

基于改进粒子群算法优化模糊神经网络的炉膛结渣预测研究

苗建杰¹, 李德波², 李慧君¹, 刘鹏宇¹

(1. 华北电力大学 能源动力与机械工程学院, 河北 保定 071003; 2. 南方电网电力科技股份有限公司, 广东 广州 510080)

摘要:为提高基于模糊神经网络的锅炉炉膛受热面结渣预测精度,提出了一种基于广义钟型隶属度函数非线性惯性权重递减调整策略的粒子群优化算法,通过适应度测试函数对比实验、结渣预测实验和预测稳定性分析对现有文献中线性惯性权重递减调整策略(LPSO)、指数型非线性惯性权重递减调整策略(IPS0)和基于广义钟型隶属度函数非线性惯性权重递减调整策略(GJPSO)进行对比分析。研究表明:本文所改进的粒子群算法可以有效地改善算法的早熟现象、平衡算法的全局和局部搜索能力、提高算法的收敛效果和稳定性。利用改进后的粒子群算法对模糊神经网络中的权值和阈值进行优化,提高了模糊神经网络的炉膛结渣预测性能。

关键词:粒子群优化算法;非线性递减惯性权重;模糊神经网络;结渣预测

中图分类号:TP183 文献标识码:A DOI:10.16146/j.cnki.rndlgc.2022.11.014

[引用本文格式]苗建杰,李德波,李慧君,等.基于改进粒子群算法优化模糊神经网络的炉膛结渣预测研究[J].热能动力工程,2022,37(11):104-114. MIAO Jian-jie, LI De-bo, LI Hui-jun, et al. Research on furnace slagging prediction based on improved particle swarm optimization and fuzzy neural network[J]. Journal of Engineering for Thermal Energy and Power, 2022, 37(11): 104-114.

Research on Furnace Slagging Prediction based on Improved Particle Swarm Optimization and Fuzzy Neural Network

MIAO Jian-jie¹, LI De-bo², LI Hui-jun¹, LIU Peng-yu¹

(1. School of Energy Power and Mechanical Engineering, North China Electric Power University, Baoding, China, Post Code: 071003; 2. Southern Power Grid Electric Power Technology Co., Ltd., Guangzhou, China, Post Code: 510080)

Abstract: In order to improve the prediction accuracy of the slagging on the heat-resistant surface of boiler furnace based on fuzzy neural network, this paper proposed a particle swarm optimization algorithm based on the nonlinear decreasing inertia weight adjustment strategy of generalized bell-shaped membership function, then through the fitness function contrast experiment, slagging prediction experiment and predictive stability analysis, analyzed the adjustment strategies of linear decreasing inertia weight (LPSO), index nonlinear decreasing inertia weight (IPS0) and nonlinear decreasing inertia weight based on generalized bell-shaped membership function (GJPSO) in existing literature comparatively. The results show that the particle swarm algorithm proposed in this paper can effectively improve the early familiarity of the algorithm, balance the overall and local search capabilities of the algorithm, and enhance the convergence effect and stability of the algorithm. The weight and threshold in the fuzzy neural network is optimized by the improved particle swarm algorithm, and the furnace slagging prediction performance of the fuzzy neural network is improved.

Key words: particle swarm optimization algorithm, nonlinear decreasing inertia weight, fuzzy neural net-

work, slagging prediction

引 言

近年来,随着燃煤电厂锅炉容量的增加以及燃煤机组调峰角色的转变,燃煤电厂锅炉积灰结渣问题尤为明显。目前,煤炭能源在我国能源构架中仍占据接近 60%,其主导地位在未来较长的一段时间内很难改变^[1],并且我国燃煤电厂动力用煤主要以含灰量较多的劣质煤为主^[2],这使得燃煤电厂锅炉受热面的积灰结渣问题尤为严重,进一步制约了我国现役和未来燃煤电厂深度调峰的发展^[3]。在燃煤电厂积灰结渣问题的研究中,人工神经网络技术以其强大的时效性及准确性被广泛应用于燃煤电厂积灰结渣预测研究^[4-7],为燃煤电厂锅炉现场优化改进提供了理论依据和技术支撑。

近年来,国内外学者就炉膛结渣预测模型开展了大量研究。杨冬等人^[8]利用炉膛平均热有效系数得到的清洁因子作为炉膛结渣程度的预测参数,该模型虽运算简单、速度快,但预测精度较低。任林等人^[9-10]先后提出基于粒子群优化的支持向量机炉膛结渣预测模型和一种采用优化量子粒子群算法的模糊 SVM 炉膛结渣预测模型,但是该量子粒子群的优化较为单一、局限。MURUA 等人^[11]从生成渣周模型、铸件计算出的渣型和不同渣成分 3 个方面进行结渣预测模型的建立,但该模型采用的模拟数据增加了研究的不可靠性。而在人工神经网络预测性能优化研究领域, Kennedy 与 Eberhart^[12]首次提出了一种全新的全局优化算法—粒子群算法 (Particle Swarm Optimization, PSO)。相较于遗传算法,该算法以其程序实现简单、调整参数少^[13]等优点被广泛应用于神经网络优化方面的研究。惯性权重作为粒子群算法中一个重要的参数,决定着当前粒子速度对后续粒子的影响程度,并同时影响着算法的全局和局部搜索能力。田震等人^[14]采用基于线性递减惯性权重调整策略的 PSO 算法对 BP 神经网络进行优化,但线性递减惯性权重不能真实地反映 PSO 算法中粒子的复杂程度,使得算法的收敛速度逐渐减慢,易陷入早熟的困境^[15]。对此,为了更好地解决线性递减惯性权重所产生的一系列问题,

研究者们提出了多种非线性惯性权重递减策略,如指数型^[16]、对数型^[17]和三角函数型^[18-20]等非线性调整策略。陈贵敏等人^[21]通过对比分析线性递减策略、凹函数递减策略和凸函数递减策略得出,凹函数惯性递减调整策略中指数函数效果最优。但凹函数使得惯性权重 w 在算法早期较快地递减到一个较小值,极易导致早熟现象的发生^[22]。

本文基于现有的非线性惯性权重递减调整策略优化粒子群算法的研究,提出了基于广义钟形隶属度函数的非线性惯性权重递减调整策略,用以平衡粒子群算法的全局和局部搜索能力,避免算法“早熟”现象的发生。采用改进的粒子群算法对“串联”型模糊神经网络^[5]中 BP 神经网络的初始权值和阈值进行优化,得到了一种新型炉膛受热面结渣预测模型。通过适应度测试函数对比实验、炉膛结渣预测实验和预测稳定性分析对所提出模型性能进行验证,得出该策略既提高了算法的收敛性能,又提高了模型的预测精度的结论。

1 基本粒子群算法

粒子群算法作为一种群体的随机优化技术,需要对随机粒子群进行初始化,并通过当前最优粒子找出最优解。设在一个 N 维空间中,有 n 个粒子组成的粒子群,其中第 i 个粒子表示为一个 d 维的向量 $\vec{X}_i = (X_{i1}, X_{i2}, \dots, X_{id})$, $i = 1, 2, \dots, n$ 。将 $\vec{X}_i$ 带入目标函数即可得到相应的适应度值,并依据适应度值大小判别解的优劣性。其中第 i 个粒子的速度为 d 维向量,记作 $\vec{V}_i = (V_{i1}, V_{i2}, \dots, V_{id})$,记第 i 个粒子当前搜索到的最优位置为 $\vec{P}_{id} = (P_{id1}, P_{id2}, \dots, P_{id})$,粒子群当前搜索到的最优位置为 $\vec{P}_{gd} = (P_{gd1}, P_{gd2}, \dots, P_{gd})$ 。粒子更新公式如下所示^[23]:

$$V_{id}^{t+1} = V_{id}^t + c_1 r_1 (P_{id}^t - X_{id}^t) + c_2 r_2 (P_{gd}^t - X_{id}^t) \quad (1)$$

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

式中: r_1, r_2 —分布在 $[0, 1]$ 的随机数,无量纲数; t —当前迭代次数; P_{id}^t —一个体最优粒子位置; P_{gd}^t —全局最优粒子位置; X —当前粒子位置; V —粒子速度; c_1, c_2 —学习因子。

1.1 粒子群算法惯性权重的改进

由式(1)不难发现粒子的速度直接影响算法的全局收敛性,但由于缺乏对粒子速度的有效控制,使得基本粒子群算法不具备较强的局部搜索能力。对此,Shi 等人^[24-25]在算法模型中引入线性递减惯性权重,实现对粒子飞行速度的有效控制与调整,粒子的速度和惯性权重表达式为:

$$V_{id}^{t+1} = w V_{id}^t + c_1 r_1 (P_{id}^t - X_{id}^t) + c_2 r_2 (P_{gd}^t - X_{id}^t)$$

(3)

$$w = w_{\max} - \frac{t(w_{\max} - w_{\min})}{t_{\max}}$$

(4)

式中: $w_{\max}$, $w_{\min}$ —惯性权重 w 最大值和最小值,无量纲数,其中 $w_{\max}=0.9$, $w_{\min}=0.4$; t —当前迭代步数; $t_{\max}$ —最大迭代步数。并且当 $w \in [0.4, 0.9]$ 时, PSO 算法在迭代中期具备最佳的搜索能力,在迭代终止前可达到有效收敛^[24-25]。

基于广义钟形隶属度函数提出了一种新型非线性惯性权重递减调整策略,公式如下:

$$w = w_{\min} + (w_{\max} - w_{\min}) \times \left[\frac{1}{1 + \left(\frac{at}{t_{\max}} \right)^b} \right]$$

(5)

式中: a , b ——调整参数,无量纲数。 a 控制曲线的下凹性能,当 b 取 1 时,曲线的下凹性与 a 值成正比,如图 1 所示; b 用于控制曲线的上凸性能,当 a 取 1 时,曲线的上凸性与 b 值成正比,如图 2 所示。

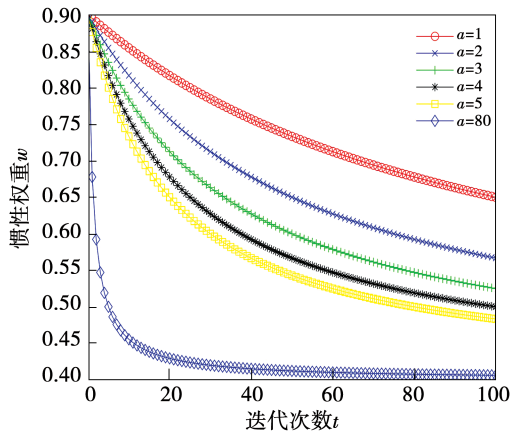


图 1 曲线下凹性图
Fig. 1 Curve concavity diagram

考虑到现有惯性权重递减调整策略在粒子群算法中的全局和局部搜索能力的不平衡性及收敛性能差等缺点,提出基于广义钟形隶属度函数的惯性权

重非线性递减调整策略:

$$w = w_{\min} + (w_{\max} - w_{\min}) \times \left[\frac{1}{1 + \left(\frac{4 \times t}{t_{\max}} \right)^4} \right]$$

(6)

由式(6)和图 3 可得,随着迭代的进行,惯性权重 w 在迭代过程早期的一段时间中缓慢下降,保证了算法在迭代早期 w 取得较大值,避免了过早的进行局部搜索而导致“早熟”现象的发生^[22];在迭代中期,惯性权重的快速下降使得算法快速地进入局部搜索,提高算法的求解效率;在迭代后期,惯性权重缓慢减小至最小值,使得算法在迭代后期稳定地进行局部搜索并最终得到最优解。该方法可以很好地平衡粒子群算法的全局和局部搜索能力,使得粒子群算法可以快速准确地找到最优解。

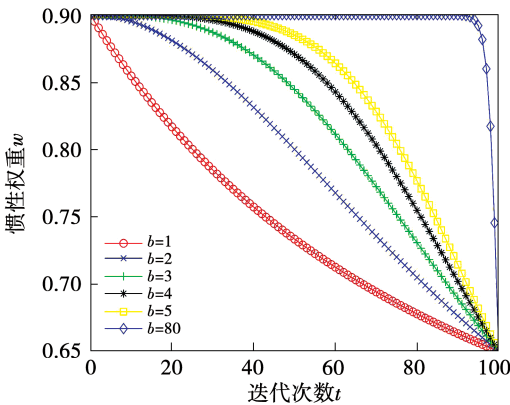


图 2 曲线上凸性图
Fig. 2 Curve convexity diagram

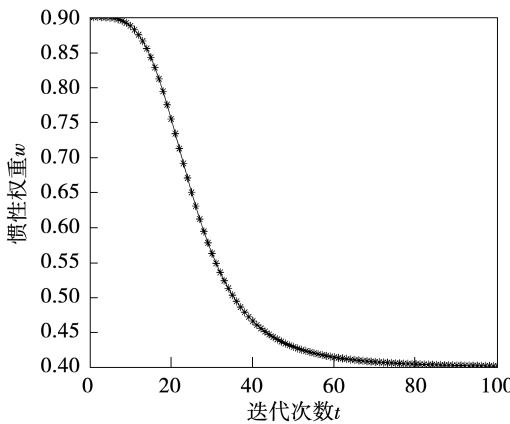


图 3 广义钟形惯性权重递减图
Fig. 3 Diagram of generalized bell-shaped decreasing inertia weight

1.2 GJPSO 算法和 GJPSO-FNN 算法流程

在改进的粒子群算法中位置迭代公式、速度迭代公式和惯性权重地带更新公式分别如式(2)、式(3)和式(6)所示。其算法流程如下:

- (1) 初始化粒子群速度和位置,确定速度与位置区间,设置粒子数、维数;
- (2) 计算各粒子适应度值,找出当前粒子的全局和局部极值;
- (3) 更新当前粒子速度和位置;
- (4) 迭代植物目标误差值或最大迭代次数,输出全局最优解,否则继续进行算法迭代。

在 GJPSO 算法流程的基础上,为了更好地解决神经网络易陷入局部最优和收敛速度慢而导致预测性能下降的问题,使用改进后的粒子算法(GJPSO - FNN)对“串联”型模糊神经网络中 BP 神经网络进行优化,以提高预测模型性能,GJPSO-FNN 算法过程如下:

- (1) 建立模糊神经网络拓扑结构,确定神经网络各层神经元个数;
- (2) 初始化粒子群参数。确定种群规模、最大迭代次数、学习因子和速度及位置的区间限定;
- (3) 将神经网络训练样本集的均方误差作为 GJPSO 算法的适应度函数,并计算粒子的适应度值。根据式(2)、式(3)和式(6)分别对位置、速度和惯性权重进行更新,进而更新得到个体最优位置和全局最优位置;
- (4) 利用 GJPSO 算法进行网络迭代,直至输出

全局最优解,即模糊神经网络的最优初始权值和阈值,并将其赋予模糊神经网络;

- (5) 利用优化后的模糊神经网络,建立最佳预测模型。

2 对比分析实验及结果

为了更好地验证 GJPSO 的寻优性能,选用 Sphere、Rosenbrock、Griewank 和 Rastrigrin 较为常用的 4 种适应度函数,分别对 IPSO^[21]与 GJPSO 在上述 4 种适应度函数下开展性能对比实验。其中, Sphere 函数和 Rosenbrock 函数为单峰函数,该类型函数只有一个全局最优解,可用于评判算法的收敛效率和效果。Griewank 函数和 Rastrigrin 函数为多峰函数,该类型函数有多个局部最优解,可很好地测试算法的“早熟”^[21]。相关适应度测试函数及其图像如表 1,图 4 ~ 图 7 所示。

为了对两种不同惯性权重调整策略的粒子群算法进行客观公正的对比,对相关参数进行统一设定,其中 $w_{\max} = 0.9, w_{\min} = 0.4$,算法迭代次数为 1 000,学习因子取 $c_1 = c_2 = 2$,算法中粒子数取 30,4 种适应度测试函数的最终寻优值均为最小值 0。在上述参数设定的基础上,分别对两种不同惯性权重调整策略的粒子群算法进行 50 次实验,记录其相应的适应度平均值、方差和平均迭代步数,并依据适应度平均值评判算法优化精度,依据方差评判算法的收敛稳定性,依据平均迭代步数评判算法的收敛速度。

表 1 适应度测试函数表
Tab. 1 Fitness function table

函数	函数表达式	维度 D	搜索空间	最大速度
Sphere	$\min f(x) = \sum_{i=1}^D x_i^2$	10	$[-100,100]$	100
Rastrigrin	$\min f(x) = \sum_{i=1}^D [x_i^2 - 10\cos(2\pi x_i) + 10]$	10	$[-10,10]$	10
Griewank	$\min f(x) = \frac{1}{4000} \sum_i x_i^2 - \prod_i \cos \frac{x_i}{\sqrt{i}} + 1$	10	$[-600,600]$	600
Rosenbrock	$\min f(x) = \sum_i^D [100 (x_{i+1} + x_i^2)^2 + (x_i - 1)^2]$	10	$[-100,100]$	100

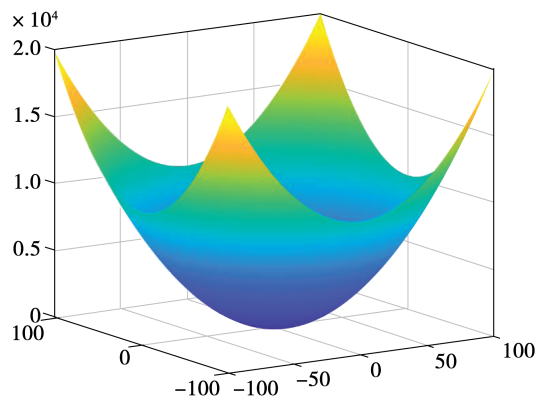


图 4 Sphere 函数图
Fig.4 Sphere function diagram

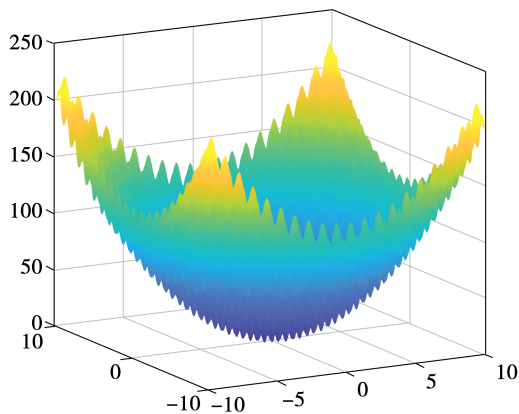


图 5 Rastrign 函数图
Fig.5 Rastrign function diagram

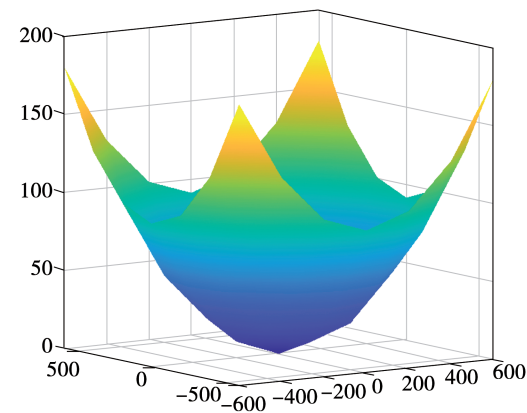


图 6 Griewank 函数图
Fig.6 Griewank function diagram

仿真结果见表 2。通过对比 IPSO^[21] 与 GJPSO 在 4 种测试函数中适应度平均值、方差以及平均迭代步数可得:GJPSO 所获得的适应度平均值和方差均优于 IPSO,GJPSO 在收敛效果、收敛稳定性和收

敛速度方法均得到大幅度提升。

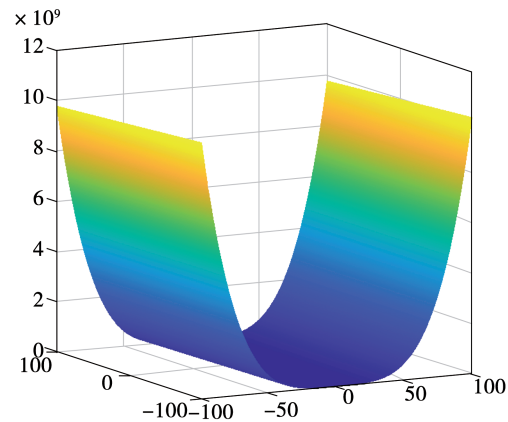


图 7 Rosenbrock 函数图
Fig.7 Rosenbrock function diagram

表 2 测试函数对比结果

Tab.2 Comparison results of test functions

测试函数	粒子群优化方法	适应度平均值	方差	平均迭代步数
Sphere	IPSO	8.196×10^{-11}	1.65×10^{-11}	>400
	GJPSO	0	0	69
Rastrigin	IPSO	4.438	2.189	>600
	GJPSO	0	0	77
Griewank	IPSO	7.88×10^{-2}	3.98×10^{-2}	>600
	GJPSO	0	0	71
Rosenbrock	IPSO	9.756	21.015	1 000
	GJPSO	6.79699×10^{-12}	1.93089×10^{-21}	490

3 GJPSO-FNN 预测炉膛受热面结渣实验

3.1 锅炉受热面结渣影响因素选取

燃煤电厂锅炉受热面的结渣是基于多因素耦合的复杂现象,其中包括煤灰特性、炉膛及燃烧器设计结构及锅炉运行工况等因素。而目前我国应用较为广泛的燃煤锅炉结渣评判指标主要包括单一性评判指标和综合评判指标^[6]。在单一性判别指标中,以软化温度 t_2 、硅比 R_C 的结渣判别准确率尤为突出。而在综合评判指标中,综合判别指数的准确率可高达 90%^[5]。另外,考虑到煤灰特性和锅炉运行方式的影响,分别引入酸碱比 $R_{B/A}$ 、硅铝比 $R_{Si/Al}$ 和无因次炉膛最高温度 φ_t 。

综上,本文选用硅铝比 $R_{\text{Si/Al}}$ 、软化温度 t_2 、硅比 R_G 、酸碱比 $R_{\text{B/A}}$ 、综合判别指数 R 和无因次炉膛最高温度 φ_t 作为模糊神经网络的输入向量。其中各评判指标公式及结渣程度界限值如下^[5]:

$$R_G = \frac{\omega(\text{SiO}_2) \times 100}{\text{Fe}_2\text{O}_3 + \omega(\text{CaO}) + \omega(\text{SiO}_2)} \quad (7)$$

$$\text{Fe}_2\text{O}_3 = 1.43\omega(\text{Fe}) + 1.11\omega(\text{FeO}) + \omega(\text{Fe}_2\text{O}_3) \quad (8)$$

$$R_{\text{B/A}} = \frac{\omega(\text{Fe}_2\text{O}_3) + \omega(\text{CaO}) + \omega(\text{MgO}) + \omega(\text{Na}_2\text{O}) + \omega(\text{K}_2\text{O})}{\omega(\text{SiO}_2) + \omega(\text{Al}_2\text{O}_3) + \omega(\text{TiO}_2)} \quad (9)$$

$$R = 1.237 R_{\text{B/A}} + 0.028 2 R_{\text{Si/Al}} - 0.002 3 t_2 - 0.018 9 R_G + 5.415 \quad (10)$$

$$\varphi_t = \frac{1\,144 + 249 [B_j Q_d / (2ab(a+b) \eta_f C_a \zeta)]}{t_2} \quad (11)$$

式中: $\omega(\text{SiO}_2)$ —二氧化硅的质量分数,%;
 $\omega(\text{CaO})$ —氧化钙的质量分数,%; $\omega(\text{Fe})$ —铁的质量分数,%; $\omega(\text{FeO})$ —氧化亚铁的质量分数,%;
 $\omega(\text{Fe}_2\text{O}_3)$ —三氧化二铁的质量分数; $\omega(\text{MgO})$ —氧化镁的质量分数,%; $\omega(\text{Na}_2\text{O})$ —氧化钠的质量分数,%; $\omega(\text{K}_2\text{O})$ —氧化钾的质量分数,%;
 $\omega(\text{Al}_2\text{O}_3)$ —氧化铝的质量分数,%; $\omega(\text{TiO}_2)$ —氧化钛的质量分数,%; B_j —耗煤量,t/h; Q_d —低位发热量,kJ/kg; a 、 b —炉膛深度和宽度,m; η_f —二次风层数,层; C_a —二次风距,mm; ζ —卫燃带修正系数,无量纲数。

表 3 不同评判指标的分类界限^[5]

Tab.3 Classification boundaries of different evaluation indicators^[5]

评判指标	轻度	中度	重度
t_2	> 1390	1260 ~ 1390	< 1260
$R_{\text{Si/Al}}$	< 1.87	1.87 ~ 2.65	> 2.65
$R_{\text{B/A}}$	0.206	0.206 ~ 0.4	> 0.4
R_G	> 78.8	66.1 ~ 78.8	< 66.1
R	< 1.5	1.5 ~ 2.5	> 2.5
φ_t	< 0.97	0.97 ~ 0.5875	> 0.5875

3.2 数据预处理

针对炉膛受热面结渣程度这一“模糊化”概念^[5],没有明显分界的问题,并且由于6种评判指标分别对应不同量级和取值范围。对此,本文一改以往采用神经网络输入数据的传统归一化处理来降低模型预测误差的方法,分别采用三角形隶属度函数(Trimf)、梯形隶属度函数(Trapmf)、高斯型隶属度函数(Gaussmf)和 π 型隶属度函数(Primf)对上述6种输入向量经模糊化处理,求得各输入向量所对应的轻度(L)、中度(M)和重度(S)的隶属度作为后续神经网络的输入向量。具体参数的结渣程度数据划分见表3。以软化温度 t_2 为例,采用三角形隶属度函数对其进行模糊化处理,以求得轻度(L)、中度(M)和重度(S)3种结渣程度所对应的隶属度值。

$$L = \begin{cases} 1, t_2 \geq 1390 \\ \frac{t_2 - 1325}{65}, 1325 < t_2 < 1390 \\ 0, t_2 \leq 1325 \end{cases} \quad (12)$$

$$M = \begin{cases} 0, |t_2 - 1325| \geq 65 \\ \frac{t_2 - 1260}{65}, 1260 \leq t_2 < 1325 \\ \frac{1390 - t_2}{65}, 1325 \leq t_2 < 1390 \end{cases} \quad (13)$$

$$S = \begin{cases} 1, t_2 \leq 1260 \\ \frac{1325 - t_2}{65}, 1260 \leq t_2 < 1325 \\ 0, t_2 \geq 1325 \end{cases} \quad (14)$$

其他输入向量的隶属度函数确定方法同软化温度 t_2 。

3.3 GJPSO-FNN 参数及结构设置

为了验证 GJPSO-FNN 的预测性能,从文献[5]和文献[7]中提取出38组不同结渣数据用于受热面结渣预测,其中利用28组作为训练集,10组作为预测集。选取如图8所示的模糊神经网络拓扑结构。由图8可知,该模糊神经网络为“串联”型模糊神经网络^[5],即6种输入向量经隶属度函数模糊化处理所形成的模糊集合传至第1隐层的18个神经元作为BP神经网络的输入向量。第1隐层可视

为真正意义上的模糊神经网络输入层,对于第 2 隐层神经元个数的确定常采用经验公式 (10)^[25]并结合实验预测结果精度进行最终确定。

$$s = \sqrt{m + n} + a \tag{15}$$

式中: s —隐层神经元个数; m —第 1 隐层神经元个数; n —输出层神经元个数; a —1~10 之间的常数,无量纲数。

模糊神经网络其他参数设置如下:隐层和输出层的传递函数均选用 logsig,最大迭代次数为 1 000,学习率为 0.01,训练目标为 0.001。其中,通过比较不同网络的预测精度,确定 Trimf、Trapmf 和 Gaussmf 模糊化处理的神经网络的第 2 隐层个数均为 8。并以轻度、中度和重度 3 种结渣程度所对应的向量 (0.9900, 0.0100, 0.0100), (0.0100, 0.9900, 0.0100) 和 (0.0100, 0.0100, 0.9900) 作为模糊神经网络的输出向量^[8]。

GJPSO 算法参数设置:种群规模为 20;最大迭代次数为 150;学习因子 c_1 、 c_2 为固定值 2;粒子的位置区间为 $[-2, 2]$,速度区间为 $[-1, 1]$;惯性权重取值范围为 $[0.4, 0.9]$ 。

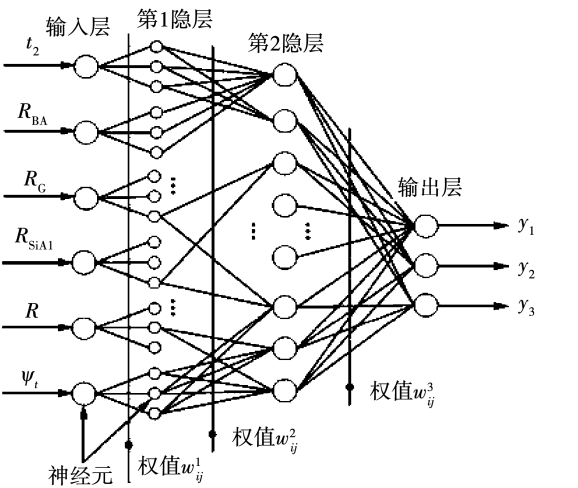


图 8 模糊神经网络拓扑结构^[7]

Fig. 8 Fuzzy neural network topology^[7]

3.4 预测结果及分析

π 型隶属度函数所构成的模糊神经网络的预测精度为 100%^[7],但由于受到参考数据的限制,不能保证该模型对所有样本数据均有精准的预测。并且

在相关研究文献^[6-7]中已对采用传统归一化处理的 BP 神经网络预测模型进行验证。所以,为了更好地评价 GJPSO-FNN 模型预测的准确性和收敛速度,通过对将输入向量经 Trimf、Trapmf 和 Gaussmf 处理所对应的模糊神经网络、基于线性递减惯性权重粒子群算法优化模糊神经网络 (LPSO-FNN)、基于指数函数递减惯性权重粒子群算法^[21]优化模糊神经网络 (IPSO-FNN) 与 GJPSO-FNN,开展结渣预测实验。利用 28 个训练集对 LPSO 算法优化模型、IPSO 算法优化模型和 GIPSO 算法优化进行训练后,利用 10 组测试集对训练完成的 3 种算法优化预测模型进行仿真验证,仿真预测结果如表 4~表 6 所示,3 种算法优化预测模型的性能效果如图 9~图 11 所示。

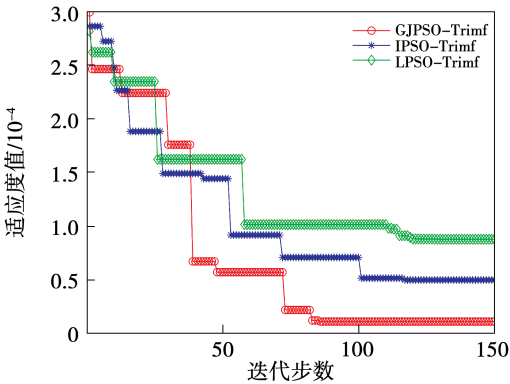


图 9 GJPSO-Trimf、IPSO-Trimf 与 LPSO-Trimf

适应度变化曲线

Fig. 9 GJPSO-Trimf, IPSO-Trimf and LPSO-Trimf

fitness change curves

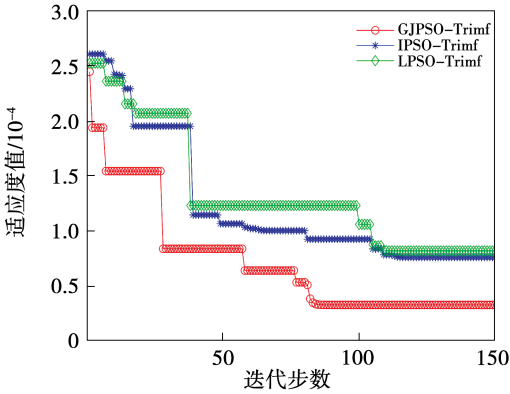


图 10 GJPSO-Trapmf、IPSO-Trapmf 与 LPSO-Trapmf

适应度变化曲线

Fig. 10 GJPSO-Trapmf, IPSO-Trapmf and LPSO-Trapmf

fitness change curves

表 4 Trimf、LPSO-Trimf、IPSO-Trimf 与 GJPSO-Trimf 预测结果

Tab.4 Trimf,LPSO-Trimf,IPSO-Trimf and GJPSO-Trimf prediction results

Trimf	LPSO-Trimf	IPSO-Trimf	GJPSO-Trimf	期望值
0.9652,0.0070,0.0004	0.9671,0.0550,0.0106	0.6056,0.0946,0.0360	0.0138,0.9912,0.0096	0.0100,0.9900,0.0100
L	L	L	M	M
0.0014,0.9781,0.0295	0.0424,0.9972,0.0051	0.0041,0.9963,0.0040	0.0084,0.9948,0.0096	0.0100,0.9900,0.0100
M	M	M	M	M
0.0473,0.9972,0.0004	0.3525,0.9225,0.0143	0.9669,0.0657,0.0102	0.9746,0.0257,0.0040	0.9900,0.0100,0.0100
M	M	L	L	L
0.9615,0.0305,0.0005	0.9879,0.0099,0.0107	0.9920,0.0115,0.0115	0.9916,0.0085,0.0098	0.9900,0.0100,0.0100
L	L	L	L	L
0.0111,0.0175,0.9745	0.0091,0.0134,0.9893	0.0126,0.0111,0.9887	0.0100,0.0105,0.9906	0.0100,0.0100,0.9900
S	S	S	S	S
0.0258,0.0738,0.5338	0.0024,0.0567,0.9931	0.0063,0.0017,0.9985	0.0086,0.0064,0.9881	0.0100,0.0100,0.9900
S	S	S	S	S
0.0107,0.0097,0.9164	0.6159,0.0004,0.9824	0.2971,0.0004,0.9964	0.0122,0.1121,0.8960	0.0100,0.0100,0.9900
S	S	S	S	S
0.0057,0.3171,0.8572	0.0115,0.0632,0.9782	0.1743,0.5040,0.3576	0.0110,0.9935,0.0477	0.0100,0.0100,0.9900
S	S	M	M	S
0.9794,0.0144,0.0002	0.9893,0.0116,0.0103	0.9929,0.0083,0.0130	0.9899,0.0103,0.1010	0.9900,0.0100,0.0100
L	L	L	L	L
0.0012,0.9877,0.0149	0.0196,0.9818,0.0094	0.0307,0.9887,0.0120	0.0103,0.9935,0.0096	0.0100,0.9900,0.0100
M	M	M	M	M

表 5 Trapmf、LPSO-Trapmf、IPSO-Trapmf 与 GJPSO-Trapmf 预测结果

Tab.5 Trapmf,LPSO-Trapmf,IPSO-Trapmf and GJPSO-Trapmf prediction results

Trapmf	LPSO-Trapmf	IPSO-Trapmf	GJPSO-Trapmf	期望值
0.7771,0.0023,0.2854	0.1184,0.7733,0.0282	0.0020,0.9766,0.0109	0.0078,0.9992,0.0004	0.0100,0.9900,0.0100
L	M	M	M	M
0.0021,0.9394,0.0223	0.0192,0.9927,0.0036	0.0106,1.0000,0.0000	0.0067,0.9998,0.0001	0.0100,0.9900,0.0100
M	M	M	M	M
0.9661,0.0298,0.0062	0.7210,0.2758,0.0114	0.9874,0.0130,0.0130	0.9914,0.0004,0.1180	0.9900,0.0100,0.0100
L	L	L	L	L
0.9281,0.0151,0.0103	0.9837,0.0169,0.0107	0.9895,0.0216,0.0086	0.9906,0.0193,0.0024	0.9900,0.0100,0.0100
L	L	L	L	L
0.0152,0.0192,0.9859	0.0106,0.0126,0.9893	0.0101,0.0103,0.9887	0.0110,0.0166,0.9888	0.0100,0.0100,0.9900
S	S	S	S	S
0.1648,0.0298,0.9813	0.0186,0.0061,0.9919	0.0099,0.0112,0.9887	0.0103,0.0031,0.9988	0.0100,0.0100,0.9900
S	S	S	S	S
0.0554,0.0302,0.9722	0.0058,0.0001,0.9495	0.0714,0.0001,0.8876	0.0252,0.0050,0.9862	0.0100,0.0100,0.9900
S	S	S	S	S
0.0149,0.1530,0.5556	0.9301,0.0026,0.1143	0.0725,0.2244,0.0030	0.1711,0.0019,0.9523	0.0100,0.0100,0.9900
S	L	M	S	S
0.9898,0.0108,0.0131	0.9853,0.0151,0.0108	0.9896,0.0099,0.0127	0.9886,0.0099,0.0082	0.9900,0.0100,0.0100
L	L	L	L	L
0.0056,0.9941,0.0014	0.0022,0.9946,0.0307	0.0113,0.9861,0.0115	0.0077,0.9994,0.0004	0.0100,0.9900,0.0100
M	M	M	M	M

表 6 Gaussmf、LPSO-Gaussmf、IPSO-Gaussmf 与 GJPSO-Gaussmf 预测结果
Tab. 6 Gaussmf, LPSO-Gaussmf, IPSO-Gaussmf and GJPSO-Gaussmf prediction results

Gaussmf	LPSO-Gaussmf	IPSO-Gaussmf	GJPSO-Gaussmf	期望值
0.0852,0.9460,0.0118	0.9742,0.0231,0.0146	0.3307,0.7792,0.0087	0.0303,0.9421,0.0100	0.0100,0.9900,0.0100
M	L	M	M	M
0.0284,0.9740,0.0222	0.0001,1.0000,0.0018	0.0021,0.9991,0.0037	0.0042,0.9898,0.0100	0.0100,0.9900,0.0100
M	M	M	M	M
0.9623,0.0466,0.0152	0.9961,0.0016,0.0471	0.9138,0.1001,0.0078	0.9911,0.0100,0.0100	0.9900,0.0100,0.0100
L	L	L	L	L
0.9636,0.0146,0.0123	0.9855,0.0206,0.0090	0.9874,0.0131,0.0105	0.9912,0.0100,0.0100	0.9900,0.0100,0.0100
L	L	L	L	L
0.0220,0.0304,0.9766	0.0126,0.0108,0.9883	0.0109,0.0104,0.9898	0.0102,0.0100,0.9900	0.0100,0.0100,0.9900
S	S	S	S	S
0.0189,0.0173,0.9859	0.0069,0.0197,0.9879	0.0452,0.0024,0.9911	0.0103,0.0100,0.9900	0.0100,0.0100,0.9900
S	S	S	S	S
0.5309,0.0013,0.9701	0.0822,0.0029,0.9799	0.8390,0.0000,0.9850	0.0313,0.0000,0.9900	0.0100,0.0100,0.9900
S	S	S	S	S
0.6908,0.0522,0.5424	0.0106,0.1661,0.8433	0.9977,0.0007,0.0471	0.0156,0.0055,0.9898	0.0100,0.0100,0.9900
L	S	L	S	S
0.9801,0.0088,0.0271	0.9885,0.0136,0.0108	0.9887,0.0134,0.0102	0.9912,0.0099,0.0100	0.9900,0.0100,0.0100
L	L	L	L	L
0.1219,0.9612,0.0068	0.0177,0.9926,0.0025	0.0144,0.9785,0.0194	0.0043,0.9898,0.0100	0.0100,0.9900,0.0100
M	M	M	M	M

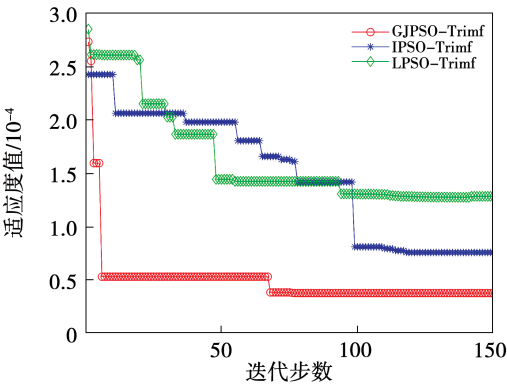


图 11 GJPSO-Gaussmf、IPSO-Gaussmf 与 LPSO-Gaussmf 适应度变化曲线
Fig. 11 GJPSO-Gaussmf, IPSO-Gaussmf and LPSO-Gaussmf fitness change curves

由表 4 ~ 表 6 所得的仿真预测结果可知,GJPSO 算法所优化的模糊神经网络预测模型的预测精度较高,其中在 GJPSO-Trapmf 和 GJPSO-Gaussmf 中的预测效果可达到 100%。由图 9 ~ 图 11 所得的适应度值和迭代步数的关系可以得出,相较于其他两种粒

子群优化算法,由于 GIPSO 算法中惯性权重呈广义钟型非线性递减,使得算法自身得以有较强的全局搜索能力,在更少的迭代步数下达到最优的稳定结果。

3.5 预测稳定性验证

考虑到粒子群算法自身的随机性对实验预测结果的影响,且为了更好地对比和评价模型的预测效果。对 LPSO-FNN、IPSO-FNN 和 GJPSO-FNN 分别进行 30 组稳定性实验验证,其结果如表 7 ~ 表 9 所示。

表 7 LPSO-Trimf、IPSO-Trimf 和 GJPSO-Trimf 预测稳定性对比

Tab. 7 LPSO-Trimf, IPSO-Trimf and GJPSO-Trimf prediction stability comparison

类型	平均预测精度/%	平均迭代步数	平均最小适应度值/ 10^{-5}
LPSO-Trimf	83	126	9.90613
IPSO-Trimf	81	115	9.40635
GJPSO-Trimf	90	94	6.97344

表 8 LPSO-Trapmf、IPSO-Trapmf 和
GJPSO-Trapmf 预测稳定性对比

Tab. 8 LPSO-Trapmf,IPSO-Trapmf and
GJPSO-Trapmf prediction stability comparison

类型	预测精 度/%	平均迭 代步数	最小适应 度值/ 10^{-5}
LPSO-Trapmf	89	118	8. 2956
IPSO-Trapmf	87	113	9. 63028
GJPSO-Trapmf	98	88	3. 88759

表 9 LPSO-Gaussmf、IPSO-Gaussmf 和
GJPSO-Gaussmf 预测稳定性对比

Tab. 9 LPSO-Gaussmf,IPSO-Gaussmf and
GJPSO-Gaussmf prediction stability comparison

类型	预测精 度/%	平均迭 代步数	最小适应 度值/ 10^{-5}
LPSO-Gaussmf	90	115	8. 15573
IPSO-Gaussmf	90	119	6. 36382
GJPSO-Gaussmf	98	82	4. 12564

预测稳定性验证的设定在一定程度上避免了由于粒子群算法自身随机性的特点对预测结果和性能所带来的影响,进一步证明了在结渣预测实验中所得结果的准确性。通过上述实验结果分析可得,在相同条件下,所设计的 GJPSO 算法比另外两种粒子群算法有着更高的预测精度和更好的收敛效果。

4 结 论

在传统粒子群算法中,惯性权重对算法的收敛速度和精度会产生较大的影响。本文通过对粒子群算法中惯性权重的分析,并在现有文献中指数型非线性递减惯性调整策略^[21]的基础上,创新性地引进基于广义钟形隶属度函数的非新型惯性权重递减调整策略,通过适应度函数对比分析实验、炉膛结渣预测实验和预测稳定性验证分析可得:

(1) 在适应度函数对比分析实验中,GJPSO 算法较 IPSO 算法具有更好的收敛效果、更强的收敛稳定性和更快的收敛速度,较好地平衡了算法的全局和局部搜索能力,避免过早地进入局部搜索而导致“早熟”现象的发生。

(2) 在炉膛结渣预测实验中,GJPSO 算法可使得“串联”型模糊神经网络中 BP 神经网络预测模型的权值和阈值得到有效的优化,避免了网络在训练

过程中易陷入局部极小值和收敛速度慢问题发生,极大地降低了训练集误差。相较于 LPSO 算法和 IPSO 算法,GJPSO 在优化模糊神经网络预测模型的预测精度和收敛效果方面得到了显著的提高。

(3) 在预测稳定性验证中,更好地验证了在结渣预测实验中所取得的预测结果的准确性,并进一步证明了 GJPSO 算法的正确性和实用性。

参考文献:

[1] 杨英明,孙建东,李全生.我国能源结构优化研究现状及展望[J].煤炭工程,2019,51(2):149-153.
YANG Ying-ming,SUN Jian-dong,LI Quan-sheng. The current situation and prospect of energy structure optimization research[J]. Coal Engineering,2019,51(2):149-153.

[2] 李德波,沈跃良,余岳溪,等.旋流燃烧煤粉锅炉主要烟气组分及分布规律试验[J].广东电力,2016,29(3):1-7.
LI De-bo,SHEN Yue-liang,YU Yue-xi,et al. Test of main flue gas components and distribution laws of swirl combustion coal boosters[J]. Guangdong Power,2016,29(3):1-7.

[3] 李德波,刘鹏宇,刘彦丰,等.新型电力系统规划下燃煤电厂锅炉机组的发展[J/OL].广东电力:1-13(2021-09-23)[2021-11-12].<http://kns.cnki.net/kcms/detail/44.1420.tm.20210920.0232.002.html>.
LI De-bo,LIU Peng-yu,LIU Yan-feng,et al. Development of the boiler unit of the new power system[J / OL]. Guangdong Power: 1-13(2021-09-23)[2021-11-12].<http://kns.cnki.net/kcms/detail/44.1420.tm.20210920.0232.002.html>.

[4] 贾志琴.基于时序神经网络受面积灰预测的研究[D].太原:中北大学,2020.
JIA Zhi-qin. Research on grey prediction of heating area based on time series neural network[D] Taiyuan:Zhongbei University,2020.

[5] 王洪亮.基于模糊神经网络的电站燃煤锅炉结渣特性研究[D].北京:华北电力大学,2011.
WANG Hong-liang. Study on slagging characteristics of power plant coal-fired boiler based on fuzzy neural network[D]. Beijing:North China Electric Power University,2011.

[6] 刘丹,周熙宏,杨冬,等.燃煤电站锅炉炉膛结渣特性计算分析[J].西安交通大学学报,2019,53(9):150-158.
LIU Dan,ZHOU Xi-hong,YANG Dong,et al. Calculation and analysis on the slagging performance of coal-fired boilers[J]. Journal of Xi'an Jiaotong University,2019,53(9):150-158.

[7] 朱超,郁翔,李峰,等.基于模糊神经网络的燃煤锅炉炉膛结渣特性研究[J/OL].洁净煤技术:1-8(2021-05-07)[2021-11-12].<http://kns.cnki.net/kcms/detail/11.3676.TD.20210507.1017.002.html>.
ZHU Chao,YU Xiang,LI Feng,et al. Study on the characteristics of coal-fired boiler furnace based on fuzzy neural network[J/OL]. Clean Coal Technology:1-8(2021-05-07)[2021-11-12].

- http://kns.cnki.net/kcms/detail/11.3676.td.20210507.1017.002.html.
- [8] 杨冬,龙俊,茆凯源,等. 1 000 MW 超超临界锅炉结渣特性预测模型[J]. 南京航空航天大学学报,2017,49(3):320-324.
- YANG Dong, LONG Jun, MAO Kai-yuan, et al. Prediction model of slagging characteristics of 1 000 MW ultra supercritical boiler[J]. Journal of Nanjing University of Aeronautics and Astronautics, 2017, 49(3):320-324.
- [9] 任林,王东风. 基于粒子群优化的 FCM-SVM 算法的锅炉燃煤结渣预测[J]. 山东电力技术,2018,45(8):46-49.
- REN Lin, WANG Dong-feng. Prediction of boiler slagging based on FCM-SVM algorithm based on particle swarm optimization[J]. Shandong Electric Power Technology, 2018, 45(8):46-49.
- [10] 任林,王东风. 基于 QPSO 优化模糊-SVM 的电站锅炉燃煤结渣特性预测[J]. 山东电力技术,2019,46(7):38-43.
- REN Lin, WANG Dong-feng. Prediction of coal slagging characteristics of utility boilers based on QPSO optimized fuzzy SVM[J]. Shandong Electric Power Technology, 2019, 46(7):38-43.
- [11] MURUA M, BOTO F, ANGLADA E, et al. A slag prediction model in an electric arc furnace process for special steel production[J]. Procedia Manufacturing, 2021, 54(2):178-183.
- [12] KENNEDY J, EBERHART R. Particle swarm optimization[C]// Proceedings of IEEE International Conference on Neural Networks. Perth, Australia; IEEE Press, 1995:1942-1948.
- [13] 黄少荣. 粒子群优化算法综述[J]. 计算机工程与设计, 2009, 30(8):1977-1980.
- HUANG Shao-rong. Summary of particle swarm optimization algorithm[J]. Computer Engineering and Design, 2009, 30(8):1977-1980.
- [14] 田震,荆双喜,赵丽娟,等. 基于粒子群优化 BP 神经网络的采煤机可靠性预测[J]. 河南理工大学学报(自然科学版), 2020, 39(1):68-74.
- TIAN Zhen, JING Shuang-xi, ZHAO Li-juan, et al. Reliability prediction of shearer based on BP neural network optimized by particle swarm[J]. Journal of Henan University of Science and Technology(Natural Science Edition), 2020, 39(1):68-74.
- [15] 李浩君,张广,王万良. 一种惯性权重与种群多样性协同调整的二进制粒子群优化算法[J]. 小型微型计算机系统, 2018, 39(3):529-533.
- LI Hao-jun, ZHANG Guang, WANG Wan-liang. Binary particle swarm optimization algorithm for coordinated adjustment of population diversity and inertia weight[J]. Small Microcomputer System, 2018, 39(3):529-533.
- [16] 张迅,王平,邢建春,等. 基于高斯函数递减惯性权重的粒子群优化算法[J]. 计算机应用研究, 2012, 29(10):3710-3712, 3724.
- ZHANG Xun, WANG Ping, XING Jian-chun, et al. Particle swarm optimization algorithm with decreasing inertia weight based on Gaussian function[J]. Computer Application Research, 2012, 29(10):3710-3712, 3724.
- [17] 陆文星,李楚. 改进 PSO 算法优化 LSSVM 模型的短期客流预测[J]. 计算机工程与应用, 2019, 55(18):247-255.
- LU Wen-xing, LI Chu. Forecasting of short-time tourist flow based on improved PSO algorithm optimized LSSVM model[J]. Computer Engineering and Applications, 2019, 55(18):247-255.
- [18] 李万,冯芬玲,蒋琦玮. 改进粒子群算法优化 LSTM 神经网络的铁路客运量预测[J]. 铁道科学与工程学报, 2018, 15(12):3274-3280.
- LI Wan, FENG Fen-ling, JIANG Qi-wei. Prediction for railway passenger volume based on modified PSO optimized LSTM neural network[J]. Journal of Railway Science and Engineering, 2018, 15(12):3274-3280.
- [19] 雷斌,陶海龙,徐晓光. 基于改进粒子群优化算法的灰色神经网络的铁路货运量预测[J]. 计算机应用, 2012, 32(10):2948-2951, 2962.
- LEI Bin, TAO Hai-long, XU Xiao-guang. Railway freight volume prediction based on grey neural network with improved particle swarm optimization[J]. Computer Applications, 2012, 32(10):2948-2951, 2962.
- [20] 赵长春,赵亮,王博. 基于改进粒子群算法的 RBF 神经网络磨机负荷预测研究[J]. 计算机测量与控制, 2020, 28(6):19-22, 27.
- ZHAO Chang-chun, ZHAO Liang, WANG Bo. Research on the load prediction of RBF neural network mill based on improved particle swarm algorithm[J]. Computer Measurement and Control, 2020, 28(6):19-22, 27.
- [21] 陈贵敏,贾建援,韩琪. 粒子群优化算法的惯性权重递减策略研究[J]. 西安交通大学学报, 2006(1):53-56, 61.
- CHEN Gui-min, JIA Jian-yuan, HAN Qi. Study on the strategy of decreasing inertia weight in particle swarm optimization algorithm[J]. Journal of Xi'an Jiaotong University, 2006(1):53-56, 61.
- [22] 姜建国,田旻,王向前,等. 采用扰动加速因子的自适应粒子群优化算法[J]. 西安电子科技大学学报, 2012, 39(4):74-80.
- JIANG Jian-guo, TIAN Min, WANG Xiang-qian, et al. Adaptive particle swarm optimization algorithm with disturbance acceleration factor[J]. Journal of Xi'an University of Electronic Science and Technology, 2012, 39(4):74-80.
- [23] 史峰,王辉,郁磊,等. MATLAB 智能算法 30 个案例[M]. 北京:北京航空航天大学出版社, 2011.
- SHI Feng, WANG Hui, YU Lei, et al. 30 Cases of MATLAB intelligent algorithm[M]. Beijing: Beijing University of Aeronautics and Astronautics Press, 2011.
- [24] SHI Y H, EBERHART R C. A modified particle swarm optimizer[C]. Proceedings of the IEEE Conference on Evolutionary Computation. Anchorage, USA, 1998:69-73.
- [25] PARK J B, LEE K S, SHIN J R, et al. A particle swarm optimization for economic dispatch with nonsmooth cost functions[J]. IEEE Transactions on Power Systems, 2005, 20(1):34-42.