http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (8): 1547-1554, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.1547.1554

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

[1]Yong Tian, [1]Bizhong Xia and [2]Yue Sun
[1]Graduate School at Shenzhen, Tsinghua University, Shenzhen 518055, China
[2]College of Automation, Chongqing University, Chongqing 400030, China

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 tack 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.

Corresponding Author: Yong Tian, Graduate School at Shenzhen, Tsinghua University, Shenzhen 518055, China

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_p and R_p are the primary compensation capacitor, track inductance and internal resistance of track, respectively; C_s, L_s and R_s 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_m is the impedance looking from the primary side.

The impedance Z_m is given by:

$$\begin{aligned} Z_m &= j\omega L_m // (j\omega L_s + \frac{1}{j\omega C_s} + R_s + R_L) \\ &= j\omega L_m // (-j\omega L_m + R_s + R_L) \\ &= R_m + j\omega L_m \end{aligned} \tag{1}$$

where, ω is the angular frequency of system; the value of R_m is $\omega^2 M^2/(R_s+R_L)$.

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):

$$R_{dc} = \frac{4\rho l_T}{\pi n_s d_s^2} \tag{2}$$

$$R_{ac} = R_{dc}[1 + \frac{(8\pi f k_s \times 10^{-7})^2}{(8\pi f k_s \times 10^{-7})^2 + R_{dc}^2}] \tag{3}$$

where, ρ is the resistivity of conductor (for copper wire, the value is 17.24×10^{-9} Ω•m under 20°C); n_s is the total number of strands; d_s is the diameter of a strand and l_T is the total length of litz wire.

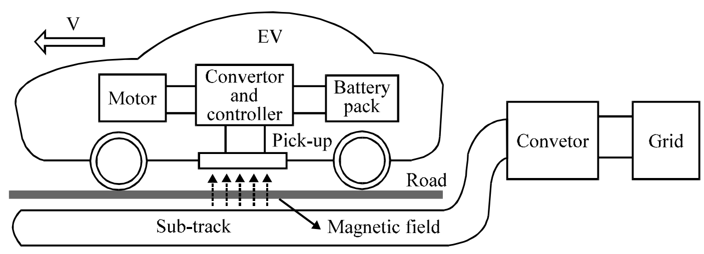

Fig. 1: Fundamental structure of RPEVs system

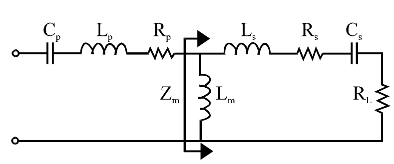

Fig. 2: Equivalent circuit of basic SS topology

The total internal resistance is therefore, given as:

$$R_p = R_{dc} + R_{ac} \quad (4)$$

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

$$\eta_p = \frac{R_m}{R_p + R_m} \quad (5)$$

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

$$\eta_s = \frac{R_L}{R_s + R_L} \quad (6)$$

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

$$\eta = \eta_p \eta_s = \frac{R_L}{R_s + R_L} \cdot \frac{1}{1 + \frac{R_p(R_s + R_L)}{\omega^2 M^2}} \quad (7)$$

Assuming parameters of system as following:

- Operating frequency f: 40 kHz
- Diameter of a single strand d_s: 0.1 mm
- Total number of strands n_s: 1000
- Size of pick-up: 1×1 m
- Turns of pickup: 20
- Size of track: 1 m×l_T
- Turns of track: 4
- Load R_L: 25 Ω
- Mutual inductance: 62 μH

Thus, from Eq. 7, the numerical relation between η and l_T can be given by:

$$\eta = \frac{9052 + 536 l_T + 268 l_T^2}{9245 + 597 l_T + 275 l_T^2 + l_T^3} \quad (8)$$

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

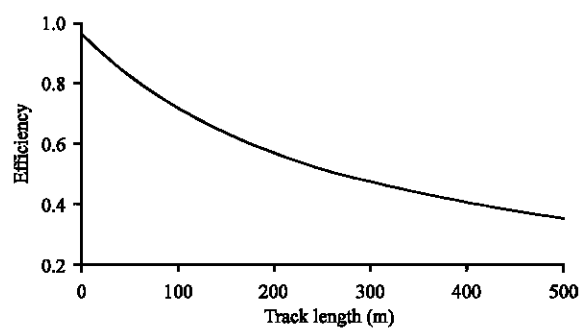

Fig. 3: Relationship between efficiency and track length

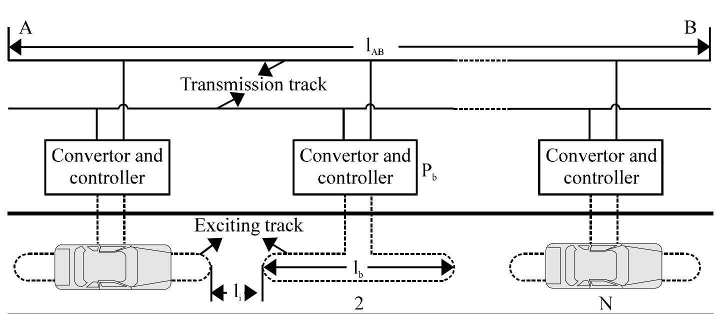

Fig. 4: Segmented power supply tracks for RPEVs

distance of each track (marked as l_b), the interval of the adjacent two tracks (marked as l_i), the number of tracks (marked as N) and the installed capacity of each single track (marked as P_b) to minimize the annual total cost. Mathematically, the problem is formulated as follows:

$$\min Z_{cst}(l_b, l_i, P_b, N) = E_{cst} + T_{cst} + L_{cst} \tag{9}$$

where, E_{cst}, T_{cst} and L_{cst} are annual equipment cost, annual track cost and annual loss cost of tracks, respectively.

E_{cst} can be given by:

$$E_{cst} = \sum_{b=1}^{N}[f(P_b)\frac{r_0(1+r_0)^{m_e}}{(1+r_0)^{m_e}-1} + u(P_b)] \tag{10}$$

where, $f(P_b)$ is the equipment cost of track b; ro is the discount rate; me is the depreciable life of equipment; $u(P_b)$ is the equipment maintenance cost of track b.

T_{cst} can be given by:

$$T_{cst} = \sum_{b=1}^{N} l_b p[\frac{r_0(1+r_0)^{m_r}}{(1+r_0)^{m_r}-1}] \tag{11}$$

where, p is the track cost per unit length; m_r is the depreciable life of tracks.

L_{cst} can be given by:

$$L_{cst} = \sum_{b=1}^{N}(\alpha_1\beta_{b1} + \alpha_2\beta_{b2})[1-\eta(l_b)]P_b \tag{12}$$

where, α_1 and α_2 are the diurnal price for electricity and nightly price for electricity, respectively; β_{b1}, β_{b2} are diurnal and nightly running time of system, respectively.

Constrains: 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:

$$l_b \geq V_{max} T_{smin} \tag{13}$$

where, V_{max} is the max speed of operating load EVs and T_{smin} 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:

$$\sum_{a \in J_b}(P_d + nP_c) + l_b R_b I_b^2 \leq \eta_{min} P_b \tag{14}$$

where, J_b 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_d is the driving power; P_c is the charging power and η_{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:

$$N(nP_c \cdot \frac{l_b}{V_{max}} - P_d \cdot \frac{l_i}{V_{min}}) \geq rP_c \tag{15}$$

where, V_{min} is the minimum speed of load EVs and r is the minimum charge ratio.

What's more, the relation among N, l_b and l_i can be expressed as:

$$N(l_b + l_i) = l_{AB} \tag{16}$$

where, l_{AB} is the total distance form position A to position B.

Fitness function: According to the external penalty method, the fitness function FT can be defined as:

$$FT = Z_{cst} + s\sum_{i=1}^{n}\max(0, g_i(x))^2 \tag{17}$$

where, $g_i(x)$ stands for ith 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.

PARTICLE SWARM OPTIMIZATION

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 solution, especially for complicated problems. In PSO, each candidate solution is called as a particle and a swarm is composed of m particles. Each single particle is associated with the following two vectors: the position vector $x_i = (x_{i1}, x_{i2}, \ldots, x_{id})$ and the velocity vector $v_i = (v_{i1}, v_{i2}, \ldots, v_{id})$, where d stands for the dimension of the searching space. Each particle adjusts its own position according to its personal best experienced position ($pbest_i$) and the global best experienced position (gbest). Then the velocity and position of ith particle in the next iteration (k+1) for fitness function evaluation can be updated by:

$$v_i^{k+1} = wv_i^k + c_1r_1(pbest_i^k - x_i^k) + c_2r_2(gbest^k - x_i^k) \tag{18}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{19}$$

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:

$$w = w_{max} - \frac{k}{k_{max}}(w_{max} - w_{min}) \tag{20}$$

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:

$$w_s = w_{max} - (w_{max} - w_{min})\frac{1 + \tanh(2sk / k_{max} - s)}{2} \tag{21}$$

$$w_r = w_{min} + rand \times w_s \tag{22}$$

where, s is a factor used to adjust the turning position of the sigmoid function; rand is a random factor used to help the algorithm to escape local optimum.

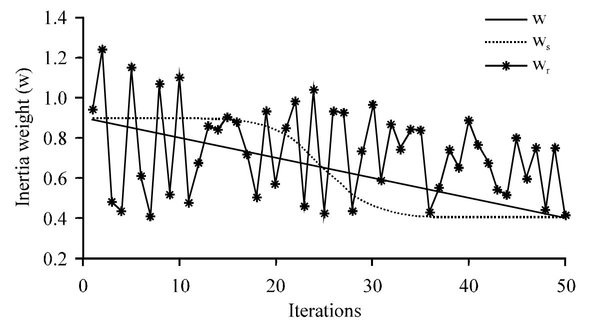

Fig. 5: Comparison curves of inertia weights

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_r 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:

$$\begin{cases} c_1 = (c_{1i} - c_{1f})(1 - k / k_{max}) + c_{1f} \\ c_2 = (c_{2i} - c_{2f})(1 - k / k_{max}) + c_{2f} \end{cases} \tag{23}$$

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^1, maximum and minimum velocity of particles v_{max} and v_{min}, initial position of particles x^1, 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_{1i}, c_{1f}, c_{2i} and c_{2f}, 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_r based on Eq. 21 and 22. Update the value of c_1 and c_2 using Eq. 23

Step 3: Update velocity v^k_i and position x^k_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 FT_i for each particle using Eq. 17. Compare it to FT^{k-1}_{pbesti} to obtain the best fitness function up to the current iteration FT^k_{pbesti}. Determine the global best value of fitness function using Ft_{gbest} = min (FT^k_{pbesti}, FT_{gbest}). Update personal best experienced position x_{pbesti} 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^{-1}
- Minimum velocity of load EVs V_{min}: 30 km h^{-1}
- Driving power demand of load EV P_d: 15 kW
- Charging power demand of load EV P_c: 15 kW
- Minimum charge ratio r: 50%
- Charging rate n: 1
- Minimum efficiency of system η_{min}: 70%
- Minimum security switching period of switching devices T_{min}: 6 sec
- Diurnal price for electricity α_1: 0.1 \$/kWh
- Nightly price for electricity α_2: 0.06 \$/kWh
- Diurnal and nightly running time of system β_{b1}: 1500 h year^{-1}
- Nightly running time of system β_{b2}: 1500 h year^{-1}
- Safety distance d_s: 0.05 km
- Track current Ib: 100 A
- Track resistance R_b: 0.48 Ω km^{-1}
- Discount rate r: 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:

$$N_p = 50,\ c_1 = c_2 = 2.0,\ c_{1i} = c_{2f} = 2.5,\ c_{1f} = c_{2i} = 0.5$$
$$w_{max} = 0.9,\ w_{min} = 0.4$$

The comparison of 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's to say, the IPSO has the smaller Z_{cst} 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,

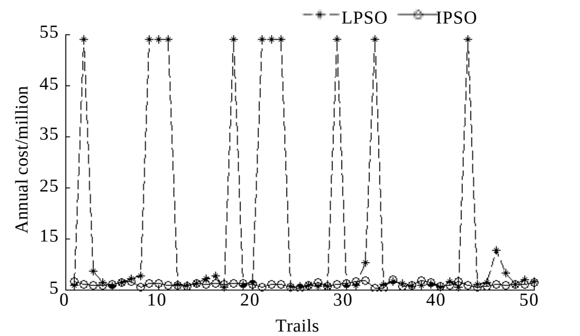

Fig. 6: Best annual costs of IPSO and LPSO over 50 trails

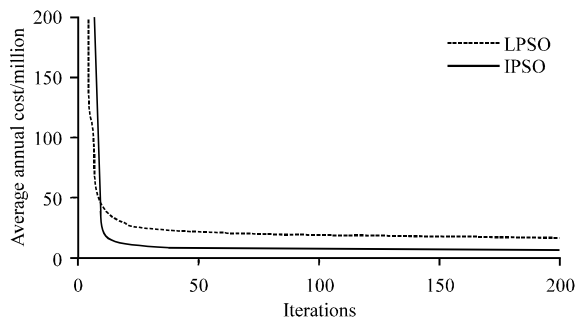

Fig. 7: Convergence characteristics of average annual cost of LPSO and IPSO over 50 trails

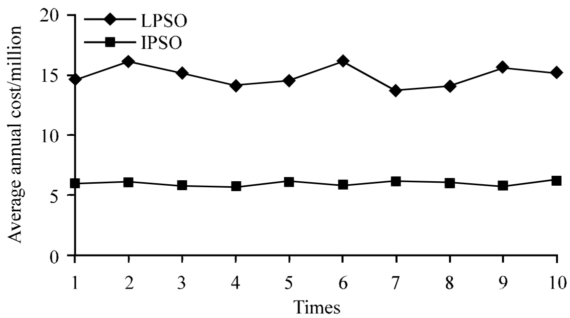

Fig. 8: Average annual cost of LPSO and IPSO over 50 trails for 10 times

Table 1: Comparison of the best numerical results of LPSO and IPSO

Numerical results	LPSO	IPSO
Track capacity P_b (kW)	802	733
Track No. N	847	870
Track distance l_b (km)	0.103	0.096
Tracks interval l_i (km)	0.015	0.016
Total cost Z_{cst} ($ million)	5.46	5.03

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 trails 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.

ACKNOWLEDGMENT

The authors would like to give our special thanks to the reviewers of this paper for their contributions to this study.

REFERENCES

Budhia, M., G.A. Covic and J.T. Boys, 2010. Magnetic design of a three-phase inductive power transfer system for roadway powered electric vehicles. Proceedings of the Vehicle Power and Propulsion Conference, September 1-3, 2010, Lille, France, 1-6.

Covic, G.A. J.T. Boys, M.L.G. Kissin and H.G. Lu, 2007. A three-phase inductive power transfer system for roadway-powered vehicles. IEEE Trans. Ind. Elec., 54: 3370-3378.

Dieu, V.N., P. Schegner and W. Ongsakul, 2011. A newly improved particle swarm optimization for economic dispatch with valve point loading effects. Proceedings of the Power Energy Society General Meeting, July 24-29, 2011, San Diego, CA., USA., pp: 1-8.

Gao, H., J. Cao and M. Diao, 2011. A simple quantum-inspired particle swarm optimization and its application. Inform. Technol. J., 10: 2315-2321.

Huang, Y., C.Z. Zang and H.B. Yu, 2012. Localization method based on modified particle swarm optimization for wireless sensor networks. Control Decis., 27: 156-160.

Huh, J., S.W. Lee, W.Y. Lee, G.H. Cho and C.T. Rim, 2011. Narrow-width inductive power transfer system for online electrical vehicles. IEE Trans. Power Elec., 26: 3666-3679.

Huh, J., W. Lee, S. Choi and C. Rim, 2012. A new cross-segmented power supply rail for roadway powered electric vehicles. Proceedings of the International Symposium on Power Electronic Distribution Generation System, June 25-28, 2012, Aalborg, pp: 291-296.

Liu, B., Y. Zhang and N. Yang, 2008. Improved particle swarm optimization method and its application in the siting and sizing of distributed generation planning Trans. China Elec. Soc., 23: 103-108.

Lu, Z.Y., S.Y. Ge and C.S. Wang, 2009. Substation location planning of the weighted voronoi diagram based on particle swarm optimization algorithm. Proc. CSEE, 29: 35-41.

Mandal, K.K., D. Jana, B. Tudu and B. Bhattachary, 2013. A new improved particle swarm optimization technique for reactive power compensation of distribution feeders. Adv. Intell. Sys. Comput., 199: 291-296.

Sallan, J., J.L. Villa, A. Llombart and J.F. Sanz, 2009. Optimal design of ICPT systems applied to electric vehicle battery charge. IEEE Trans. Ind. Elec., 56: 2140-2149.

Sinha, D., P.K. Sadhu, N. Pal and A. Bandyopadhyay, 2010. Computation of inductance and AC resistance of a twisted litz-wire for high frequency induction cooker. Proceedings of the International Conference on Industrial Electronic, Control and Robotnic, December 2010, Rourkela, India, pp: 85-90.

Tian, Y., Y. Sun, Y. Su, Z. Wang and C. Tang, 2012. Neural network-based constant current control of dynamic wireless power supply system for electric vehicles. Inf. Technol. J., 7: 876-883.

Yang, L.Y., J.Y. Zhang and W.J. Wang, 2009. Selecting and combining classifiers simultaneously with particle swarm optimization. Inform. Technol. J., 8: 241-245.

Yang, M.J., G.Y. Gu and L.M. Zhu, 2013. Parameter identification of the generalized Prandtl?Ishlinskii model for piezoelectric actuators using modified particle swarm optimization. Sens. Actuators A: Phys., 189: 254-265.

Zhu, F.Y., W. Qi and Z.G. Shen, 2012. APSO-RVM for fault detection of liquid rocket engines test-bed. Inform. Tech. J., 11: 1496-1501.