Scholar Publishing Group
Kinetic Mechanical Engineering
https://doi.org/10.38007/KME.2022.030407
ISSN 2790-2676 Vol. 3, Issue 4: 54-62

Internal Combustion Engine Based on Particle Swarm Optimization Algorithm

Xubin Qi*

Xishan Coal Power (Group) Co., LTD, Railway Company, China

qixubin3611@163.com

**corresponding author*

Keywords: Particle Swarm Optimization, Internal Combustion Engine, Engineering Applications, Fuel Consumption Optimization

Abstract: Today, the development of the automobile market is still very rapid, the prospect is still very bright. However, with the increasing number of cars, it also brings the shortage of oil resources, air pollution and other problems. Therefore, to improve the economic performance of vehicles and improve their emission performance has become the goal of major auto manufacturers. This paper mainly studies the application of internal combustion engine engineering based on particle swarm optimization algorithm. Firstly, this paper takes ADVISOR as the model building platform and combines Simulink to build different modules. Then the application of particle swarm optimization algorithm in internal combustion engine engineering is optimized, and two configuration schemes are obtained by using particle swarm optimization algorithm. The economic comparison of different configuration schemes verifies the necessity and superiority of typical driving conditions in the study of optimal configuration.

1. Introduction

In recent years, Chinese car sales kept a high growth rate, but with the continuous use of vehicles and other means of transportation, the resulting environmental and energy problems are outstanding [1-2]. In terms of the environment, currently existing vehicles mainly use hydrocarbon fuel combustion to obtain the energy needed to drive the car. Automobile internal combustion engine, however, is often idealized state, the exhaust gas produced by incomplete combustion contains a large amount of nitrogen oxide and carbon monoxide (CO) and unburned hydrocarbons (HC) and so on, which not only has toxicity to human body, and if directly discharged into the air, will have a serious pollution to the atmosphere and the ecological environment, [3-4]. In terms of energy, oil, the main power energy of automobiles, is a non-renewable energy. The amount of oil that can be maintained by global oil resources depends entirely on the discovery of new oil storage sites and the accumulated refined oil products [5]. It has become increasingly difficult and expensive to find new deposits of oil underground. According to statistics, the world's remaining oil reserves can only be used for the world for several decades, making the popularization of energy saving work with the urgency of The Times. One of the keys to solve the two social problems of environmental pollution and energy shortage is to improve the combustion efficiency of gasoline engine fuel. Researchers from all over the world have also taken improving the economy and emission performance of automobiles as an important research topic, which has important research value and practical significance [6].

Since the 20th century, intelligent optimization algorithms such as genetic algorithm, ant colony algorithm, artificial immune network, crowd search algorithm and particle swarm optimization algorithm have been proposed successively [7]. These new algorithms have been widely used in a very short time and provide new ideas and directions for the research of optimization theory. Particle swarm optimization (PSO) is a population random search algorithm. There are many problems worthy of further study, such as how to improve the local optimal solution ability of the algorithm, how to solve the optimal solution accuracy of the algorithm, how to reduce the computational complexity and so on. Many scholars have improved PSO mainly from three aspects: improving weight value, increasing algorithm diversity, and mixing with other algorithms [8]. The global search ability and the local search ability are mainly balanced by the weight. For the linear weight reduction, the global search ability of the algorithm is strong in the initial stage, and the local search ability is enhanced in the later stage. A scholar conducted experiments on the weight of the algorithm, analyzed how to choose fixed weight and variable weight, and analyzed the influence of inertia weight on algorithm optimization from the aspects of population size and topology structure of the algorithm [9]. Some scholars used fuzzy rules to adjust the inertia weight of the algorithm, formulated corresponding fuzzy rules and membership functions for the inertia weight, and realized the online adjustment of the inertia weight. The results showed that the fuzzy adaptive adjustment of the inertia weight was better than the linear reduction of the inertia weight [10].

Incomplete combustion of gasoline engine (gasoline engine) fuel will lead to environmental pollution and energy waste, which will degrade its economic performance and emission performance. In this paper, a new fuel consumption control method for internal combustion engine is proposed by using particle swarm optimization technology.

2. Particle Swarm Optimization Algorithm Applied to Internal Combustion Engine Engineering

2.1. Internal Combustion Engine Model Building

In the process of automobile research, the use of computer model building and simulation analysis is an essential link, which can not only improve the work efficiency and shorten the development cycle, but also help enterprises reduce the cost of research and development. Among them, the development of energy management strategy of hybrid electric vehicle needs to be completed with the help of computer. After designing the vehicle control strategy, the control strategy is embedded in the simulation software for simulation analysis, and then the control strategy is debugged according to the simulation results. In order to achieve the above goals, the accuracy and calculation speed of simulation software are required very high.

At present, the commonly used vehicle development software mainly includes AVL's CRUISE and the open source vehicle simulation software jointly developed by National Renewable Energy

Laboratory (NREL) and Matlab/Simulink ADVISOR. Among them, CRUISE uses forward simulation, and its characteristic is that the signal transmission path in the simulation process is consistent with that in the actual use process.

ADVISOR is a backward simulation software, and the signal transmission direction in the simulation process is opposite to that in the actual use process. Compared with forward simulation analysis, backward simulation analysis is more used in vehicle performance testing. Therefore, this paper chooses ADVISOR as the development environment, establishes the SHVS model and energy management strategy, and compares and analyzes the energy consumption under different control strategies.

Based on mechanics, the building of automobile power system model analyzes the speed, acceleration, resistance, driving force and other parameters of the vehicle during normal driving through the theory of automobile dynamics. The running process of the vehicle can be regarded as the process of control signal transmission among various components in the powertrain. In this paper, ADVISOR is taken as the model building platform and Simulink is used to build different modules.

In order to ensure the accuracy of the simulation, the accuracy of the engine model should be ensured as much as possible in the process of building the engine model. Therefore, the change of torque/speed, the change of vehicle speed, the calculation of emission and the calculation of fuel consumption rate should be considered in the model. In the simulation model, the engine model is mainly composed of four parts, which are controller module, torque calculation module, speed calculation module and energy consumption and emission calculation module. The controller interface module is mainly used to receive the signal of the engine control module. Through the module, the output torque and output speed of the engine can be obtained. The engine torque calculation module can calculate the engine torque through the engine speed. It should be noted that the maximum value of the inertia torque and torque of the engine should be considered in the calculation process. The main function of the engine speed calculation module is to calculate the current engine speed according to the speed, clutch signal and transmission signal, and output to the next stage module; Energy consumption and emission module is the main function of the engine fuel consumption were calculated in the process of operation, through the calculation of fuel consumption results further calculate the HC, NOx, CO emissions of pollutants, it is important to note when calculating the vehicle fuel consumption and emissions started to consider the engine start, cold start and hot start need to calculated separately.

2.2. Particle Swarm Optimization Algorithm

(1) Mathematical principles

Suppose there are m particles in a D-dimensional space, and each particle ignores its volume. If there is an ith particle, its position is Xi(xi1 , xi2 ,…, xiD), i =1,2, …, m; The velocity is Vi(vi1 ,vi2 ,…, viD), i =1,2, …, m; The basis for judging the position is to substitute Xi into the objective function and calculate its fitness value to judge the position of Xi. At the same time, the particle will record its best position in its current flight experience as Pi(pi1 , pi2 ,…, pidD), i =1,2,…,m, while the best position of the population obtained by comparing the flight experience of all particles in the population is recorded as Pg(pg1 , pg2 ,…, pgD), i =1,2, …, m[11-12]. And each particle determines the change of flight speed and direction according to the flight experience of individuals and groups, as shown in the following formula:

$$V_{id}(t+1) = v_{id}(t) + c_1 r_1 (p_{id} - x_{id}(t)) + c_2 r_2 (p_{gd} - x_{id}(t)) \tag{1}$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \tag{2}$$

In the above equation, i=1,2... ,m stands for the number of particles, d=1,2... n represents the corresponding solution space solved and the number of features in data; c1 and c2 are learning factors, representing the acceleration weight of particles flying to the individual and group optimal positions; r1 and r2 are uniform numbers randomly distributed between [0,1] [13-14]. Therefore, the self-velocity of a particle is composed of three parts: the original velocity of the particle itself, the velocity change obtained by the influence of its own flight experience, and the velocity change obtained by the influence of the group [15]. This fully shows that the update of the particle's flying speed is based on the maintenance of its own speed, and then the optimal speed is obtained by reflecting on itself and learning group experience, so as to fly to a better position [16].

(2) Optimize the Settings

The learning factor parameter represents the acceleration weight of the particle flying to the individual best position and the group best position respectively, which is a reflection on its own flight experience and learning the group's flight experience at the same time, and has a great influence on the search for optimization results [17]. By referring to the conclusions of other scholars: the value of self-reflective cognitive part is higher than that of the social part of the learning group, which will cause the particles to fly over the search space; However, the value of the social part of the learning group is higher than that of the self-reflective cognition part, which will lead to the premature convergence of the particles to the local extreme point. The learning factors c1 and c2 are as equal as possible, and their sum is best equal to 4. Therefore, the learning factors c1 and c2 are both set to 2, and the weights of self-cognition and learning group experience are updated respectively [18].

There is no inertia weight factor in the initial velocity update formula of the particle swarm optimization algorithm, but this leads to the loss of the ability of particle velocity update, so that the ability to explore the global optimal point is greatly weakened. Therefore, w is added as the inertia weight factor after improvement. The larger w is, the particle will conduct global detection with a larger step size, and thus the farther distance it can reach, while the smaller w is, the particle's step size decreases, but its search of the detected space is more careful and accurate. At present, the strategy of linearly decreasing inertia weights is generally adopted internationally is no longer set as a fixed value, but a parameter that can change dynamically according to the degree of the algorithm, as shown in Equation (3).

$$w(t) = w_{\min} + \frac{iter_{\max} - iter}{iter_{\max}} (w_{\max} - w_{\min}) \tag{3}$$

Where, wmax is the inertia weight at the end, while wmin is the initial inertia weight, which is usually set at 0.9 and 0.4 respectively. itermax and iter represent the maximum number of iterations and the current number of iterations, respectively.

Usually, the population number of values in the range of 10 to 100, for more complex optimization problem, can put the number of population increased to 100 or more, but some scholars research thinks, particle swarm optimization algorithm is not sensitive to population number is, in fact, too much population number in addition to increasing optimization of time, the significance of the optimization results are not big. In this paper, in order to determine the optimal number of population for fuel consumption optimization, a pre-experiment was carried out, and it was found that under the condition of 2500r/min speed and 120Nm torque, usually 30 iterations can already determine the optimization result within a range of a small floating value. In order to reduce the test time and improve the efficiency, the number of populations of 40, 50, 60, and 70 were respectively used to conduct the comparison test when the maximum number of iterations was set to 30 and the learning factor and inertia factor were set as specified above. The experimental results show that when the population number is 60, the optimization result of fuel consumption is the best.

3. Optimization Configuration Experiment of Internal Combustion Engine

This article USES the Australian regional rail transit the parameters of the traditional internal combustion engine car, the use of two kinds of schemes for power system optimization configuration, one way according to the requirements of vehicle power and the input power capacity allocation after the particle swarm optimization, first plan according to the traditional method based on line traction calculation of vehicle case full line power as input, Compare and analyze two kinds of optimal configuration scheme under different power demand.

The power demand corresponding to the working condition sequence established based on the method with the minimum deviation of the overall characteristic parameters is selected for optimal configuration. The comparison scheme selects the power demand according to the traditional method: traction calculation is carried out for the four lines in Australia according to the minimum time division method. In order to meet the power and energy consumption demand of the locomotive running on all the lines, the line with the largest power and energy consumption demand is selected as the input for optimal configuration.

Due to the slope of lines and curves and the driver driving habits of the influence of different factors, such as, the requirements in the process of vehicles running in the actual power fluctuation is bigger, and in the traction calculation, usually minimum time division method is used to make cars running on the road in the online time the shortest, so the vehicle power demand for vehicle actual operating power outsourcing attentive, The power and energy demand obtained by simulation are different from the actual operation results, and have a great influence on the results of optimal configuration.

4. Analysis of Experimental Results

4.1. Scheme 1 is Compared with the Original Scheme

Table 1. Comparison of one-way fuel consumption cost between Scheme 1 and the original configuration

	0	1.5	3	4.5	6
Original plan	0	1035	2592	4005	5931
Plan1	0	894	2178	3720	4853

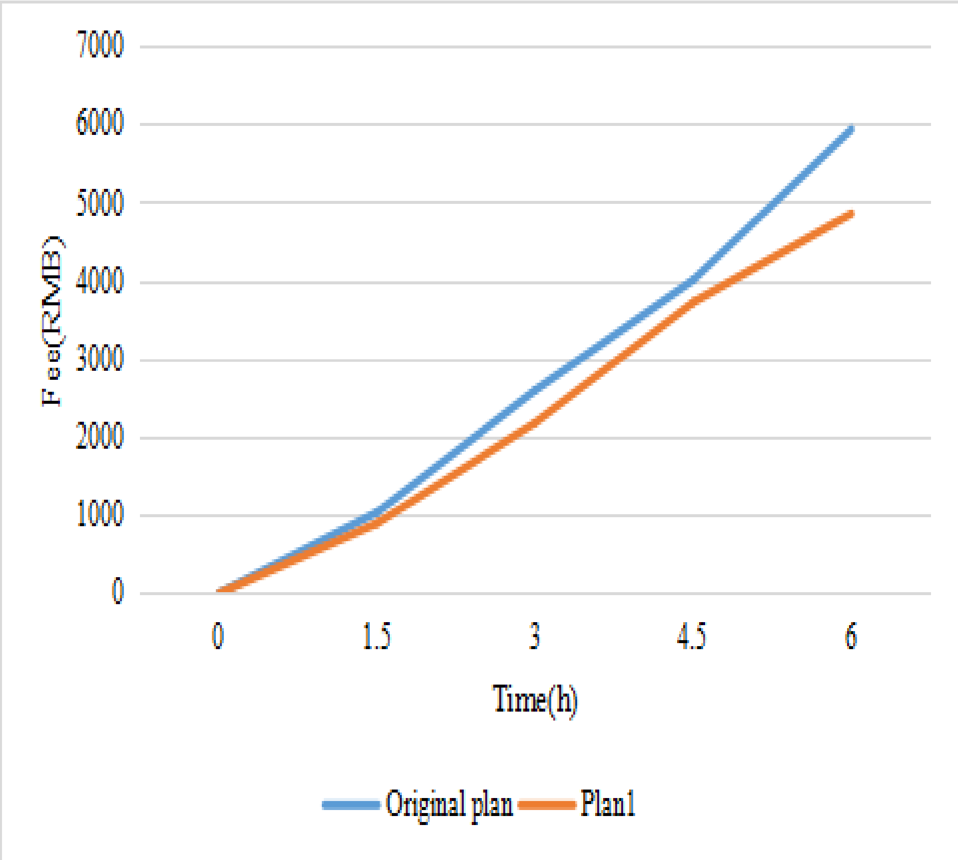

Figure 1. Statistical results of fuel consumption of optimized configuration scheme 1 and original scheme

As shown in Table 1 and Figure 1, the fuel cost for one-way operation of the original configuration scheme is 5931 Yuan. After optimized configuration by particle swarm optimization algorithm, the single trip fuel consumption cost of locomotive operation is 4853 yuan, which is 1078 yuan lower than that of traditional diesel locomotive operation, and the fuel saving rate reaches 18.17%.

4.2. Scheme 2 is Compared with the Original Scheme

Table 2. Comparison of one-way fuel consumption cost between optimized configuration scheme 2 and original configuration

	0	1.5	3	4.5	6
Original plan	0	1035	2592	4005	5931
Plan2	0	987	2346	3679	5103

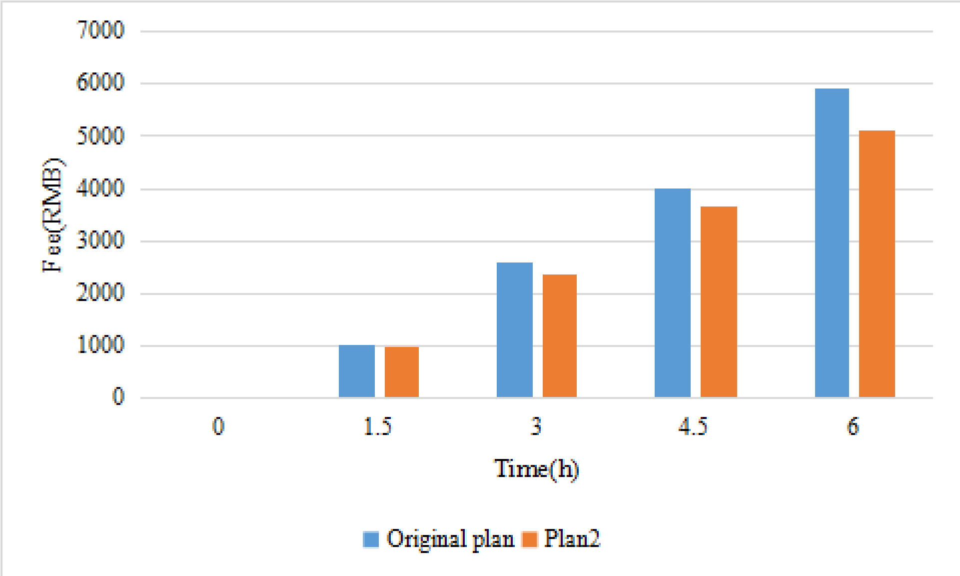

Figure 2. Plan 2 and the original configuration of fuel consumption cost statistics

As shown in Table 2 and Figure 2, after optimized configuration by particle swarm optimization algorithm, the single trip fuel consumption cost of locomotive operation is 5103 yuan, which is 828 yuan lower than that of traditional diesel locomotive operation, and the fuel saving rate reaches 13.96%.

4.3. Compare the Two Schemes

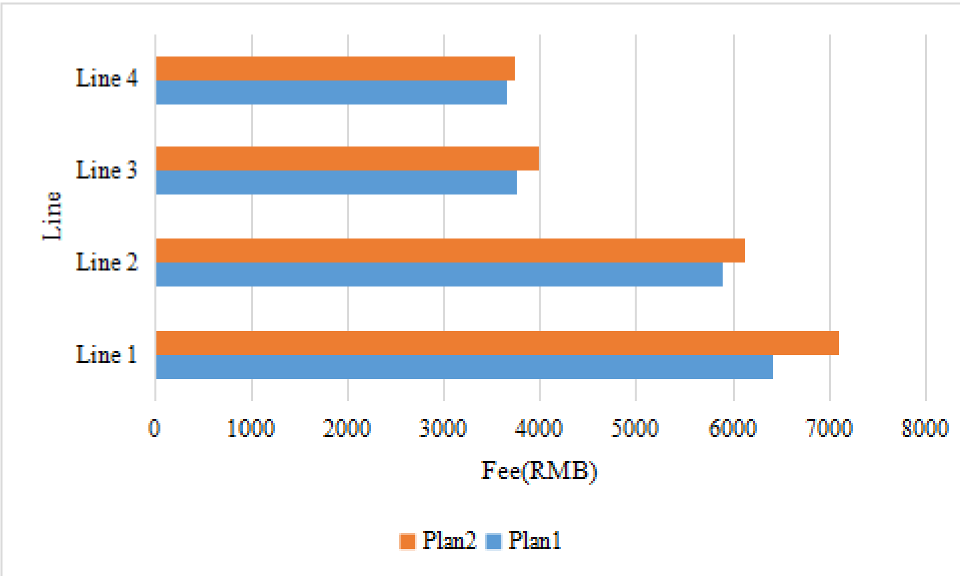

Figure 3. The total cost of running a locomotive one way

As shown in FIG. 3, the one-way operation fuel cost of scheme 1 is significantly lower than that of the original configuration scheme and Scheme 2, while the one-way operation cycle fuel cost of scheme 2 is similar to that of the original configuration scheme.

5. Conclusion

Particle swarm optimization (PSO) algorithm has the shortcoming that it is easy to fall into the local search optimal solution, so this paper improves the PSO algorithm to achieve the goal of fast search speed and high convergence accuracy, and applies the algorithm to the internal combustion engine engineering application. Research of this paper implements for engine fuel consumption optimization, more smooth and at the same time, the fuel consumption curve of engine efficiency greatly improved, but still some deficiencies and problems need to be improved: particle swarm optimization algorithm is now one of the evolutionary algorithm, the algorithm of similar algorithm and ant colony algorithm, the fish and wolves, etc. In the future research work, these optimization algorithms can be tried to optimize the output response and control parameters of the model, and study whether these algorithms can further optimize the required output corresponding, so as to further improve the engine performance through calibration optimization.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] Fonseca L, Olmeda P, Novella R, et al. Internal combustion engine heat transfer and wall temperature modeling: an overview. Archives of Computational Methods in Engineering, 2020, 27(5): 1661-1679. https://doi.org/10.1007/s11831-019-09361-9

[2] Kavuri C, Kokjohn S L. Exploring the potential of machine learning in reducing the computational time/expense and improving the reliability of engine optimization studies. International Journal of Engine Research, 2020, 21(7): 1251-1270. https://doi.org/10.1177/1468087418808949

[3] Reitz R D, Ogawa H, Payri R, et al. IJER editorial: The future of the internal combustion engine. International Journal of Engine Research, 2020, 21(1): 3-10. https://doi.org/10.1177/1468087419877990

[4] Magdas V B, Moldovanu D, Mastan D C. Intake and exhaust pipe optimization for an internal combustion engine//IOP Conference Series: Materials Science and Engineering. IOP Publishing, 2019, 568(1): 012048. https://doi.org/10.1088/1757-899X/568/1/012048

[5] Arat H T. Alternative fuelled hybrid electric vehicle (AF-HEV) with hydrogen enriched internal combustion engine. International Journal of Hydrogen Energy, 2019, 44(34): 19005-19016. https://doi.org/10.1016/j.ijhydene.2018.12.219

[6] Di Mauro A, Chen H, Sick V. Neural network prediction of cycle-to-cycle power variability in a spark-ignited internal combustion engine. Proceedings of the Combustion Institute, 2019, 37(4):

4937-4944. https://doi.org/10.1016/j.proci.2018.08.058

[7] Sterlepper S, Fischer M, Claßen J, et al. Concepts for Hydrogen Internal Combustion Engines and Their Implications on the Exhaust Gas Aftertreatment System. Energies, 2021, 14(23): 8166. https://doi.org/10.3390/en14238166

[8] Shrivastava N, Khan Z M. Application of soft computing in the field of internal combustion engines: a review. Archives of Computational Methods in Engineering, 2018, 25(3): 707-726. https://doi.org/10.1007/s11831-017-9212-9

[9] Holjevac N, Cheli F, Gobbi M. Multi-objective vehicle optimization: Comparison of combustion engine, hybrid and electric powertrains. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 2020, 234(2-3): 469-487. https://doi.org/10.1177/0954407019860364

[10] Zavadskas E K, Čereška A, Matijošius J, et al. Internal combustion engine analysis of energy ecological parameters by neutrosophic MULTIMOORA and SWARA methods. Energies, 2019, 12(8): 1415. https://doi.org/10.3390/en12081415

[11] Dhanachandra N, Chanu Y J. An image segmentation approach based on fuzzy c-means and dynamic particle swarm optimization algorithm. Multimedia tools and applications, 2020, 79(25): 18839-18858. https://doi.org/10.1007/s11042-020-08699-8

[12] Trivedi V, Varshney P, Ramteke M. A simplified multi-objective particle swarm optimization algorithm. Swarm Intelligence, 2020, 14(2): 83-116. https://doi.org/10.1007/s11721-019-00170-1

[13] Bento M E C. A hybrid particle swarm optimization algorithm for the wide-area damping control design. IEEE Transactions on Industrial Informatics, 2021, 18(1): 592-599. https://doi.org/10.1109/TII.2021.3054846

[14] Rajendran G B, Kumarasamy U M, Zarro C, et al. Land-use and land-cover classification using a human group-based particle swarm optimization algorithm with an LSTM Classifier on hybrid pre-processing remote-sensing images. Remote Sensing, 2020, 12(24): 4135. https://doi.org/10.3390/rs12244135

[15] Tabibi S, Ghaffari A. Energy-efficient routing mechanism for mobile sink in wireless sensor networks using particle swarm optimization algorithm. Wireless Personal Communications, 2019, 104(1): 199-216. https://doi.org/10.1007/s11277-018-6015-8

[16] Abdul-Adheem W R. An enhanced particle swarm optimization algorithm. International Journal of Electrical and Computer Engineering, 2019, 9(6): 4904. https://doi.org/10.11591/ijece.v9i6.pp4904-4907

[17] Tharwat A, Elhoseny M, Hassanien A E, et al. Intelligent Bézier curve-based path planning model using Chaotic Particle Swarm Optimization algorithm. Cluster Computing, 2019, 22(2): 4745-4766. https://doi.org/10.1007/s10586-018-2360-3

[18] Fakhouri H N, Hudaib A, Sleit A. Multivector particle swarm optimization algorithm. Soft Computing, 2020, 24(15): 11695-11713. https://doi.org/10.1007/s00500-019-04631-x