A Novel Fixed-Point Selection Method for MAP Icons Based on Improved PSO Algorithm (Postprint)

Authors: Cheng Zhun, Lu Kai, Qian Yu, Lu Zhen, Lu Zhixiong

Date: 2018-06-19T00:00:00+00:00

Abstract

To improve the control performance of MAP diagram-based control systems and effectively reduce their storage requirements, a novel method for optimal selection of calibration points in MAP diagrams based on an improved particle swarm optimization algorithm is proposed. Taking the MAP diagram employed in hydraulic mechanical continuously variable transmission (HMCVT) ratio control systems as an example, the two variables on the horizontal axis are equally partitioned within their domains, and the improved particle swarm optimization algorithm is utilized to determine the number and position of coordinate points within each partitioned segment. The selection process employs multi-objective optimization principles, combining the average error between actual values of 100 randomly generated points and linearly interpolated values from the MAP diagram with the number of selected calibration points. To enhance algorithmic execution efficiency, improvements are made to the iteration criterion, inertia weight, and learning factors of the particle swarm optimization algorithm. The results demonstrate that the improved particle swarm optimization algorithm exhibits rapid convergence and high optimization accuracy; MAP diagrams with satisfactory control performance can be generated using only minimal calibration data.

Full Text

New Method of MAP Fixed-Point Selection Based on Improved PSO Algorithm

Cheng Zhun, Lu Kai, Qian Yu, Lu Zhen, Lu Zhixiong†
College of Engineering, Nanjing Agricultural University, Nanjing 210031, China

Abstract

To improve the driving effect of MAP-based control systems while effectively reducing storage requirements, this paper proposes a novel method for optimal selection of calibration points in MAP diagrams using an improved particle swarm optimization algorithm. Taking the MAP diagram from a hydraulic mechanical continuously variable transmission (HMCVT) ratio control system as an example, the two variables of the abscissa are equally divided within their definition domains, and the improved particle swarm algorithm is employed to select the number and position of coordinate points in each segment. The selection process employs multi-objective optimization principles that combine the average error between actual values of 100 randomly generated points and their linearly interpolated values from the MAP diagram with the number of selected calibration points. To enhance algorithmic efficiency, the iteration criteria, inertia weight, and learning factors of the particle swarm optimization are improved. Results demonstrate that the improved particle swarm algorithm exhibits fast convergence and high optimization precision, enabling the creation of effective MAP diagrams with minimal calibration data.

Keywords: improved particle swarm optimization algorithm; MAP diagram; control system; hydraulic mechanical continuously variable transmission

0 Introduction

MAP diagrams serve as the core of electronic control systems, providing control parameters for the system and can also be referred to as experimental data charts in engineering applications. Typically stored in controllers (ECU) as two-dimensional or three-dimensional charts [1, 2], control data retrieved from MAP diagrams through table lookup methods can effectively reduce ECU computational load, improve system efficiency, decrease response time, and enhance control performance. Current research on MAP diagrams for electronic control systems remains limited [3-6].

Previous studies have explored various approaches to MAP diagram optimization. Literature [7] established a BP neural network model for the calibration system and employed an Adaptive Neuro-Fuzzy Inference System (ANFIS) for nonlinear interpolation, demonstrating effective reduction in MAP calibration experiments while maintaining accuracy. Literature [8] developed a relatively accurate MAP model for nickel-metal hydride battery State of Charge (SOC) estimation using curve translation methods, though the large data volume required segmentation and compression to improve lookup speed and reduce storage space. Literature [9] calibrated SCR control parameter MAP diagrams based on extensive experiments, achieving detailed MAP diagrams at the cost of increased calibration workload. Literature [10] designed and studied a diesel engine Urea-SCR control system, calibrating MAP diagrams for engine exhaust flow, original NOx concentration, fuel supply, exhaust temperature, and maximum NOx conversion efficiency, but employed fixed step sizes within operating ranges during experimental calibration. Literature [11] utilized an output-feedback reference model adaptive control algorithm to calibrate MAP diagrams for clutch engagement control systems, significantly improving system performance, but the MAP construction process required parameter tuning and lacked investigation into the number of data points. Literature [12] optimized energy management MAP diagrams for plug-in parallel hybrid configurations, enabling lookup-based determination of optimal gear shifting, torque distribution, and drive modes, but failed to address calibration data precision and quantity.

Although these studies improved the accuracy of control parameters obtained from MAP diagrams to varying degrees, nonlinear interpolation methods increase the difficulty of real-time processing in general controller logic and fail to fundamentally reduce the number of calibration points in MAP diagrams, thereby not decreasing ECU storage space. To address these issues and effectively reduce data point quantity in MAP diagrams while maintaining control parameter precision and ECU processing speed, this paper proposes an optimal selection method for calibration points in MAP diagrams based on an improved particle swarm algorithm. Using the optimal economic transmission ratio MAP diagram from an HMCVT control system as a case study, this research aims to provide theoretical guidance for MAP diagram acquisition in other domains.

1 Hydraulic Mechanical CVT Optimal Economic Transmission Ratio MAP Diagram

The hydraulic mechanical continuously variable transmission (HMCVT) is a type of continuously variable transmission used in vehicles. The calculation formula for obtaining its economic transmission ratio MAP diagram is as follows:

$$\min()ecvtgfx\eta = egcvt\eta x$$

where g represents the engine' s effective fuel consumption rate, η_{cvt} denotes the HMCVT transmission efficiency, and x is a three-dimensional vector comprising engine speed, torque, and HMCVT transmission ratio.

The HMCVT optimal economic transmission ratio MAP diagram is constructed by plotting HMCVT transmission ratio values that satisfy equation (1) across different engine speeds and torques. An example economic transmission ratio MAP diagram is shown in [Figure 1: see original paper].

2 Improved Particle Swarm Algorithm

Particle Swarm Optimization (PSO) is a stochastic optimization algorithm based on bionics that simulates natural bird flocking behavior. Essentially an evolutionary algorithm based on swarm intelligence, PSO iteratively searches for optima through communication among group members and individual memory of historical best positions [13-17]. The velocity update employs the following formula:

$$11122()()ddddddiiiigivvcrpxcrpx\omega + = + - + -$$

where v_i^d represents the flight velocity of the i-th particle at the d-th iteration; ω is the inertia weight; c_1 and c_2 are learning factors; r_1 and r_2 are random numbers between 0 and 1; p_i^d is the historical best value of the i-th particle at the d-th iteration; and p_g^d is the historical best value among all particles at the d-th iteration.

The PSO algorithm is significantly influenced by its parameters. If particles converge too quickly toward individual or group historical best positions, a conformity effect occurs, making the algorithm prone to premature convergence. To improve convergence speed and optimization precision, the following improvements are implemented:

a) Adaptive variation of inertia weight ω. The inertia weight affects both local and global optimization capabilities of the algorithm. Larger weights enhance global coarse search ability, while smaller weights strengthen local fine search ability. When the target function' s descent rate is slow, large weights are needed to escape local optima; when the descent rate is fast, small weights are required for precise search. To match inertia weight with algorithm iteration status, a lookup table method is designed to determine inertia weight. During iteration, if the target function decreases by 0-30%, ω is randomly generated in the interval [0.2, 0.7]; if the decrease is 30-100%, ω references the previous iteration' s value; if the target function shows no change for 5 consecutive generations, ω is set to 1; if no change occurs for 10 consecutive generations, ω is set to 2.

b) Precise local search requirements in later algorithm stages are ensured by continuously decreasing learning factors c_1 and c_2. Learning parameter improvements are detailed in literature [18].

c) Introduction of the Metropolis criterion from simulated annealing algorithms, expressed as:

$$()ETPe\Delta - =$$

where P represents the probability of accepting inferior solutions; ΔE is the difference between target function values of two consecutive generations; and T is the temperature parameter in simulated annealing, which continuously decreases with iteration count. The Metropolis criterion enables the PSO algorithm to accept inferior solutions with a certain probability during early and middle iteration stages, avoiding premature convergence and increasing the likelihood of finding global optima.

To verify the effectiveness of the improved PSO algorithm, the following test function is employed:

$$T222121222212sin(,)[10.001()]xxfxxxx+=++$$

This test function has a unique minimum value of 0 at point (0, 0). With a particle swarm size of 20 and maximum iteration count of 20, test results are shown in [Figure 2: see original paper].

3 Method for Optimal Selection of MAP Calibration Points

The positions and quantities of calibration data points in the MAP diagram serve as decision variables. To better align with algorithmic programming and practical optimization requirements, the two independent variable coordinates in the MAP diagram are divided into 5 equal segments within their definition domains, with the number of coordinates in each segment serving as decision variables during algorithm execution. Using the HMCVT economic transmission ratio MAP diagram as an example, the decision variables are defined as:

$$1234512345[,,,,,,,,,]Xqqqqqppppp=$$

where q_i represents the number of selected coordinate points in the i-th equal segment of speed within its definition domain, and p_i represents the number of selected coordinate points in the i-th equal segment of torque within its definition domain.

The values of selected coordinate points within each segment are determined by evenly distributing them according to interval length and quantity. Two optimization objectives are established. The first objective is the average error between actual values and values obtained through simple linear interpolation from the MAP diagram for 100 randomly generated speed and torque conditions. The target function f_1 for the i-th particle at the d-th generation is calculated as:

$$10011()(1)100$$

where X_i^d is the i-th particle at the d-th generation; z_j is the actual transmission ratio value at the j-th random operating condition (with randomly generated speed and torque); and z_j' is the transmission ratio value obtained through linear interpolation at the j-th random operating condition.

The second optimization objective is the number of calibration data points in the MAP diagram. The target function f_2 for the i-th particle at the d-th generation is calculated as:

$$521()()dijjjfXpq == + \sum$$

Since the optimization involves two target functions of different magnitudes, a weight coefficient assignment method is employed to handle this multi-objective optimization problem.

4 Experimental Results and Analysis

The proposed improved PSO algorithm is applied to optimally select calibration data points in the HMCVT economic transmission ratio MAP diagram. The particle swarm size is set to 50 with a maximum iteration count of 200. The iterative evolution results are shown in [Figure 3: see original paper].

According to [Figure 2: see original paper], the improved PSO algorithm proposed in this paper achieves the minimum value by the 5th generation and exits the iteration loop. In contrast, the standard PSO algorithm falls into a local minimum at the 9th generation without finding the optimal solution, instead locating a solution at (-5, 8) with a corresponding value of 0.00071.

The number of coordinate points selected for speed and torque in each segment is shown in . The MAP diagram plotted using the optimally selected calibration points is presented in [Figure 4: see original paper].

By employing simple linear interpolation based on [Figure 4: see original paper] to obtain transmission ratio values for 100 random operating conditions, the average error compared to actual transmission ratio values is only 3.7%. The MAP diagram selects 28 speed coordinates and 17 torque coordinates, with total calibration points amounting to 15.9% of those in the original [Figure 1: see original paper].

5 Conclusion

a) The proposed adaptive inertia weight coefficient improvement method effectively enhances the convergence speed and optimization precision of the PSO algorithm. This method combines the inertia weight coefficient with the descent rate of the algorithm’ s objective function, dynamically determining each generation’ s inertia weight value through a lookup table approach. Results demonstrate that the test function’ s minimum value is found in only 5 iterations.

b) The proposed evolutionary algorithm-based method for optimal selection of calibration data points in MAP diagrams efficiently reduces data volume. Using the HMCVT economic transmission ratio MAP diagram as an example, the optimized data volume is reduced to 15.9% of the original, substantially decreasing ECU storage requirements. The employed lookup method uses the simplest linear interpolation, facilitating ECU processing and computation. In this case, the MAP diagram’ s average error is only 3.7%.

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