

深度学习在电力系统预测中的应用

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摘要 电力系统预测主要包括负荷预测、出力预测以及健康状态预测等。通过负荷预测, 可以优化电力生产规划, 从而更好地实现电能的精细化分配; 通过出力预测, 可以有效提升新能源电力消纳能力, 实现电能的充分及合理利用; 通过电力设备健康状态预测, 可以及时发现设备运行隐患, 从而进一步保障电力系统平稳安全运行。深度学习凭借其卓越的特征分析和预测能力, 被广泛应用于电力系统运行及维护。本文首先归纳介绍了电力系统预测深度学习模型的特点、适用场景; 其次, 梳理了深度学习在面向民用及工业场景负荷预测、光伏及风电出力预测、机械及非机械设备健康状态预测中的应用前沿; 最后, 对深度学习在电力系统预测中所面临的关键问题、发展趋势进行了总结和展望。

关键词 电力系统; 深度学习; 负荷预测; 出力预测; 健康状态预测

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A survey of power system prediction based on deep learning

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ABSTRACT Power system is one of the largest and complex artificial engineering in the modern society. With the development of intelligence, digitization and long-distance technology, a large number of multi-source, multi-state and heterogeneous operational data have emerged. As a new trend direction of machine learning, deep learning has shown potential in data feature extraction and pattern recognition. Because of its excellent ability in data analysis and prediction, it is widely used in power system, which has a significant impact on optimizing power production planning, improving power production efficiency and energy utilization, and ensuring the smooth operation of the system influence. Based on massive quantities of data and by means of deep learning, it can better fit the nonlinear relationship between the factors affecting the subsequent operational state of the system, so as to further improve the prediction accuracy. Power system prediction includes load forecasting, new energy power prediction and state-of-health prediction. Power production planning can be optimized using load forecasting; thus, electrical energy can be finely dispatched. The capacity of new energy power consumption is improved through power prediction to reasonably use electrical energy. Potential equipment hazards can be timely found using power equipment health state prediction, thereby ensuring safe and smooth operation. First, in this paper, the characteristics and applicable scenarios of typical deep learning models are introduced, among them, deep belief network and stacked auto encoder belong to stack structure, so the structure is flexible and easy to expand, which is suitable for the modeling and feature extraction of unrelated data type; convolutional neural network shares convolution kernel internally to reduce the number of network parameters and is good at processing high-dimensional data type; recurrent neural network has feedforward and feedback connections, so

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it is suitable for processing sequence data with pre and post dependence. Second, the application frontiers of predictive power systems based on deep learning are reviewed, which include civil and industrial scenarios, photovoltaic and wind power, mechanical and non-mechanical equipment health state prediction. Finally, facing the challenges of power system in energy efficient allocation, high proportion of new energy power consumption, highly stable operation of power equipment and so on, the key problems and future development trends are presented.

KEY WORDS power system; deep learning; load forecasting; new energy power prediction; health state prediction

现代电力系统结构日益复杂, 规模不断扩大, 若仅仅依靠传统的物理建模方法, 难以充分应对运行分析需求^[1]. 结合多源数据, 深度学习已广泛应用于电力系统预测. 通过采集运维数据、设备数据等电力系统各环节基础数据, 结合深度学习技术, 可以较好地拟合影响电力系统后续运行状态各因素之间的非线性关系^[2], 建立预测模型, 实现电力系统预测, 如负荷预测^[3]和出力预测^[4]等. 本文着重对目前研究较多的几种预测, 包括电力系统负荷预测、新能源出力预测和电力设备健康状态预测的应用情况进行归纳和梳理. 针对不同的应用场景, 电力系统负荷预测分为面向民用场景的负荷预测和面向工业场景的负荷预测; 针对不同的预测对象, 出力预测分为光伏出力预测和风电出力预测; 针对不同的设备种类, 健康状态预测分为机械类设备健康状态预测和非机械设备健康状态预测.

1 深度学习模型

1.1 深度信念网络

深度信念网络 (Deep belief networks, DBN) 改善了模型训练易陷入局部最优, 且学习 (收敛) 耗时偏长以及需要大量标签数据等问题^[5]. 由于采用前馈式网络结构, DBN 适用于处理前后无关联序列数据, 并凭借深度特征提取能力强等优点, 被广泛应用于电力系统预测领域, 为新能源出力预测^[6-7]、负荷预测^[8]、电力设备健康状态预测^[9]等方面提供了新的解决思路.

1.2 卷积神经网络

卷积神经网络 (Convolutional neural networks, CNN) 与 DBN 相比, 最主要的差别在于随机初始值和逐层训练方式, 并且在卷积操作后, 数组内的元素仍可保留原始位置关系^[10]. 同时, 由于在运算中共享卷积核, 因而进一步减少了模型参数数量, 并适用于处理多维数组. 在电力系统预测分析实际应用场景中, 常用于考虑时空相关性的负荷预测、出力预测及健康状态识别等^[11-13].

1.3 循环神经网络

循环神经网络 (Recurrent neural networks, RNN) 由于各层神经元之间包含前馈和反馈连接^[14], 因而适用于处理具有前后依赖关系的序列数据. 为解决 RNN 只能记忆“短期”信息这一缺陷^[15], 一些改进后的 RNN 结构被提出, 其中, 门控循环单元 (Gate recurrent unit, GRU) 和长短期记忆模型 (Long short term memory, LSTM) 即为典型代表^[16-17]. RNN 常用于改善功率剧烈波动场景下的预测精度, 如面向工业现场的负荷预测^[18]、复杂天气条件下的新能源出力预测^[19]等.

1.4 堆叠自编码

堆叠自编码 (Stacked auto encoders, SAE) 与 DBN 模型结构相似, 二者主要区别在于: 每层自编码器之间为非对称连接^[20], 因而模型结构更加易于拓展. 研究者在原始自编码器的基础上进行了一系列优化, 使之更适用于电力系统预测, 如基于去噪自编码器的配电设备健康状态预测^[21], 基于卷积自编码器的光伏出力预测^[22]等.

基于以上分析, 几种典型的深度学习预测模型对比如表 1 所示.

2 电力系统负荷预测

电力系统负荷预测是指在一定时间尺度下, 通过探寻负荷历史数据中的规律, 即建立输入输出之间的非线性关系, 来预测未来电力负荷需求值, 对减少由于意外负荷变化引起的电力调度问题, 优化区域内电力工程建设规划, 保证电力系统的稳定运行, 具有重要意义^[23-24]. 按照应用场景不同, 可分为面向民用场景的负荷预测和面向工业场景的负荷预测. 选取了 19 篇负荷预测代表性文献, 分类总结如表 2 所示.

由表 2 可知, 负荷预测多采用 RNN 模型, 占总数的 52.6%.

2.1 面向民用场景的负荷预测

面向民用场景的用电负荷具有一定的分散性, 通常要将多个用电单元整体考虑. Cheng 等^[30]提出了一种基于 CNN 的民用建筑负荷预测方法,

表 1 典型的深度学习预测模型对比

Table 1 Comparison of typical deep learning prediction models

Model	Main feature	Apply data type	Typical application scenario
DBN	Unsupervised learning No need for large number of label data, and the training difficulty is low	Sequence data without correlation before and after(Time series data)	Load forecasting, power prediction, equipment health state prediction
CNN	Supervised learning Random initial value, sample data without preprocessing	Sequence data without correlation before and after, (Multidimensional data)	Load forecasting under multi energy spatiotemporal coupling, power prediction considering spatiotemporal correlation, health state forecasting
RNN	Supervised learning Both feedforward and feedback connections are included	Sequence data correlated before and after	Load forecasting and power prediction under the scenario of severe power fluctuation
SAE	Unsupervised learning Asymmetric connection, simple structure, easy to expand	Sequence data without correlation before and after	Power prediction, equipment health state prediction

表 2 电力系统负荷预测分类

Table 2 Classification of power system load forecasting

Deep learning	Civil scenario load forecasting	Industrial scenario load forecasting	Proportion/%
DBN	[8]	[25–27]	21.1
CNN	[13, 28–30]	–	21.1
RNN	[31–37]	[17,18,38]	52.6
SAE	[39]	–	5.2

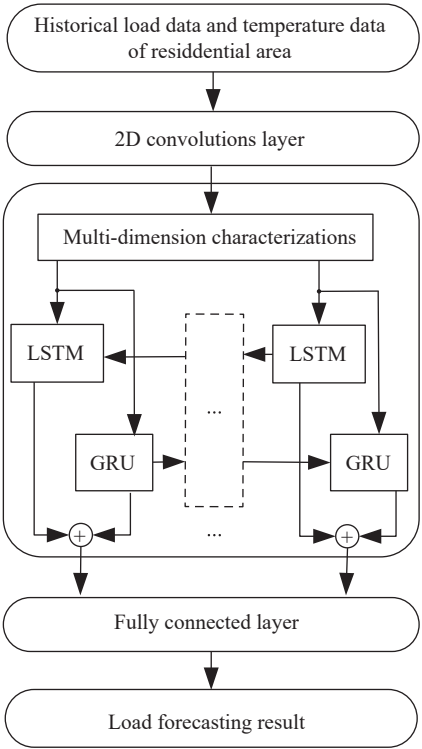


图 1 基于双向 LSTM-GRU 的居民区用电负荷预测

Fig.1 Residential area load forecasting based on bidirectional LSTM-GRU

首先, 将历史负荷序列按时间依赖程度划分为两个部分; 并将来自多个数据采集位点的温度、湿度等气象数据进行聚类; 其次, 结合区域内历史负荷和气象数据, 通过在 CNN 网络中引入压缩和激励

网络, 自动得出不同特征的重要程度, 并用权值表示. 在此基础上, 结合时间依赖程度, 对关联程度不同的特征做进一步加强或抑制, 改善了特征冗余问题, 实验结果表明, 相对于采用支持向量机、LSTM 等方法, 这种方法的预测精度提升了 15.1% ~ 20.9%. Peng 等^[39] 利用 SAE 提取了不同层次的历史数据特征, 在此基础上, 分别构建了不同参数和结构的预测模型, 通过将每个预测模型的输出进行叠加重构, 获取负荷预测输出.

Hosein 等^[36] 提出了一种基于 LSTM-GRU 的负荷预测模型, 如图 1 所示. 将历史负荷数据和温度数据的输入序列重新排列成二维矩阵:

$$L = \begin{bmatrix} L_1 & L_2 & \cdots & L_{24} \\ L_{25} & L_{26} & \cdots & L_{48} \\ \vdots & \vdots & \ddots & \vdots \\ L_{(D-1) \times 24 + 1} & L_{(D-1) \times 24 + 2} & \cdots & L_{24D} \end{bmatrix} \quad (1)$$

$$T = \begin{bmatrix} T_1 & T_2 & \cdots & T_{24} \\ T_{25} & T_{26} & \cdots & T_{48} \\ \vdots & \vdots & \ddots & \vdots \\ T_{(D-1) \times 24 + 1} & T_{(D-1) \times 24 + 2} & \cdots & T_{24D} \end{bmatrix} \quad (2)$$

式中, $L_1 \dots L_{24D}$ 和 $T_1 \dots T_{24D}$ 分别为历史负荷值和环境温度值. 在特征提取阶段, 使用二维卷积层提取电力负荷和温度数据的重要信息, 卷积核的行数 f_{col} 和列数 f_{row} 分别为:

$$f_{\text{col}} = \{n | n = 1, 2, \dots, 24 : \text{ACC}_n > \text{TH}\} \quad (3)$$

$$f_{\text{row}} = \{m + 1 | m \geq 0 : \text{ACC}_{24m+1} > \text{TH}\} \quad (4)$$

式中, ACC_n 表示滞后阶数, 在负荷时间序列中, $\text{TH} > 0.8$; 在温度时间序列中, $\text{TH} > 0.9$. 完成特征提取后, 通过 GRU 前向传播和 LSTM 反向传播, 可同时利用前后两个时间间隔内的特征信息. 相对基于前馈神经网络或支持向量机等方法, 预测精度提高了 6.9% ~ 11.7%.

现有大多数深度学习方法只能单独捕获认知不确定性(预测模型结构或超参数的不确定性)或

偶然不确定性(输入数据的不确定性),并转化为模型参数或输出的概率分布^[40]。为此,Sun 等^[37]通过对 LSTM 的网络权值和偏差参数分别构造先验分布以及推导输入数据的后验分布,同时捕获认知及偶然不确定性,结果表明,与未引入贝叶斯估计的 LSTM 预测模型相比,预测结果的均方根误差降低了 27.6%。

2.2 面向工业场景的负荷预测

与民用或商业建筑用电方式不同,工业用电场景需考虑大功率冲击负荷带来的影响,相比民用场景下的负荷预测,工业场景随机性波动较强,负荷预测难度相对更高^[41-42]。

工业电力系统各用电环节之间通常会存在一定的耦合关系,Mao 等^[27]提出了一种基于 LSTM 的负荷预测模型,通过增加样本多样性来减少模型的方差,并引入参与因子来表示相邻节点之间的耦合关系,预测结果的平均误差降低了 25.4%。

Kong 等^[43]提出了一种基于 DBN 的工业场景负荷预测方法,在模型优化阶段,通过将受限玻尔兹曼机(Restricted boltzmann machine, RBM)中的可见层节点二值变量替换为带独立高斯噪声的实值变量,来构造高斯-伯努利受限玻尔兹曼机(Gaussian-Bernoulli RBM, GB-RBM),以此来解决实值数据转换为二进制数据时,易产生噪声的问题^[38]。GB-RBM 的能量函数 $E(v, h|\theta)$ 以及可见单元 v_i 和隐藏单元 h_j 状态为 (v, h) 时的概率分布 $P(v, h|\theta)$ 分别为:

$$E(v, h|\theta) = - \sum_{i=1}^m \frac{(v_i - a_i)^2}{2\sigma_i^2} - \sum_{j=1}^k b_j h_j - \sum_{i=1}^m \sum_{j=1}^k \frac{v_i}{\sigma_i} W_{ij} h_j \tag{5}$$

$$P(v, h|\theta) = \frac{e^{-E(v, h|\theta)}}{\sum_{v, h} e^{-E(v, h|\theta)}} \tag{6}$$

式中, $\theta = \{W, a_i, b_j\}$ 为 GB-RBM 的结构参数; W 表示 v_i 与 h_j 之间的连接权重; a_i 表示 v_i 的偏置; b_j 表示 h_j 的偏置; σ_i 为 v_i 对应的高斯噪声的标准差。在性能优化阶段,通过采用误差约束和无监督学习的混合预训练方法,使 GB-RBM 模型的输出最大程度地拟合训练数据。实验结果表明,该方法可以更有效地处理实值序列数据,负荷预测的平均相对误差维持在 0.9% ~ 3.7%。

3 新能源出力预测

新能源出力预测主要通过构建反映光照强度、风速与输出功率之间非线性关系或功率变化趋势的预测模型,并充分利用历史出力数据、天气

数据,对深度学习模型进行训练,最终实现多尺度新能源未来出力情况的全面感知和精准预测^[44-45]。选取了 26 篇出力预测代表性文献,分类总结如表 3 所示。

表 3 电力系统出力预测分类
Table 3 Classification of power prediction

Deep learning	Photovoltaic power prediction	Wind power prediction	Proportion/%
DBN	[7, 44, 46]	[6, 47-50]	30.8
CNN	[11, 51-55]	[56-57]	34.6
RNN	[58-59]	[19, 60-61]	19.2
SAE	[22]	[2, 4, 62]	15.4

由表 3 可知,出力预测多采用 CNN 和 DBN 模型,分别占总数的 34.6% 和 30.8%。

3.1 光伏出力预测

光伏出力受云量、雨、雾等天气条件影响较大,需结合多源天气数据来获得较为精确的预测结果^[63]。文献[51-53]利用光伏发电历史数据、云量图像等,分解出包含不同特征信息的二维数组,预测了不同时间尺度下,不同容量光伏阵列的输出功率。Zang 等^[54]提出了一种基于混合 CNN 架构的光伏出力预测模型。通过引入 Residual network,建立前后层之间的“短路连接”,有助于训练过程中梯度的反向传播,改善了网络模型退化问题;通过引入 Dense convolutional network,增强了特征传播及特征复用,有助于降低模型的复杂程度。与预测模型中单独采用 Residual network 或 Dense convolutional network 架构相比,预测结果的均方误差分别降低了 22.2% 和 29.4%。Wang 等^[58]在基于长短时记忆递归神经网络的日前(0 ~ 24 h)光伏功率预测模型的基础上,考虑了基于序列相关性,通过同时跟踪光伏历史出力、天气等数据反映出的出力周期性波动和随机性波动规律,改善了训练数据不足时,LSTM 预测模型易出现的过拟合问题。

结合历史出力数据的不同特点,按早晚时段或高低频率等方式,先对预测对象进行分解,再按照分解结果分别进行预测是目前光伏出力预测的研究热点之一^[59, 64]。Yan 等^[55]利用快速傅立叶变换进行频谱分析,并结合历史数据特征,得到光伏功率波形高低频率的最佳分界点。如图 2 所示,在此基础上,使用 CNN 分别对光伏出力波动高频部分和低频部分进行预测,与反向传播神经网络相比,分解后采用的 CNN 预测模型,预测结果平均绝对百分比误差降低了 45.2%,预测模型的训练效率提高了 84.3%。

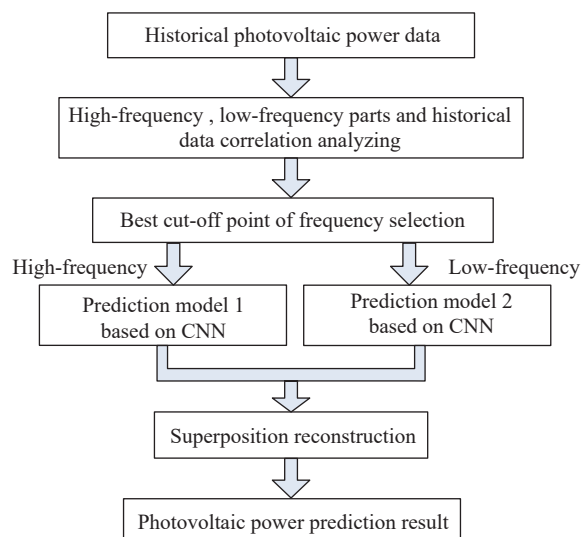


图2 基于CNN和频域分解的光伏出力预测

Fig.2 Photovoltaic power forecasting based on CNN and frequency-domain decomposition

3.2 风电出力预测

与光伏出力相比,风电出力受天气影响相对较小,但波动性及间歇性更强,因而历史数据的随机性更加明显^[65]. Khodayar等^[48]针对时空风速预测问题,采用递归LSTM模型来提取每个风电场

的时空特征,并将该时空特征输入图卷积神经网络中,与其他深度学习模型,如DBN和SAE相比,可以更好地从历史风速序列数据中学习更深层次的风电出力特征. Wang等^[66]考虑到输入数据的不确定性,通过K-means聚类对天气数据进行预处理,得到了对预测精度影响较大的样本数据,为提高DBN模型的预测性能,将可见层受限玻尔兹曼机替换为高斯-伯努利受限玻尔兹曼机,实验结果表明,相对于传统反向传播神经网络,预测精度提高了44.2%. Song等^[60]提出了一种集合经验模式分解-稀疏自编码器的超短期风电出力预测方法. 针对高频部分,建立了SAE预测模型;对于低频部分,引入了埃尔曼神经网络预测模型,与高低频同时采用埃尔曼神经网络的预测模型相比,加入SAE后的预测模型均方根误差降低了1.8%. Zhang等^[49]利用奇异谱分析,将原始风电功率序列分解为趋势和随机波动两部分,如图3所示,利用DBN和最小二乘支持向量机(Least square support vector machine, LSSVM)分别对趋势分量和随机波动分量进行预测,与两个分量都采用LSSVM相比,加入DBN后的预测结果均方根误差降低了21.2%.

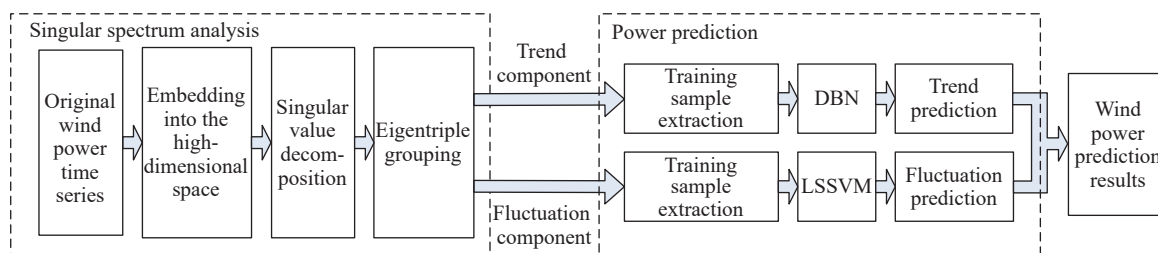


图3 基于DBN和奇异谱分析的风电出力预测

Fig.3 Wind power forecasting based on DBN and singular spectrum analysis

在整个出力预测过程中,仅采用一种深度学习模型,可能无法达到期望的预测效果^[50],在特征提取、模型训练等不同环节分别采用深度学习模型变得越来越流行,此类方法提高了风电出力的预测精度,但也增加了算法的复杂程度. Liu等^[57]将原始风电数据分解为时间特征(不同时段)、空间特征(相邻风机的数据)和运行特征(桨距角控制),在此基础上,通过CNN网络,从多个维度提取风电出力的潜在特征,最后训练相应数量的GRU编码器和全连接解码器单元,完成风电出力预测模型的构建,与单独采用GRU预测模型相比,预测结果的均方根误差降低了14.5%. Hossain等^[61]提出了一种由CNN、GRU和全连接神经网络组成的深度学习预测模型,CNN从原始数据中自

动学习复杂特征,并结合GRU模型,防止梯度随时间的推移而不断下降,与传统反向传播神经网络相比,预测模型的平均绝对百分比误差降低了24.1%.

4 电力设备健康状态预测

电力系统健康状态预测主要通过各类运行数据、系统参数以及专家知识等,结合深度学习方法建立预测模型,从而对关键设备未来的健康状况进行预测^[67]. 按照不同的部件划分,可以分为机械类设备健康状态预测和非机械类设备健康状态预测. 选取了18篇代表性文献,分类总结如表4所示.

由表4可知,电力系统健康状态预测多采用SAE模型,占总数的44.5%.

表 4 电力系统健康状态预测分类

Table 4 Classification of power system health state prediction

Deep learning	Mechanical equipment health state prediction	Non-mechanical equipment health state prediction	Proportion/%
DBN	[9, 68]	[69]	16.7
CNN	[70–71]	[11]	16.7
RNN	[72]	[73–75]	22.2
SAE	[67, 76–80]	[21, 81]	44.5

4.1 机械类设备健康状态预测

电力系统机械类设备健康状态预测主要集中在发电环节, 如风机齿轮、旋转轴承等部位. Jiang 等^[78]提出了一种基于去噪自编码器 (Denoising autoencoder, DAE) 的风机齿轮健康状态预测方法. 首先, 构建 DAE 模型, 同时将滑动窗应用于时间序列数据, 以获取不同健康状态特征之间的非线性关系和对时间的依赖程度; 其次, 利用多元正态数据离线建立参考故障指标; 最后, 将处理后的实时采集数据与参考故障指标阈值进行比较, 在线识别风机齿轮的潜在故障. 经实际历史数据验证, 此方法的预测误差率低于 10.0%.

当数据量足够时, 深度学习方法可提供更为良好的实现效果; 若没有足够的数量支撑时, 预

测效果往往难以体现^[82]. Lu 等^[72]在使用生成对抗网络进行数据扩充的基础上, 结合 ISO10816-3 : 2009 定义的各阶段轴承健康状态阈值对 LSTM 预测模型训练, 完成轴承退化轨迹预测, 经轴承运行故障数据集测试, 平均预测误差降低了 29.2%. 为了充分利用有限的原始输入数据, Meng 等^[79]在已有研究的基础上, 通过注入高斯噪声来改变正则化参数, 随着预测模型层数的增加, 正则化参数会不断优化, 与支持向量机和反向传播神经网络相比, 预测准确率分别提高了 46.1% 和 35.5%.

传统健康状态特征提取方式通常需要手动或在系统中增加额外的测量装置来获得设备运行数据, 为此, Yang 等^[71]考虑两种最常见的退化模式 (突然增加趋势和缓慢增加趋势), 为每个待训练模式建立了不同的早期健康状态判别模型和风机轴承健康状态 CNN 预测模型, 实际验证结果表明, 相对于已有预测模型, 如支持向量回归模型, 均方根误差降低了 58.3%. Xia 等^[80]结合历史数据, 将发电机轴承生命周期划分为 n 个健康阶段, 如图 4 所示, 利用相应退化阶段的训练数据, 构建并训练电机轴承健康状态预测模型, 与同样采用 SDA 进行特征提取, 但未进行健康阶段划分的方法相比, 预测平均相对误差降低了 18.7%.

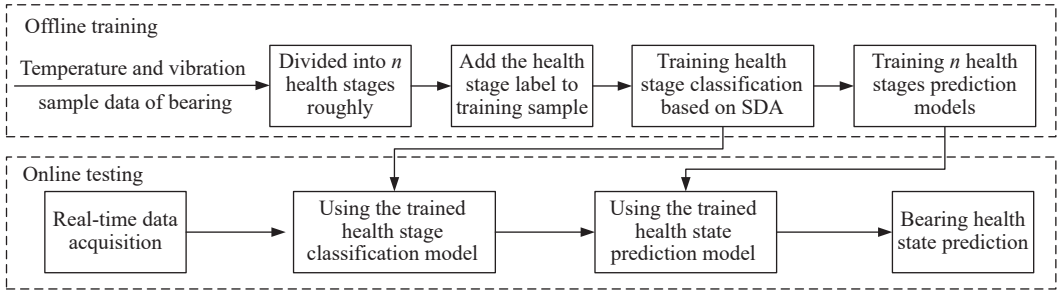


图 4 基于 SDA 的发电机轴承健康阶段划分及健康状态预测

Fig.4 Health stage segment and health state prediction of generator bearing based on SDA

4.2 非机械设备健康状态预测

非机械类设备健康状态预测多集中在电气控制装置、变压器等部位^[83], 在实际工况中, 这些设备的工作状态频繁变化, 因而采集到的一般为不规则信号, 增加了健康状态特征提取的难度, 为此, Sun 等^[81]提出了一种基于堆叠去噪自编码器的风力发电系统通信及传感器健康状态特征提取方法. 首先, 分析了数据集异常值特征; 其次, 利用堆叠去噪自编码器来提取故障特征; 最后, 采用基于密度网格的聚类方法, 对故障特征进行聚类, 并通过添加窗口, 根据异常数据的持续时间,

将异常值分类为孤立异常值、缺失数据和可用故障数据. 经风机实际运行数据验证, 该模型可有效地从高维数据集中提取更深层次的健康状态特征.

Su 等^[74]基于互相关系数的变分模态分解来分离原始振动信号的有效模式, 并采用短时特征双阈值法来完成特征状态划分. 由于单通道收缩自编码器提取的特征缺乏时间维度信息, 因此选择多个收缩自编码器通道, 以均匀采样时间间隔同步提取连续特征向量, 同时, 将多个并行收缩自编码器在不同时间提取的特征融合在一起, 从而使

得最终提取出的特征具有时间信息,在此基础上,构建了针对单个断路器的多通道卷积自编码器 LSTM 预测模型,与 CNN 等预测模型相比,预测精度提高了 9.8%。

Ma 等^[75]提出了一种基于 LSTM 的变压器健康状态预测方法。假设变压器健康状态出现误判时,由于误判造成的损失程度,即损失权重值可表示为:

$$\eta_i^s = \begin{cases} \frac{e^{|1-p_i^s|}}{e^{|1-p_i^s|}} s = n_i \\ 1 - \frac{e^{|1-p_i^s|}}{e^{|1-p_i^s|}} s = 1, 2, 3, \dots, s \text{ and } s \neq n_i \end{cases} \quad (7)$$

式中, n_i 是第 i 个训练样本的状态标签; p_i^s 为样本处于误判状态时的概率。在得到损失权重值的基础上,构建了具有可变阈值和动态权重的交叉熵损失函数:

$$L_{al} = \eta_i^{n_i} E_{al} + \sum_{s=1,2,3,\dots,s \text{ and } s \neq n_i}^S \eta_i^s [-\lg(1-p_i^s)] \quad (8)$$

式中, E_{al} 表示交叉熵损失。建立交叉熵损失函数的目的,是为了减少残差收缩网络中的误差传递,提高网络对正常和异常变压器状态的敏感性。实验结果表明,所提预测模型平均误差可维持在 0.3% 以内。

5 展望

在碳达峰、碳中和目标指引下,电力系统在能源高效调配、新能源电力高比例消纳、电力设备高稳定性运行等方面的挑战也在不断增强。未来,可以从以下 3 方面开展进一步研究:

(1) 现有负荷预测方法通常以历史负荷作为模型训练数据,实际上,负荷变化情况与温度、风速甚至现阶段国家或地方政策,电力用户所在行业的经济形势等多种因素密切相关,例如面向工业场景的中长期负荷预测,外部经济形势直接影响着工业厂区生产经营状况,进而影响用电负荷。因此,可考虑加入更多相关影响因素,以进一步改善负荷预测精度。

(2) 当前的新能源出力预测基本以集中式新能源出力为主,对分布式新能源出力预测的研究仍有待进一步展开。与集中式相比,分布式新能源出力的波动性与随机性更加突出,影响因素更多,除温度、风速、云量等常规天气数据外,地形、地貌等地理条件对于预测精度的影响不容忽视。深度学习可以有效地提取多源数据的时间和空

间特征,并进行融合,从而展现出分布式新能源出力预测方面的潜力。

(3) 电力系统故障往往具有并发性特点,即某种故障除了直接影响特定电力设备正常运行,也可能间接造成其他设备失效,现有基于深度学习的健康状态预测方法多针对不变工况以及单一设备失效问题,在实际工程应用中缺乏泛化性,可考虑对变化工况及多种设备失效模式下的电力系统健康状态预测进行深入研究。

参 考 文 献

- [1] Goodfellow I, Bengio Y, Courville A. *Deep Learning*. Cambridge: The MIT Press, 2016
- [2] Wang L, Tao R, Hu H L, et al. Effective wind power prediction using novel deep learning network: Stacked independently recurrent autoencoder. *Renew Energy*, 2021, 164: 642
- [3] Ahmad T, Chen H X. Deep learning for multi-scale smart energy forecasting. *Energy*, 2019, 175: 98
- [4] Chen J F, Zhu Q M, Li H Y, et al. Learning heterogeneous features jointly: A deep end-to-end framework for multi-step short-term wind power prediction. *IEEE Trans Sustain Energy*, 2020, 11(3): 1761
- [5] Wang G M, Qiao J F, Guan L N, et al. Review and prospect on deep belief network. *Acta Autom Sin*, 2021, 47(1): 35
(王功明, 乔俊飞, 关丽娜, 等. 深度信念网络研究现状与展望. 自动化学报, 2021, 47(1): 35)
- [6] Li H Z, Fu G, Sun W Q. Short-term wind power forecasting method based on deep recurrent belief network. *Autom Electr Power Syst*, 2021, 45(15): 85
(李宏仲, 付国, 孙伟卿. 基于深度递归信念网络的风电功率短期预测方法. 电力系统自动化, 2021, 45(15): 85)
- [7] Chang G W, Lu H J. Integrating gray data preprocessor and deep belief network for day-ahead PV power output forecast. *IEEE Trans Sustain Energy*, 2020, 11(1): 185
- [8] Cheng Q, Pei X B, Fang Z, et al. Short-term load forecasting method for low voltage users based on deep belief neural network // 2020 IEEE Sustainable Power and Energy Conference. Chengdu, 2020: 2564
- [9] Gu Y H, Liu S, He L F, et al. Research on failure prediction using DBN and LSTM neural network // 2018 57th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE). Nara, 2018: 1705
- [10] Ganguly B, Chaudhuri S, Biswas S, et al. Wavelet kernel-based convolutional neural network for localization of partial discharge sources within a power apparatus. *IEEE Trans Ind Inform*, 2021, 17(3): 1831
- [11] Wang C, Kou P. Wind speed forecasts of multiple wind turbines in a wind farm based on integration model built by convolutional neural network and simple recurrent unit. *Trans China Electrotech*

- Soc*, 2020, 35(13): 2723
(王晨, 寇鹏. 基于卷积神经网络和简单循环单元集成模型的风电场多风机风速预测. 电工技术学报, 2020, 35(13): 2723)
- [12] Gao W, Guo M F, Xu L B. Recognition method of internal overvoltage type for distribution network via improved CWD-CNN. *Electr Mach Control*, 2020, 24(8): 131
(高伟, 郭谋发, 许立彬. 基于改进CWD-CNN的配电网内部过电压类型识别方法. 电机与控制学报, 2020, 24(8): 131)
- [13] Li R, Sun F, Ding X, et al. Ultra short-term load forecasting for user-level integrated energy system considering multi-energy spatio-temporal coupling. *Power Syst Technol*, 2020, 44(11): 4121
(栗然, 孙帆, 丁星, 等. 考虑多能时空耦合的用户级综合能源系统超短期负荷预测方法. 电网技术, 2020, 44(11): 4121)
- [14] Xu Z, Zhang G, Wang H M, et al. Error compensation of collaborative robot dynamics based on deep recurrent neural network. *Chin J Eng*, 2021, 43(7): 995
(徐征, 张弓, 汪火明, 等. 基于深度循环神经网络的协作机器人动力学误差补偿. 工程科学学报, 2021, 43(7): 995)
- [15] Yang C, Jiang W X, Guo Z W. Time series data classification based on dual path CNN-RNN cascade network. *IEEE Access*, 2019, 7: 155304
- [16] Hochreiter S, Schmidhuber J. Long short-term memory. *Neural Comput*, 1997, 9(8): 1735
- [17] Xia M, Shao H D, Ma X D, et al. A stacked GRU-RNN-based approach for predicting renewable energy and electricity load for smart grid operation. *IEEE Trans Ind Inform*, 2021, 17(10): 7050
- [18] Tan M, Yuan S P, Li S H, et al. Ultra-short-term industrial power demand forecasting using LSTM based hybrid ensemble learning. *IEEE Trans Power Syst*, 2020, 35(4): 2937
- [19] Chen M R, Zeng G Q, Lu K D, et al. A two-layer nonlinear combination method for short-term wind speed prediction based on ELM, ENN, and LSTM. *IEEE Internet Things J*, 2019, 6(4): 6997
- [20] Hinton G E, Osindero S, Teh Y W. A fast learning algorithm for deep belief nets. *Neural Comput*, 2006, 18(7): 1527
- [21] Liu R M, Feng S Y, Cai Y M, et al. State assessment and fault prediction method of distribution terminal based on SDAE and hierarchical Bayesian // 2019 *IEEE Sustainable Power and Energy Conference*. Beijing, 2019: 2783
- [22] Fu Y W, Chai H, Zhen Z, et al. Sky image prediction model based on convolutional auto-encoder for minutely solar PV power forecasting. *IEEE Trans Ind Appl*, 2021, 57(4): 3272
- [23] Zhu J C, Yang Z L, Chang Y, et al. A novel LSTM based deep learning approach for multi-time scale electric vehicles charging load prediction // 2019 *IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia)*. Chengdu, 2019: 3531
- [24] Xiao B, Zhou C, Mu G. Review and prospect of the spatial load forecasting methods. *Proc CSEE*, 2013, 33(25): 78
(肖白, 周潮, 穆钢. 空间电力负荷预测方法综述与展望. 中国电机工程学报, 2013, 33(25): 78)
- [25] Yang Z Y, Liu J Y, Liu Y B, et al. Transformer load forecasting based on adaptive deep belief network. *Proc CSEE*, 2019, 39(14): 4049
(杨智宇, 刘俊勇, 刘友波, 等. 基于自适应深度信念网络的变电站负荷预测. 中国电机工程学报, 2019, 39(14): 4049)
- [26] Shi J Q, Tan T, Guo J, et al. Multi-task learning based on deep architecture for various types of load forecasting in regional energy system integration. *Power Syst Technol*, 2018, 42(3): 698
(史佳琪, 谭涛, 郭经, 等. 基于深度结构多任务学习的园区型综合能源系统多元负荷预测. 电网技术, 2018, 42(3): 698)
- [27] Tan M, Liu Y, Meng B M, et al. Multinodal forecasting of industrial power load using participation factor and ensemble learning // 2020 *IEEE 4th Conference on Energy Internet and Energy System Integration*. Wuhan, 2020: 745
- [28] Zhao Y, Wang H M, Kang L, et al. Temporal convolution network-based short-term electrical load forecasting. *Trans China Electrotech Soc*, 2022, 37(5): 1242
(赵洋, 王瀚墨, 康丽, 等. 基于时间卷积网络的短期电力负荷预测. 电工技术学报, 2022, 37(5): 1242)
- [29] Xu J H, Wang X W, Yang J J. Short-term load density prediction based on CNN-QRLightGBM. *Power Syst Technol*, 2020, 44(9): 3409
(许佳辉, 王向文, 杨俊杰. 基于CNN-QRLightGBM的短期负荷概率密度预测. 电网技术, 2020, 44(9): 3409)
- [30] Cheng L L, Zang H X, Xu Y, et al. Probabilistic residential load forecasting based on micrometeorological data and customer consumption pattern. *IEEE Trans Power Syst*, 2021, 36(4): 3762
- [31] Wei A, Mao D J, Han W L, et al. Short-term load forecasting based on EMD and long short-term memory neural networks. *J Eng Therm Energy Power*, 2020, 35(4): 203
(魏骛, 茅大钧, 韩万里, 等. 基于EMD和长短期记忆网络的短期电力负荷预测研究. 热能动力工程, 2020, 35(4): 203)
- [32] Wang Z P, Zhao B, Ji W J, et al. Short-term load forecasting method based on GRU-NN model. *Autom Electr Power Syst*, 2019, 43(5): 53
(王增平, 赵兵, 纪维佳, 等. 基于GRU-NN模型的短期负荷预测方法. 电力系统自动化, 2019, 43(5): 53)
- [33] Wang Z P, Zhao B, Jia X, et al. Short-term power load forecasting method based on difference decomposition and error compensation. *Power Syst Technol*, 2021, 45(7): 2560
(王增平, 赵兵, 贾欣, 等. 基于差分分解和误差补偿的短期电力负荷预测方法. 电网技术, 2021, 45(7): 2560)
- [34] Chen H W, Wang S X, Wang S M, et al. Aggregated load forecasting method based on gated recurrent unit networks and model fusion. *Autom Electr Power Syst*, 2019, 43(1): 65
(陈海文, 王守相, 王绍敏, 等. 基于门控循环单元网络与模型融合的负荷聚合体预测方法. 电力系统自动化, 2019, 43(1): 65)
- [35] Ma Y, Zhang Q, Ding J J, et al. Short term load forecasting based on iForest-LSTM // *IEEE 14th Conference on Industrial Electronics and Applications*. Xi'an, 2019: 2278
- [36] Eskandari H, Imani M, Moghaddam M P. Convolutional and recurrent neural network based model for short-term load forecasting. *Electr Power Syst Res*, 2021, 195: 107173

- [37] Sun M Y, Zhang T Q, Wang Y, et al. Using Bayesian deep learning to capture uncertainty for residential net load forecasting. *IEEE Trans Power Syst*, 2020, 35(1): 188
- [38] Salakhutdinov R, Hinton G. Using deep belief nets to learn covariance kernels for Gaussian processes // *Proceedings of the 20th International Conference on Neural Information Processing Systems*. New York, 2007: 1249
- [39] Peng W, Xu L W, Li C D, et al. Stacked autoencoders and extreme learning machine based hybrid model for electrical load prediction. *J Intell Fuzzy Syst*, 2019, 37(4): 5403
- [40] Gal Y, Ghahramani Z. Dropout as a bayesian approximation: Representing model uncertainty in deep learning // *Proceedings of the 33rd International Conference on International Conference on Machine Learning*. New York, 2016: 1050
- [41] Mitra P, Vittal V, Pourbeik P, et al. Load sensitivity studies in power systems with non-smooth load behavior. *IEEE Trans Power Syst*, 2017, 32(1): 705
- [42] Liu Y, Zhang H, Zhang A M. Improved load forecasting method based on load characteristics under demand-side response. *Power Syst Prot Control*, 2018, 46(13): 126
(刘云, 张杭, 张爱民. 需求侧响应下基于负荷特性的改进短期负荷预测方法. 电力系统保护与控制, 2018, 46(13): 126)
- [43] Kong X Y, Li C, Zheng F, et al. Improved deep belief network for short-term load forecasting considering demand-side management. *IEEE Trans Power Syst*, 2020, 35(2): 1531
- [44] Tan X Y, Liu F, Ma J J, et al. Ultra-short-term pv power forecasting model based on dbn and t-s time-varying weight combination. *Acta Energaie Solaris Sin*, 2021, 42(10): 42
(谭小钰, 刘芳, 马俊杰, 等. 基于DBN与T-S时变权重组合的光伏功率超短期预测模型. 太阳能学报, 2021, 42(10): 42)
- [45] Lai C W, Li J H, Chen B, et al. Review of photovoltaic power output prediction technology. *Trans China Electrotech Soc*, 2019, 34(6): 1201
(赖昌伟, 黎静华, 陈博, 等. 光伏发电出力预测技术研究综述. 电工技术学报, 2019, 34(6): 1201)
- [46] Du J L, Liu Y Y, Liu Z J. Study of precipitation forecast based on deep belief networks. *Algorithms*, 2018, 11(9): 132
- [47] Zhang C Y, Chen C L P, Gan M, et al. Predictive deep boltzmann machine for multiperiod wind speed forecasting. *IEEE Trans Sustain Energy*, 2015, 6(4): 1416
- [48] Khodayar M, Wang J H. Spatio-temporal graph deep neural network for short-term wind speed forecasting. *IEEE Trans Sustain Energy*, 2019, 10(2): 670
- [49] Zhang Y C, Le J, Liao X B, et al. A novel combination forecasting model for wind power integrating least square support vector machine, deep belief network, singular spectrum analysis and locality-sensitive hashing. *Energy*, 2019, 168: 558
- [50] Miao C X, Li H, Wang X, et al. Data-driven and deep-learning-based ultra-short-term wind power prediction. *Autom Electr Power Syst*, 2021, 45(14): 22
(苗长新, 李昊, 王霞, 等. 基于数据驱动和深度学习的超短期风电功率预测. 电力系统自动化, 2021, 45(14): 22)
- [51] Zang H X, Cheng L L, Ding T, et al. A hybrid method for short-term photovoltaic power forecasting based on deep convolutional neural network. *IET Gener Transm Distribution*, 2018, 12(20): 4557
- [52] Wang H Z, Yi H Y, Peng J C, et al. Deterministic and probabilistic forecasting of photovoltaic power based on deep convolutional neural network. *Energy Convers Manag*, 2017, 153: 409
- [53] Sun Y C, Szűcs G, Brandt A R. Solar PV output prediction from video streams using convolutional neural networks. *Energy Environ Sci*, 2018, 11(7): 1811
- [54] Zang H X, Cheng L L, Ding T, et al. Day-ahead photovoltaic power forecasting approach based on deep convolutional neural networks and meta learning. *Int J Electr Power Energy Syst*, 2020, 118: 105790
- [55] Yan J C, Hu L, Zhen Z, et al. Frequency-domain decomposition and deep learning based solar PV power ultra-short-term forecasting model. *IEEE Trans Ind Appl*, 2021, 57(4): 3282
- [56] Hong Y Y, Rioflorido C L P P. A hybrid deep learning-based neural network for 24-h ahead wind power forecasting. *Appl Energy*, 2019, 250: 530
- [57] Liu X, Yang L X, Zhang Z J. Short-term multi-step ahead wind power predictions based on A novel deep convolutional recurrent network method. *IEEE Trans Sustain Energy*, 2021, 12(3): 1820
- [58] Wang F, Xuan Z M, Zhen Z, et al. A day-ahead PV power forecasting method based on LSTM-RNN model and time correlation modification under partial daily pattern prediction framework. *Energy Convers Manag*, 2020, 212: 112766
- [59] Zhang Q, Ma Y, Li G L, et al. Applications of frequency domain decomposition and deep learning algorithms in short-term load and photovoltaic power forecasting. *Proc CSEE*, 2019, 39(8): 2221
(张倩, 马愿, 李国丽, 等. 频域分解和深度学习算法在短期负荷及光伏功率预测中的应用. 中国电机工程学报, 2019, 39(8): 2221)
- [60] Song L Q, Xie Q Y, He Y K, et al. Ultra-short-term wind power combination forecasting model based on MEEMD-SAE-Elman // *2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference*. Chongqing, 2020: 1844
- [61] Hossain M A, Chakraborty R K, Elsayah S, et al. Predicting wind power generation using hybrid deep learning with optimization. *IEEE Trans Appl Supercond*, 2021, 31(8): 1
- [62] Wang H Z, Wang G B, Li G Q, et al. Deep belief network based deterministic and probabilistic wind speed forecasting approach. *Appl Energy*, 2016, 182: 80
- [63] Jing B, Tan L N, Qian Z, et al. An overview of research progress of short-term photovoltaic forecasts. *Electr Measur Instrum*, 2017, 54(12): 1
(荆博, 谭伦农, 钱政, 等. 光伏发电短期预测研究进展综述. 电测与仪表, 2017, 54(12): 1)
- [64] Wang Y F, Fu Y C, Xue H. Ultra-short-term forecasting method of photovoltaic power generation based on Chaos-EEMD-PFBD

- decomposition and GA-BP neural networks. *Acta Energiæ Solaris Sin*, 2020, 41(12): 55
(王育飞, 付玉超, 薛花. 基于Chaos-EEMD-PFBD分解和GA-BP神经网络的光伏发电功率超短期预测法. 太阳能学报, 2020, 41(12): 55)
- [65] Yan J, Gao C Y, Yu G B. Comparative analysis of prediction errors based on offshore wind power characteristics. *Comput Integr Manuf Syst*, 2020, 26(3): 648
(闫健, 高长元, 于广滨. 基于海上风电功率特性的预测误差对比分析. 计算机集成制造系统, 2020, 26(3): 648)
- [66] Wang K J, Qi X X, Liu H D, et al. Deep belief network based k -means cluster approach for short-term wind power forecasting. *Energy*, 2018, 165: 840
- [67] Sun C, Ma M, Zhao Z B, et al. Deep transfer learning based on sparse autoencoder for remaining useful life prediction of tool in manufacturing. *IEEE Trans Ind Inform*, 2019, 15(4): 2416
- [68] Su L C, Xing M L, Zhang H. Fault detection of key components of wind turbine based on combination prediction model. *Acta Energiæ Solaris Sin*, 2021, 42(10): 220
(苏连成, 邢美玲, 张慧. 基于组合预测模型的风电机组关键部位故障检测. 太阳能学报, 2021, 42(10): 220)
- [69] Qi B, Wang Y M, Zhang P, et al. Deep recurrent belief network model for trend prediction of transformer oil chromatography data. *Power Syst Technol*, 2019, 43(6): 1892
(齐波, 王一鸣, 张鹏, 等. 面向变压器油色谱趋势预测的深度递归信念网络. 电网技术, 2019, 43(6): 1892)
- [70] Guo L, Lei Y G, Li N P, et al. Machinery health indicator construction based on convolutional neural networks considering trend burr. *Neurocomputing*, 2018, 292: 142
- [71] Yang B Y, Liu R N, Zio E. Remaining useful life prediction based on a double-convolutional neural network architecture. *IEEE Trans Ind Electron*, 2019, 66(12): 9521
- [72] Lu H, Vahid B, Nemani V P, et al. GAN-LSTM predictor for failure prognostics of rolling element bearings // *IEEE International Conference on Prognostics and Health Management*. Detroit, 2021: 1
- [73] Dai J J, Song H, Sheng G H, et al. Prediction method for power transformer running state based on LSTM network. *High Volt Eng*, 2018, 44(4): 1099
(代杰杰, 宋辉, 盛戈皞, 等. 采用LSTM网络的电力变压器运行状态预测方法研究. 高电压技术, 2018, 44(4): 1099)
- [74] Sun S G, Wen Z T, Du T H, et al. Remaining life prediction of conventional low-voltage circuit breaker contact system based on effective vibration signal segment detection and MCCA-E-LSTM. *IEEE Sens J*, 2021, 21: 21862
- [75] Ma X, Hu H, Shang Y Z. A new method for transformer fault prediction based on multifeature enhancement and refined long short-term memory. *IEEE Trans Instrum Meas*, 2021, 70: 1
- [76] Zhao H S, Liu H H, Hu W J, et al. Anomaly detection and fault analysis of wind turbine components based on deep learning network. *Renew Energy*, 2018, 127: 825
- [77] Lu B L, Liu Z H, Wei H L, et al. A deep adversarial learning prognostics model for remaining useful life prediction of rolling bearing. *IEEE Trans Artif Intell*, 2021, 2(4): 329
- [78] Jiang G Q, Xie P, He H B, et al. Wind turbine fault detection using a denoising autoencoder with temporal information. *IEEE/ASME Trans Mechatron*, 2018, 23(1): 89
- [79] Meng Z, Zhan X Y, Li J, et al. An enhancement denoising autoencoder for rolling bearing fault diagnosis. *Measurement*, 2018, 130: 448
- [80] Xia M, Li T, Shu T X, et al. A two-stage approach for the remaining useful life prediction of bearings using deep neural networks. *IEEE Trans Ind Inform*, 2019, 15(6): 3703
- [81] Sun Z X, Sun H X. Stacked denoising autoencoder with density-grid based clustering method for detecting outlier of wind turbine components. *IEEE Access*, 2019, 7: 13078
- [82] Chen Z Q, Chen X D, Olivira J, et al. Application of deep learning in equipment prognostics and health management. *Chin J Sci Instrum*, 2019, 40(9): 206
(陈志强, 陈旭东, Olivira J, 等. 深度学习在设备故障预测与健康管理中的应用. 仪器仪表学报, 2019, 40(9): 206)
- [83] Fang X L, Yang Q, Liu G F, et al. Power supply restoration strategy for offshore multi-platform interconnected power system with faults. *Autom Electr Power Syst*, 2021, 45(7): 53
(方晓伦, 杨强, 刘国锋, 等. 海上多平台互联电力系统故障后的供电恢复策略. 电力系统自动化, 2021, 45(7): 53)