed as follows:

$$N_g = 50, c_1 - c_2 = 2.0, c_{fr} - c_{cf} = 2.5, c_{rel} - c_{rel} = 0.5$$
$$w_{min} = 0.9, w_{max} = 0.4$$

The comparison of the optimal solution of IPSO with LPSO is presented in Table 1. It can be seen from Table 1 that the minimum annual cost of IPSO is $5.03 million, however, this number of LPSO is $5.46 million. That is to say, the IPSO has the smaller $Z_{min}$ than the LPSO.

Figure 6 shows the best results achieved by the two methods over 50 trails. It indicates that the IPSO is more accurate and consistent in searching for the global optimum in the most trails than the LPSO method.

Figure 7 shows the convergence characteristics for optimal annual cost of the two methods. It shows that the convergence rates of the two methods are approximate.
but the IPSO can achieve a smaller average annual cost which is more important for the segmented tracks planning problem.

Figure 8 shows the comparison of the average annual cost of the 50 trials among the 10 times. It tells us that the IPSO always can achieve a better result more than the LPSO and is more consistent in all times.

CONCLUSION

The segmented tracks planning of roadway inductive power supply system for electric vehicles is a multi-parameter, multi-objective, multi-constrain and discrete nonlinear optimization problem. In this study, the nonlinear programming model has been proposed and an IPSO method has been efficiently implemented to solve this model. With the modifying by decreasing inertia weight according to sigmoid function with a random factor and using self-adapting study factors, both the global search capability and solution quality have been considerably improved in comparison with the LPSO method. The result comparisons from the planning case have shown that the IPSO is more accurate and consistent in minimizing the annual cost for the segmented tracks planning problem.

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