DOI: 10. 19650/j. cnki. cjsi. J2108366

多策略改进麻雀算法与 BiLSTM 的变压器故障诊断研究*

王雨虹,王志中,付　华,王淑月,王留洋
(　　125105)

摘　要: , (MISSA) (BiLSTM) 。 (DGA) , 9 , Softmax ; Logistic 、 (SSA) ; , MISSA , , (KPCA) , 。 , 94% PSO-BiLSTM、GWO-BiLSTM SSA-BiLSTM , 11. 33%、8. 67%、6%, 。

关键词: ; ; ; ;
中图分类号: TM411　TH165. 3　**文献标识码**: A　**国家标准学科分类代码**: 470. 40

Research on transformer fault diagnosis based on the improved multi-strategy sparrow algorithm and BiLSTM

Wang Yuhong, Wang Zhizhong, Fu Hua, Wang Shuyue, Wang Liuyang
(*Faculty of Electrical and Control Engineering, Liaoning Technical University, Liaoning 125105, China*)

Abstract: To enhance the low precision of transformer fault diagnosis, a model based on multi-strategy improved sparrow algorithm (MISSA) and bidirectional long short-term memory network (BiLSTM) is proposed. Based on dissolved gas analysis (DGA) technology in oil, the uncoded ratio method is used to extract 9-dimensional fault features of the transformer as the input of the model for network training. The Softmax function is used to obtain fault diagnosis types in the output layer. The sparrow search algorithm (SSA) is improved by logistic chaos mapping, uniformly distributed dynamic adaptive weights and dynamic Laplacian operator. In the initial solution set, the multi-strategy improved Sparrow algorithm (MISSA) is used to optimize the target hyperparameters. In this way, the transformer fault diagnosis accuracy is optimized, and the kernel principal component analysis (KPCA) is used to reduce the dimension of fault feature indexes, and the convergence speed of the model is accelerated. Compared with PSO-BiLSTM, GWA-BiLSTM and SSA-BILSTM fault diagnosis models, the diagnostic accuracy of the proposed model is 94%, which is 11. 33%, 8. 67% and 6% higher than those of PSO-BiLSTM, GWA-BiLSTM and SSA-BiLSTM fault diagnosis models, respectively. It is verified that the proposed method can effectively improve the performance of transformer fault diagnosis.

Keywords: transformer; dissolved gas in oil; sparrow algorithm; deep learning; kernel principal component analysis

0　引　言

, [1-2]。

, , , [3]。 , (H_2、CH_4、C_2H_6) ,

:2021-08-04　Received Date: 2021-08-04
* : (51974151,71771111)、 ( ) (2019GJWZD002)、 (LT2019007)、 (LJ2019QL015)、 (LJKZ0352)

[4]。，（dissolved gas analysis，DGA）[5]。

，DGA 、（support vector machine，SVM）、。[6]，；[7]，SVM，；[8-9]，。

，、。、，。（bidirectional long short term memory，BiLSTM），[10-11]。BiLSTM，，，[12]。

，（multi-strategy improved sparrow search algorithm，MISSA）BiLSTM。，（kernel principal component analysis，KPCA），；，Logistic、；，MISSA BiLSTM，；，KPCA MISSA-BiLSTM，。，。

1 油中溶解气体成分特征的提取

$\boldsymbol{X}_{n\times m} = [\boldsymbol{x}_1,\boldsymbol{x}_2,\boldsymbol{x}_3,\cdots,\boldsymbol{x}_n]^{\mathrm{T}},\boldsymbol{x}_i \in \boldsymbol{R}^N, i = 1,2,\cdots,n$ i m 。$\boldsymbol{X}$ [13]，：

$$\boldsymbol{K} = (K_{ef})_{p\times p} = \boldsymbol{K}(z_e,z_f) = (\phi(z_e),\phi(z_f)) \tag{1}$$

：ϕ ；$e,f = 1,2,\cdots,p$。

$\widetilde{\boldsymbol{K}}$，：

$$\widetilde{\boldsymbol{K}} = \boldsymbol{K} - \boldsymbol{L}_N\boldsymbol{K} - \boldsymbol{K}\boldsymbol{L}_N + \boldsymbol{L}_N^{\mathrm{T}}\boldsymbol{K}\boldsymbol{L}_N \tag{2}$$

：$\boldsymbol{L}_N$ 。$\widetilde{\boldsymbol{K}}$ [14] λ $\boldsymbol{\nu}$。85% s ，$\boldsymbol{Y}$，：

$$\boldsymbol{Y} = \boldsymbol{K}^{\mathrm{T}} \cdot \left[\frac{1}{\sqrt{\lambda_1}}\boldsymbol{\nu}_1, \frac{1}{\sqrt{\lambda_2}}\boldsymbol{\nu}_2, \cdots, \frac{1}{\sqrt{\lambda_s}}\boldsymbol{\nu}_s\right] \tag{3}$$

2 SSA 算法

[15]（sparrow search algorithm，SSA）。SSA N，D 。

：

$$x_{id}^{t+1} = \begin{cases} x_{id}^t \cdot \exp\left(\dfrac{-i}{\alpha \cdot T}\right), R_2 < ST \\ x_{id}^t + Q \cdot \boldsymbol{L}, R_2 \geqslant ST \end{cases} \tag{4}$$

：x_{id}^t ；T ；α $(0,1]$ ；Q ，；$\boldsymbol{L}$ ；R_2 ；ST 。

：

$$x_{id}^{t+1} = \begin{cases} Q \cdot \exp\left(\dfrac{xw_d^t - x_{id}^t}{i^2}\right), & i > \dfrac{n}{2} \\ xb_d^{t+1} + |x_{id}^t - xb_d^{t+1}|\boldsymbol{A}^+ \cdot \boldsymbol{L}, \end{cases} \tag{5}$$

：xw_d^t ；x_{id}^t ；xb_d^{t+1} $t+1$ ；$\boldsymbol{A}$ 。

：

$$x_{id}^{t+1} = \begin{cases} xb_d^t + \beta(x_{id}^t - xb_d^t), & f_i \neq f_g \\ x_{id}^t + K\left(\dfrac{x_{id}^t - xw_d^t}{|f_i - f_w| + \varepsilon}\right), & f_i = f_g \end{cases} \tag{6}$$

：β ；K ，-1 1 ；f_i、f_w f_g 、；ε ，0 。

2.1 MISSA 算法

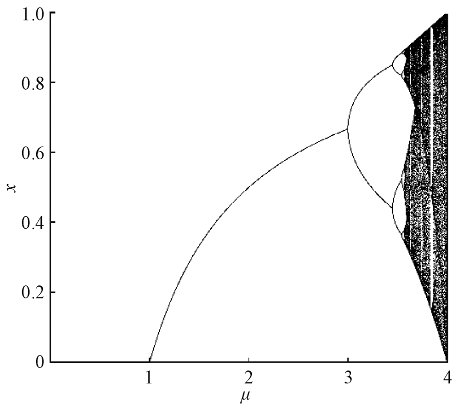
1) Logistic

[16]。Logistic [17]，，。

：

$$x_{k+1} = \mu x_k(1 - x_k) \tag{7}$$

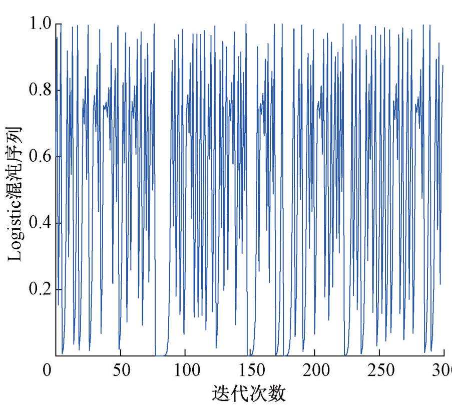
：$\mu \in (0,4]$；k ，$x \in (0,1)$。x_0，μ $[3.569\,9, 4.0]$，[18]。μ ，Logistic x 1 。



1

Fig. 1 Sequence distribution under different bifurcation parameters

1 , $0<\mu\leqslant3.5699$, x ; μ , x , , $3.5699<\mu\leqslant4$, x 0 1 ; $\mu=4$, 。 , $\mu=4$ Logistic , 300 , Logistic 2 。



2 Logistic

Fig. 2 Logistic chaotic sequence

(8) Logistic , 。

$$X = X_{lb} + (X_{lb} - X_{ub}) X_{k+1} \tag{8}$$

, X_{lb}、X_{ub} , , X 。

2)

SSA , , , , 。 , 。

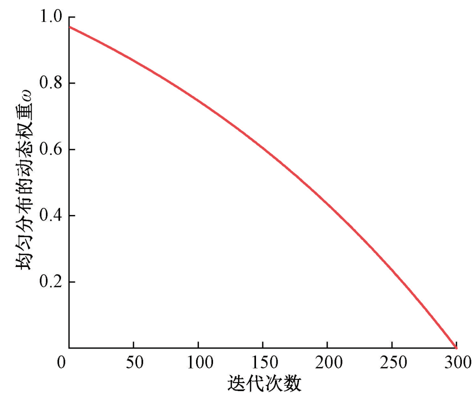
:

$$x_{id}^{t+1} = \begin{cases} x_{id}^{t} \cdot \omega \cdot \exp\left(\dfrac{-i}{\alpha \cdot T}\right), & R_2 < ST \\ x_{id}^{t} + Q \cdot \boldsymbol{L}, & R_2 \geqslant ST \end{cases} \tag{9}$$

, ω :

$$\omega = \delta \begin{pmatrix} \omega_{\text{initial}} - (\omega_{\text{initial}} - \omega_{\text{final}}) \\ \times \dfrac{1}{e-1} \times \left(e^{\frac{t}{T_{\text{iteration}}}} - 1\right) \end{pmatrix} \tag{10}$$

: ω_{initial} ω_{final} ; $\delta \in [0,1]$ 。 (10) 3 。



3

Fig. 3 Uniformly distributed dynamic adaptive weight change curve

3 , , ω , ; , ω , 。 , δ ω , ; , ω , δ , ω , , 。

3)

, , , , 。 , [19], , SSA 。 [20] :

$$f(x) = \frac{1}{2b}\exp\left(-\frac{|x-a|}{b}\right), \quad -\infty < x < \infty \tag{11}$$

: a ; b 。 $u \in [0,1]$, β:

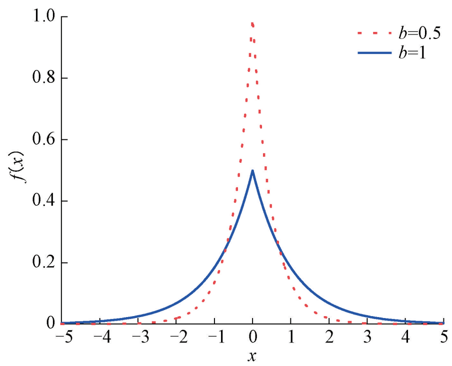
$$\beta = \begin{cases} a - b\ln(u), & u \leqslant \dfrac{1}{2} \\ a + b\ln(u), & u > \dfrac{1}{2} \end{cases} \tag{12}$$

:

$$
\begin{aligned}
y_i^{(1)} &= x_i^{(1)} + \beta \left| x_i^{(1)} - x_i^{(2)} \right| \\
y_i^{(2)} &= x_i^{(2)} + \beta \left| x_i^{(1)} - x_i^{(2)} \right|
\end{aligned} \tag{13}
$$

b

4 。



4

Fig. 4 Laplace density function curve

4 , $b=1$ $f(x)$, ,

。 :

$$
\beta = \begin{cases} a - \ln(u), u \leqslant \dfrac{1}{2} \\ a + \ln(u), u > \dfrac{1}{2} \end{cases}, r \leqslant 1 - t/T_{\max} \tag{14}
$$

$b=0.5$, $f(x)$, ,

, 。 :

$$
\beta = \begin{cases} a - \dfrac{1}{2}\ln(u), u \leqslant \dfrac{1}{2} \\ a + \dfrac{1}{2}\ln(u), u > \dfrac{1}{2} \end{cases}, r > 1 - t/T_{\max} \tag{15}
$$

: $r \in [0,1]$; t 、$T_{\max}$, $1-t/T_{\max} \in [0,1]$ 。

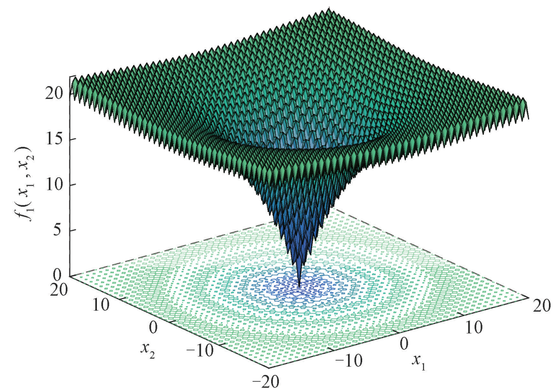
2.2 算法测试

Ackely Griewank , MISSA , SSA 、 [21] (particle swarm optimization, PSO) [22] (grey wolf optimizer, GWO) , 300, 3。

Ackely , 5 , (16) 。

$$
f_1(x) = -20\exp\left(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - \exp\left(\frac{1}{d}\sum_{i}^{d}\cos(2\pi x_i)\right) + 20 \tag{16}
$$

, x $[-32,32]$, 0。



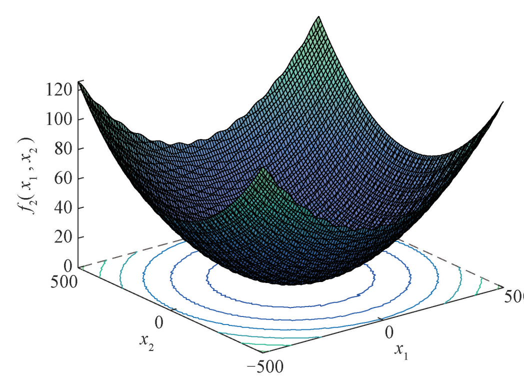
5 $f_1(x)$

Fig. 5 Test function $f_1(x)$

Griewank , 6 , (17):

$$
f_2(x) = \frac{1}{4\ 000}\sum_{i=1}^{n}(x_i^2) - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \tag{17}
$$

, x $[-600,600]$, 0。

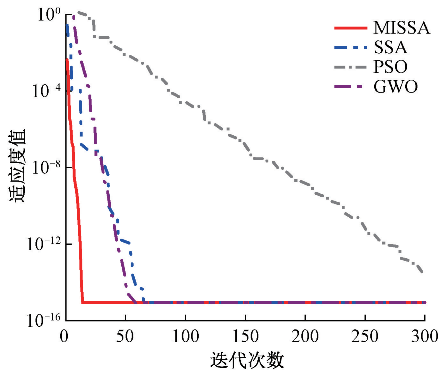


6 $f_2(x)$

Fig. 6 Test function $f_2(x)$

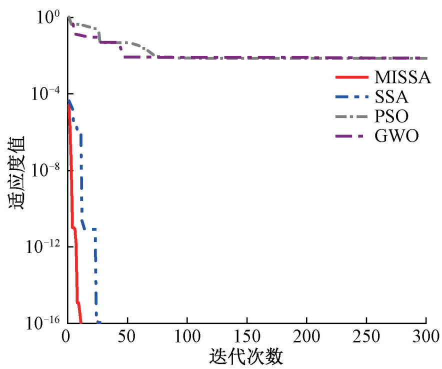
$f_1(x)$ $f_2(x)$ 30 , 7 8 。

7 8 , f_1 , PSO , MISSA 14 , SSA GWO 65 53 。 f_2 , 4 , GWO PSO , ; MISSA 12 0, SSA 33 。 f_1 f_2 4 , 、 SSA 、PSO GWO 。



7 MISSA,SSA,PSO GWO $f_1(x)$

Fig. 7 The $f_1(x)$ function optimization process of MISSA, SSA, PSO and GWO



8 MISSA,SSA,PSO GWO $f_2(x)$

Fig. 8 The $f_2(x)$ function optimization process of MISSA, SSA, PSO and GWO

3 BiLSTM 算法

BiLSTM (long short-term memory, LSTM) , LSTM 、[23]。

,

。

$$f_t = \sigma[\boldsymbol{W}_f(h_{t-1}, \boldsymbol{x}_t) + \boldsymbol{b}_f] \tag{18}$$

: σ Sigmoid ; $\boldsymbol{x}$, h_{t-1} ; t ; $\boldsymbol{W}$ $\boldsymbol{b}$ 。

, Sigmoid tanh

:

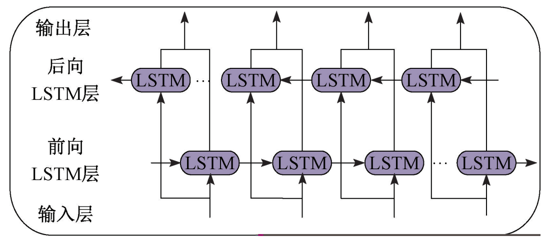
$$\begin{cases} i_t = \sigma[\boldsymbol{W}_i(h_{t-1}, \boldsymbol{x}_t) + \boldsymbol{b}_i] \\ \widetilde{C}_t = \tanh[\boldsymbol{W}_c(h_{t-1}, \boldsymbol{x}_t) + \boldsymbol{b}_c] \\ C_t = f_t C_{t-1} + i \widetilde{C}_t \end{cases} \tag{19}$$

: i_t ; C_t , $\widetilde{C}_t$ tanh 。

C_t, h_t, :

$$\begin{cases} o_t = \sigma[\boldsymbol{W}_o(h_{t-1}, \boldsymbol{x}_t) + \boldsymbol{b}_o] \\ h_t = o_t \tanh C_t \end{cases} \tag{20}$$

LSTM LSTM BiLSTM [24], 9 。



9 BiLSTM

Fig. 9 Schematic diagram of BiLSTM structure

9 , LSTM $\overrightarrow{h}_t$ LSTM $\overleftarrow{h}_t$, BiLSTM y_t [25]。BiLSTM

:

$$\overrightarrow{h}_t = LSTM(\boldsymbol{x}_t, \overrightarrow{h}_{t-1}) \tag{21}$$

$$\overleftarrow{h}_t = LSTM(\boldsymbol{x}_t, \overleftarrow{h}_{t+1}) \tag{22}$$

$$y_t = \boldsymbol{W}_{\overrightarrow{h}y}\overrightarrow{h}_t + \boldsymbol{W}_{\overleftarrow{h}y}\overleftarrow{h}_t + \boldsymbol{b}_y \tag{23}$$

: $\boldsymbol{W}_{\overrightarrow{h}y}$ $\boldsymbol{W}_{\overleftarrow{h}y}$; $\boldsymbol{b}_y$

。

3.1 基于 BiLSTM 的深度网络构建

10 , BiLSTM 、BiLSTM 、 、Softmax 。 9 ; KPCA BiLSTM ; BiLSTM ; Softmax , (24) 。

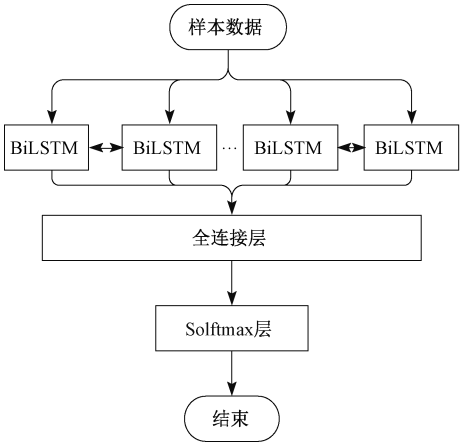
$$\mathrm{Softmax}(z_i) = \frac{e^{z_i}}{\sum_{c=1}^{C} e^{z_c}} \tag{24}$$

, z , z_i z i ; C 。

3.2 基于 MISSA-BiLSTM 的变压器故障诊断模型

BiLSTM , MISSA BiLSTM , 。BiLSTM [26],

:



10 BiLSTM

Fig. 10 BiLSTM deep network construction

G_1、 G_2、 ζ。

BiLSTM 1 。

表 1 BiLSTM 超参数寻优区间

Table 1 BiLSTM hyperparameter optimization interval

G_1	[0~100]
G_2	[0~100]
ζ	[0.001~0.1]

MISSA-BiLSTM

11 。

1) N, D,

T, (8) , ,

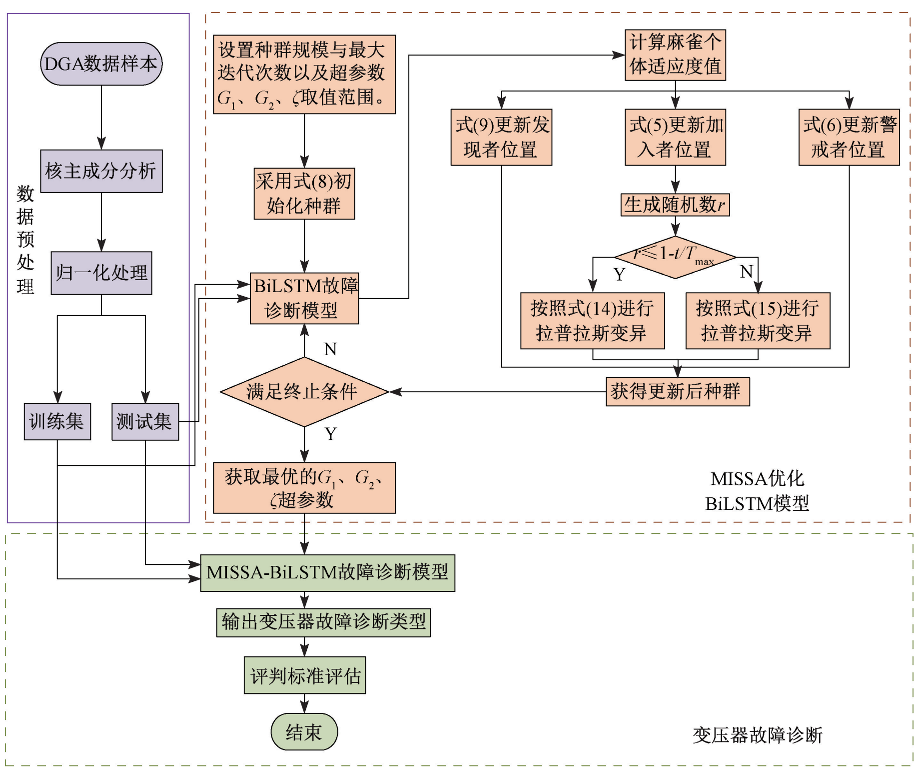
。

2) BiLSTM ,

。

3)

, 。



11 MISSA-BiLSTM

Fig. 11 Fault diagnosis model based on MISSA-BiLSTM

4) (9)、(5)、(6) 、 、 ,

；

: r, $r\leq 1-t/T_{max}$, (14)

, (15) 。

5) , 。

。

6) , ,

BiLSTM, 4)

7) MISSA MISSA-BiLSTM , Softmax 。

4 实验测试及分析

3 : [27-28]、IEC TC 10 。 , (H_2、CH_4、C_2H_6、C_2H_4、C_2H_2) 。 5 。 5 , [29]。 , 9 CH_4/ H_2、C_2H_2/C_2H_4、C_2H_4/C_2H_6、C_2H_2/(TH)、H_2/(H_{2+} TH)、C_2H_4/(TH)、C_2H_6/(TH)、CH_4/(TH)、($CH_{4+}C_2H_4$)/(TH) , TH , (CH_4、C_2H_6、C_2H_4、C_2H_2) 。 974 750 8∶2 。 , 。 0~6, 、 、 、 、 、 7 。 2 。

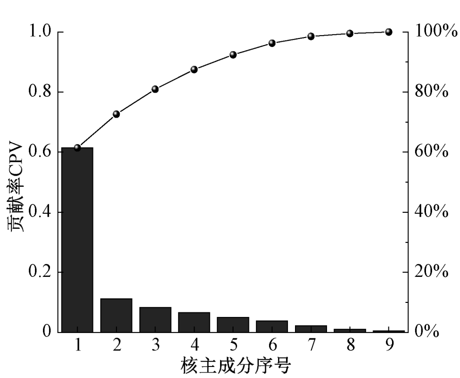
表 2 样本数据的分布

Table 2 Distribution of sample data

	76	98	79	84	89	78	96
	27	20	18	24	23	13	25

4.1 变压器故障数据预处理

KPCA 9 , 。 Pareto 12 。



12

Fig. 12 Pareto diagram of nuclear principal component analysis

12 , 4 0.875 2, 4 85% , 4 , 10 , 3 。

表 3 主成分的特征向量

Table 3 Eigenvectors of principal components

1	2	3	4
0.413 9	−0.110 9	−0.021 7	0.009 5
−0.111 2	0.020 0	0.168 8	0.048 0
0.172 5	−0.120 8	−0.005 3	−0.017 5
−0.115 3	0.241 0	0.413 4	0.201 3
−0.174 2	0.139 5	0.289 9	0.109 5
0.053 1	−0.093 5	0.032 7	−0.013 5
−0.131 8	0.048 0	0.175 3	0.080 6
−0.198 6	0.039 1	−0.097 7	0.067 9
0.596 9	−0.059 2	0.041 3	−0.014 1
0.142 4	−0.004 2	0.240 6	0.110 1

4.2 不同故障诊断模型诊断结果分析

K (K-nearest neighbor, KNN)、(extreme learning machine, ELM)、SVM、(extreme gradient boosting, XGBoost) 4 , BiLSTM , 30 , , 、 , 4 。

表 4 不同模型重复训练结果

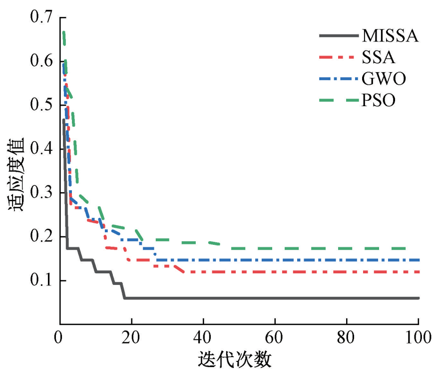
Table 4 Repeated training results of different models

KNN	0.780 0	0.713 3	0.754 0
ELM	0.753 3	0.686 7	0.727 3
SVM	0.766 7	0.700 0	0.734 6
XGBoost	0.800 0	0.746 7	0.760 6
BiLSTM	0.840 0	0.773 3	0.808 6

4 , BiLSTM 30 0.808 6。 , 。

4.3 算法寻优比较

MISSA BiLSTM ,
PSO、GWO SSA 。
13 。



13
Fig. 13 Fitness change curves

13 ,4 PSO
。 Logistic 、
MISSA,
18 , ,
MISSA BiLSTM
。

4.4 不同故障诊断模型对比分析

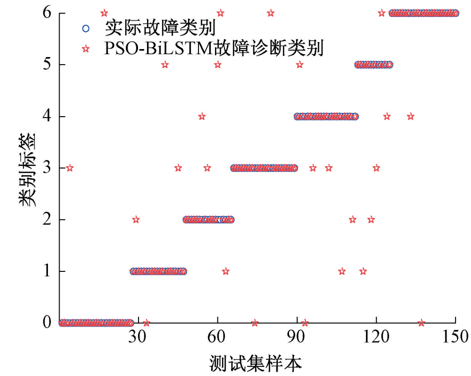
KPCA MISSA-BiLSTM
, Softmax PSO、GWO
SSA BiLSTM , 5,
14~17 。

表 5 变压器故障诊断结果

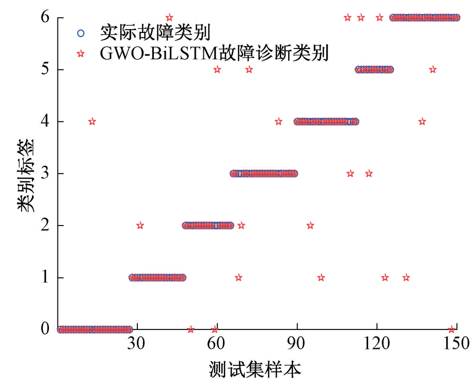
Table 5 Transformer fault diagnosis results

	PSO-BiLSTM	GWO-BiLSTM	SSA-BiLSTM	MISSA-BiLSTM
	0.851 8	0.962 9	0.962 9	1.000 0
	0.800 0	0.850 0	0.950 0	0.900 0
	0.722 2	0.888 9	0.833 3	0.888 9
	0.916 7	0.833 3	0.875 0	0.958 3
	0.739 1	0.782 6	0.826 0	0.956 5
	0.615 3	0.692 3	0.846 1	0.769 2
	0.920 0	0.880 0	0.840 0	1.000 0

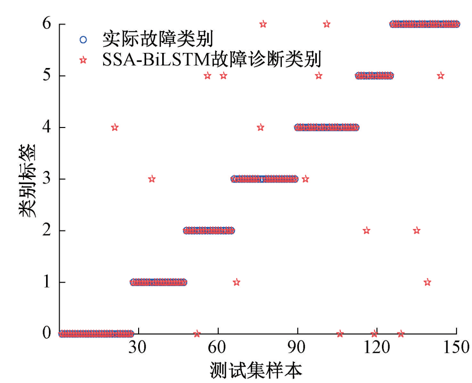
14~17 , MISSA-BiLSTM
, ,



14 PSO-BiLSTM
Fig. 14 PSO-BiLSTM fault diagnosis results

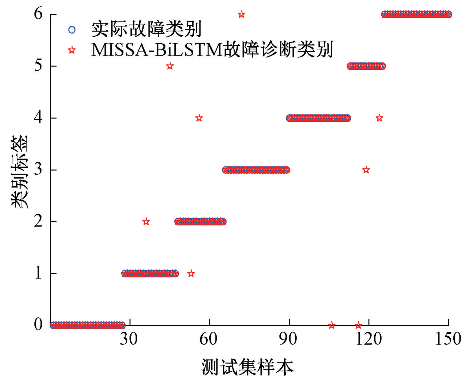


15 GWO-BiLSTM
Fig. 15 GWO-BiLSTM fault diagnosis results



16 SSA-BiLSTM
Fig. 16 SSA-BiLSTM fault diagnosis results

, , 94%。PSO-BiLSTM、
GWO-BiLSTM SSA-BiLSTM
82.67%、85.33%、88%。 ,
BiLSTM ,
。



17 MISSA-BiLSTM

Fig. 17 MISSA-BiLSTM fault diagnosis results

5 结 论

Logistic 、

，

， ，

。 MISSA

BiLSTM ， BiLSTM

，

(KPCA) ，

。 PSO-BiLSTM、GWO-BiLSTM

SSA-BiLSTM ，

，

。

参考文献

[1] , , , .

[J].

,2021,36(10):2161-2168.

FAN X H, LIU J F, ZHANG Y Y, et al. Evaluation of transformer oil-immersed paper insulation aging state based on frequency domain dielectric spectroscopy and support vector machine [J]. Transactions of China Electrotechnical Society,2021,36(10):2161-2168.

[2] YANG D, QIN J, PANG Y, et al. A novel double-stacked autoencoder for power transformers DGA signals with imbalanced data structure[J]. IEEE Transactions on Industrial Electronics, 2021, DOI:10.1109/TIE.2021.3059543.

[3] , , , .

[J]. ,

2020,34(1):81-89.

ZHANG CH L,HE Y G,DU B L, et al. Intelligent fault diagnosis method of power transformer based on deep learning [J]. Journal of Electronic Measurement and Instrumentation,2020,34(1):81-89.

[4] , , . ISSA SVM

[J]. ,2021,35(3):

123-129.

LI H M,ZHANG Y,ZHANG Y. Research on transformer fault diagnosis based on ISSA optimized SVM [J]. Journal of Electronic Measurement and Instrumentation, 2021,35(3):123-129.

[5] , , , .

[J].

,2021,36(S1):84-94.

GE L J, LIAO W L, WANG Y S, et al. Transformer fault data enhancement method based on improved automatic encoder under conditions of insufficient data[J]. Transactions of the Chinese Society of Electrical Engineering,2021,36(S1):84-94.

[6] ZHOU Y CH,YANG X H, TAO L Y, et al. Transformer fault diagnosis model based on improved gray wolf optimizer and probabilistic neural network[J]. Energies, 2021,14(11): DOI:10.3390/EN14113029.

[7] , , . VSRP β-GWO-SVM

[J]. , 2021,

47(10):3635-3641.

XIE G M, NI L SH, CAO Y. Transformer fault identification method based on VSRP and β-GWO-SVM[J]. High Voltage Technology, 2021, 47(10):3635-3641.

[8] , .

[J]. ,2019,56(15):143-147.

WANG CH M, ZHU Y L. Transformer fault diagnosis based on deep noise reduction extreme learning machine [J]. Electrical measurement & instrumentation, 2019,56(15):143-147.

[9] , , , .

[J]. ,2015,51(8):49-53.

LYU ZH, ZHOU Q, ZHOU K, et al. Transformer fault diagnosis based on genetic algorithm improved extreme learning machine [J]. High Voltage Apparatus, 2015, 51(8):49-53.

[10] , , , .
[J]. , 2018, 44 (4): 1078-1084.
DU X M, QIN J F, GUO SH Y, et al. Text mining of typical failure cases of power equipment [J]. High Voltage Technology, 2018, 44(4): 1078-1084.

[11] , , , .
Bi-LSTM DGA [J]. , 2020, 40(8): 184-193.
WU X X, HE Y G, DUAN J J, et al. Bi-LSTM transformer DGA fault diagnosis method considering complex time series correlation characteristics[J]. Power Automation Equipment, 2020, 40(8): 184-193.

[12] DEVI A S, MARAGATHAM G, K BOOPATHI, et al. Hourly day-ahead wind power forecasting with the EEMD-CSO-LSTM-EFG deep learning technique [J]. Soft Computing, 2020, 24(16): 12391-12411.

[13] , , , .
[J]. , 2021, 42(4): 160-168.
FU H, ZHAO J CH, FU Y, et al. Soft measurement of coal mine gas emission based on quantum particle swarm and deep learning [J]. Chinese Journal of Scientific Instrument, 2021, 42(4): 160-168.

[14] CHEN B, HUANG D, ZHANG F. The modeling method of a vibrating screen efficiency prediction based on KPCA and LS-SVM [J]. International Journal of Pattern Recognition and Artificial Intelligence, 2019, 33(7): 1950009.1-1950009.21.

[15] XUE J, SHEN B. A novel swarm intelligence optimization approach: Sparrow search algorithm [J]. Systems Science & Control Engineering An Open Access Journal, 2020, 8(1): 22-34.

[16] DOKEROGLU T, SEVINE E, KUCUKYILMAZ T, et al. A survey on new generation metaheuristic algorithms[J]. Computers & Industrial Engineering, 2019, 137: 106040.

[17] YU Y, GAO SH, CHENG SH, et al. CBSO: A memetic brain storm optimization with chaotic local search [J]. Memetic Computing, 2018, DOI: 10.1007/s12293-017-0247-0.

[18] ZHANG C, DING S. A stochastic configuration network based on chaotic sparrow search algorithm[J]. Knowledge-Based Systems, 2021, 220(10): 106924.

[19] , , .
[J/OL]. : 1-14[2021-08-02]. http://kns.cnki.net/kcms/detail/11.5602.tp.20210603.1301.004.html.
WANG Y G, LI X, GUAN L ZH. An improved whale optimization algorithm for solving high-dimensional optimization problems [J/OL]. Computer Science and Exploration: 1-14[2021-08-02]. http://kns.cnki.net/kcms/detail/11.5602.tp.20210603.1301.004.html.

[20] DEEP K, BANSAL J C. Optimization of directional overcurrent relay times using laplace crossover particle swarm optimization (LXPSO) [C]. World Congress on Nature & Biologically Inspired Computing, IEEE, 2010.

[21] , , , . PSO-ELM
AdaBoost [J]. , 2020, 56(5): 39-46.
HUANG X B, WANG X, TIAN Y, et al. Transformer fault diagnosis method based on PSO-ELM fusion dynamic weighted AdaBoost [J]. High Voltage Apparatus, 2020, 56(5): 39-46.

[22] , , , .
[J]. ( ), 2020, 54(11): 2266-2272.
XIE L, HENG X D, LIU Y, et al. Transformer fault diagnosis based on linear discriminant analysis and step-by-step machine learning [J]. Journal of Zhejiang University (Engineering Science Edition), 2020, 54(11): 2266-2272.

[23] SHUAI Z, RISTOVSKI K, FARAHAT A, et al. Long short-term memory network for remaining useful life estimation[C]. 2017 IEEE International Conference on Prognostics and Health Management (ICPHM), IEEE, 2017.

[24] WANG SH X, WANG X, WANG SH M, et al. Bi-directional long short-term memory method based on attention mechanism and rolling update for short-term load forecasting[J]. International Journal of Electrical Power and Energy Systems, 2019, 109, DOI: 10.1016/j.ijepes.2019.02.022.

[25] , , , . Bi-LSTM

[J]. ,2021,45(7):2719-2730.

LI Y ZH, LIU X L, XING F F, et al. Daily peak load forecasting based on Bi-LSTM and feature correlation analysis[J]. Power System Technology, 2021, 45 (7): 2719-2730.

[26] LI W, NG W, WANG T, et al. HELP: An LSTM-based approach to hyperparameter exploration in neural network learning[J]. Neurocomputing, 2021, 442 (11), DOI: 10. 1016/J. NEUCOM. 2020. 12. 133.

[27] . [D]. : ,2013.

YIN J L. Research on fault diagnosis method of oil-immersed power transformer based on correlation vector machine[D]. Bao Ding: North China Electric Power University, 2013.

[28] . [D]. : ,2019.

TIAN X F. Research on transformer fault diagnosis based on improved bat algorithm to optimize support vector machine[D]. Cheng Du: Xihua University, 2019.

[29] , , , . XGBoost [J]. , 2021,41(2):200-206.

ZHANG Y W, FENG B, CHEN Y, et al. Optimization of XGBoost based fault diagnosis method of oil-immersed transformer based on genetic algorithm[J]. Electric Power Automation Equipment, 2021, 41(2): 200-206.

作者简介

王雨虹,2002 ,2008 ,2020 , , 、 。

E-mail: yuhong0804001@126.com

Wang Yuhong received her B. Sc. degree, M. Sc. degree, and Ph. D. degree all from Liaoning Technical University in 2002, 2008, and 2020, respectively. She is currently an associate professor at Liaoning Technical University. Her main research interests include coal mine safety detection, electrical information detection technology and fault diagnosis.

王志中( ),2015 , , 。

E-mail: 766659596@qq.com

Wang Zhizhong (Corresponding author) graduated from Shandong Agricultural Engineering College in 2015. He is currently a master student at Liaoning Technical University. His main research interests include electrical information detection technology and fault diagnosis.