Research on Knowledge Management of Novel Power System Based on Deep Learning

Zhengping Lin[1],* and Jiaxin Lin[2]

[1]Electric Power Research Institute of China Southern Power Grid Company, China (e-mail: zhengping_lin@hotmail.com).
[2]Guangdong Power Grid Co.,Ltd, China (e-mail: jiaxinlincsg@hotmail.com).

Abstract

With the rapid development of information technology, power system has been developed and applied rapidly. In the power system, fault detection is very important and is one of the key means to ensure the operation of power system. How to effectively improve the ability of fault detection is the most important issue in the research of power system. Traditional fault detection mainly relies on manual daily inspection, and power must be cut off during maintenance, which affects the normal operation of the power grid. In case of emergency, the equipment can not be powered off, which may lead to missed test and bury potential safety hazards. To solve these issues, in this paper, we study the knowledge management based power system by employing the deep learning technique. Specifically, we firstly introduce the data augmentation in the knowledge management based power system and the associated activated functions. We then develop the deep network architecture to extract the local spatial features among the data of the knowledge management based power system. We further provide several training strategies for the data classification in the knowledge management based power system, where the cross entropy based loss function is used. Finally, some experimental results are demonstrated to show the effectiveness of the proposed studies for the knowledge management based power system.

1. Introduction

With the rapid development of information technology [1–4], power system has been developed and applied rapidly. In the power system, fault detection is very important and is one of the key means to ensure the operation of power system [5, 6]. How to effectively improve the ability of fault detection is the most important issue in the research of power system. Traditional fault detection mainly relies on manual daily inspection, and power must be cut off during maintenance, which affects the normal operation of the power grid. In case of emergency, the equipment can not be powered off, which may lead to missed test and bury potential safety hazards [7, 8]. As the test procedure is cumbersome, the time is concentrated, and the task

is urgent. Moreover, the workload of the workers is large, and it is easily affected by human factors. The maintenance period is long, and some faults are easy to develop rapidly in this period, resulting in accidents. The test voltage is less than 10kV, and the actual operation voltage of the equipment is larger than this value. Meanwhile, due to the power failure during the test, the magnetic field, temperature, electric field and surrounding environment during the operation of the equipment cannot be truly reflected, so the test results may not be consistent with the actual operation.

The rapid development of artificial intelligence technology provides a new perspective and idea for the daily operation of new power systems [9–12]. Artificial intelligence technology represented by deep learning has been widely used in image recognition, wireless communication, video surveillance and other industries, and it has achieved remarkable results. For

---

*Corresponding author. Email: zhengping_lin@hotmail.com

example, applying deep learning to signal detection can intelligently mine the transmission characteristics of the system and significantly improve the signal detection rate of the system. Applying deep learning into pattern recognition can adaptively mine the features of images without artificially designing the features of images, and effectively improve the accuracy of image recognition. Applying deep learning into speech recognition can also adaptively mine the intrinsic features of speech and significantly improve the accuracy of speech recognition. With the help of deep neural networks, deep learning can adaptively learn the characteristics of analyzing objects and identifying them, which provides a new idea for fault detection of power system.

Recently, the development of knowledge management provides a new viewpoint for the power system. The knowledge management based system is a very important asset of a team. It is basically an information system which can gather information from environments and then perform the data processing. After that, the knowledge management based system share the result among the nodes or users in the network. In this way, the knowledge learning and sharing are enhanced, and the usage efficiency of knowledge is also improved. The application of knowledge management into the power system has attracted much attention recently.

In this paper, we study the knowledge management based power system by employing the deep learning technique. Specifically, we firstly introduce the data augmentation in the knowledge management based power system and the associated activated functions. We then develop the deep network architecture to extract the local spatial features among the data of the knowledge management based power system. We further provide several training strategies for the data category in the knowledge management based power system, where the cross entropy based loss function is used. Finally, some experimental results are demonstrated to show the effectiveness of the proposed studies for the knowledge management based power system.

2. Methodology

2.1. Data augmentation

For the knowledge management based power system, we use the data augmentation strategies to increase the diversity of data samples and reduce the dependence of the deep model on some attributes. In this way, we can improve the model generalization ability without actually collecting new data. For example, we can crop the image in different ways to make the object appear in different positions in the image, which can also reduce the sensitivity of the model to the target position. Adjusting the brightness, contrast and saturation of
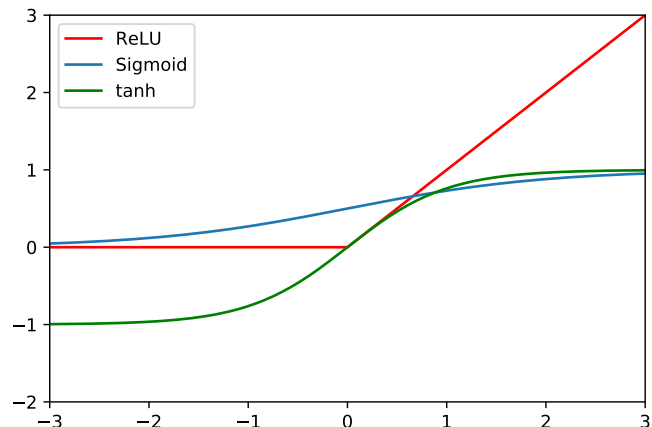

Figure 1. Comparison between several activated functions for the knowledge management based power system.

the image can help reduce the color sensitivity of the model. In this paper, a combination of random flipping, rotational scaling and adding noise is used to expand the dataset to achieve a better performance.

2.2. Network architecture

For the knowledge management based power system, a convolutional neural network is adapted due to its ability of extracting local spatial features, and it can reduce the number of computational complexity by parameter sharing. For the feature I with input size $D_F \times D_F \times M$ and $N \times D_K \times D_K$ convolution kernels, the output feature map G with K can be expressed as, [13–15]

$$G_{k,l,n} = f\left(\sum_{i,j,m} K_{i,j,m,n} \cdot I_{k+i-1,l+j-1,m} + b_{i,j,m,n} \right), \quad (1)$$

where b is the bias, and $f(\cdot)$ is the activated function. We use the ReLU function in this paper, given by [16–18]

$$f(x) = \begin{cases} x, & \text{if} \quad x \geq 0 \\ 0, & \text{if} \quad x < 0 \end{cases}. \quad (2)$$

We use the above ReLU function, as the Sigmoid and Tanh functions are prone to saturation phenomenon, that is, they are insensitive to large input and output, and the gradient is close to 0, where the gradient vanishing is easy to occur in back propagation. The ReLU function returns 1 when the gradient is greater than 0, which effectively alleviates the vanishing of gradient. At the same time, the calculation is very simple, and the training convergence speed is much faster than the former.

Notably, in order to further accelerate the convergence and improve the model accuracy, the batch normalization (BN) is applied before the ReLU function, given by [19–21]

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^{m} x_i,$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2,$$

$$\widehat{x_i} \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}},$$ (3)

$$y_i \leftarrow \gamma \widehat{x_i} + \beta,$$

where x is the input feature, y is the output of BN, and ϵ is a slight noise. Notations γ and β are learnable parameters [22, 23]. Moreover, pooling layers are followed and used to downsample the feature map. The architecture of used network architecture is composed of a sequence of convolutional layers, pooling layers as well the full connected networks are followed the last layers to output prediction. The softmax function is used to map the output into probabilistic representation [24],

$$\Pr(i) = \text{Softmax}(z^{(i)}) = \frac{e^{z^{(i)}}}{\sum_{j=0}^{n} e^{z^{(j)}}}.$$ (4)

The whole network architecture is shown in Table. 2.

2.3. Training strategies

For data classification in the knowledge management based power system,we use the cross entropy based loss function to evaluate the distance between the prediction and label, given by [25, 26]

$$Loss = \frac{1}{N} \sum_{i=0}^{N} \left(- \sum_{c=1}^{n} y_{i,c} \log p_{i,c} \right).$$ (5)

We adapt the Adam optimizer to update the weights, and the cosine annealing learning rate is applied in this paper, given by [27, 28]

$$\gamma_t = \gamma_{min} + \frac{1}{2}(\gamma_{max} - \gamma_{min})\left(1 + \cos\left(\frac{t - T_w}{T - T_w}\pi\right)\right),$$ (6)

where γ_t is the learning rate at the t-th round, and T_w and T are the number of warm up epochs and total epochs, respectively. In this paper, T_w and T are set to 5 and 50, respectively.

3. Experiment

Table 1. Comparison of test accuracy for the knowledge management based power system.

	Baseline	BN	BN+Ag
Test Accuracy	72.48	77.68	**78.92**

Table 2. Comparison of test accuracy of several network architectures for the knowledge management based power system.

	FLOPs	Param	ACC
2-MLP	3.15M	3150K	63.06
3-MLP	3.67M	3670K	63.75
2-CNN	**1.68M**	**17.50K**	76.50
3-CNN	1.97M	27.17K	**78.92**
4-CNN	2.27M	100K	76.64

3.1. Dataset

For the knowledge management based power system, a total of 10028 samples are collected and divided into training set, validation set and test dataset. The training set in the knowledge management based power system is used to train the deep model, and the model with the best performance in the validation set is used to evaluate in the test dataset. It is worth noting that samples of the test and validation sets do not overlap with the training set.

3.2. Numerical results

Fig 3. illustrate the accuracy versus training epoch for the knowledge management based power system, where the red curve is the result of using BN technology, and the black curve represents the result without BN. We can find from the figure that the curve with BN technology increases rapidly, and shows the stability in the training processing. In contrast, the curve without BN has obvious jitter in the training process and is difficult to converge. This is because that if batch normalization is not used, the trained data distribution of each layer is different, and the network needs more overhead to learn the new distribution, which makes the network model more complicated and slow down the convergence.

Table. 1 shows the test accuracy of three methods for the knowledge management based power system, where we refer the CNN without using BN to "baseline", "BN" denotes the CNN with BN technology and "BN+Ag" means that both BN and data augment are used. From the table, we can find that "BN+Ag" achieves a better accuracy gain of 1.24% and 6.44% compared to "BN" and baseline, respectively. These results indicate that the effectiveness of adding BN and data augment in the training processing.
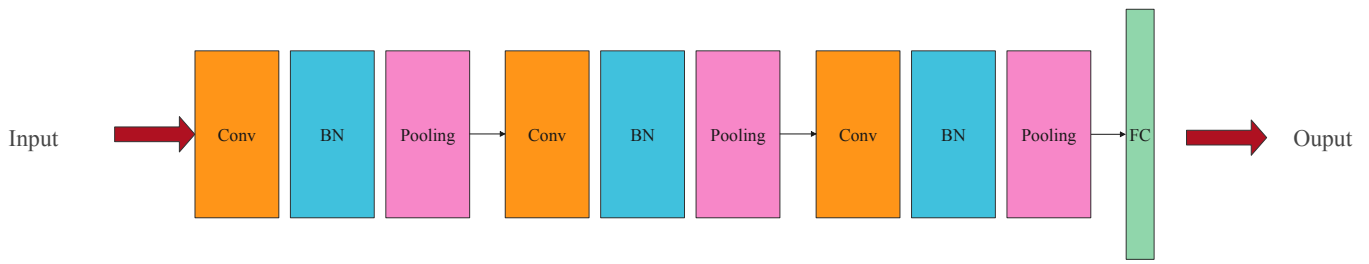
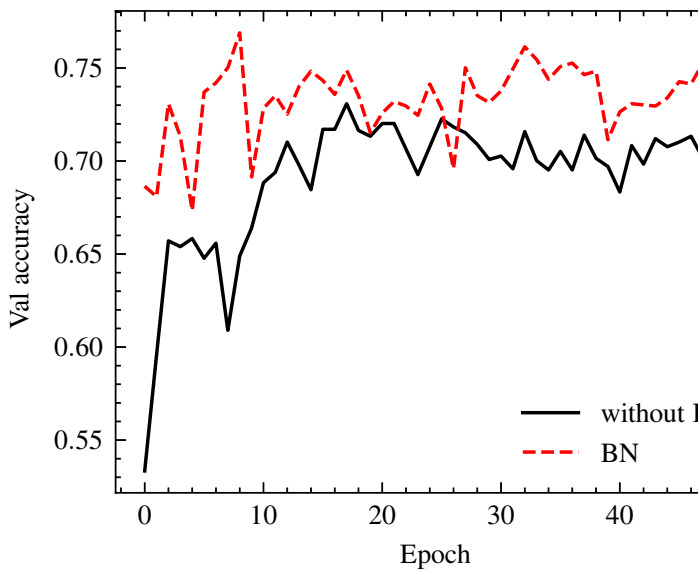**Figure 2.** Network architecture for the knowledge management based power system.

Figure 3. Accuracy on validation set versus training epoch for the knowledge management based power system.

Figure 4. Accuracy on validation set versus training epoch with several activated functions for the knowledge management based power system.

Table. 2 compares the performance and complexities of several network architectures including multilayer perception (MLP) and CNN with different depths, for the knowledge management based power system. Specifically, the MLP is set to 2 and 3 layer, and we also test the CNN with 2, 3, and 4 layers. From the table, we can find that the CNN architectures show the superiority over the MLP model, with accuracy gain up to 25%. In addition, the number of floating point operations (FLOPs) and parameters of CNN architectures are significantly less than those of MLP. These indicate that the stacked convolution kernel can still extract features in rich spatial space and reduce the number of parameters required for calculation to reduce the possibility of overfitting. Regarding to the CNN architectures, we can find that the model complexity increases with the model depth. However, the accuracy does not increase with model depth. In particular, the 3-layer CNN achieves the best accuracy. This is because that the 2-layer CNN lacks of adequate receptive field, and can not extract enough non-local
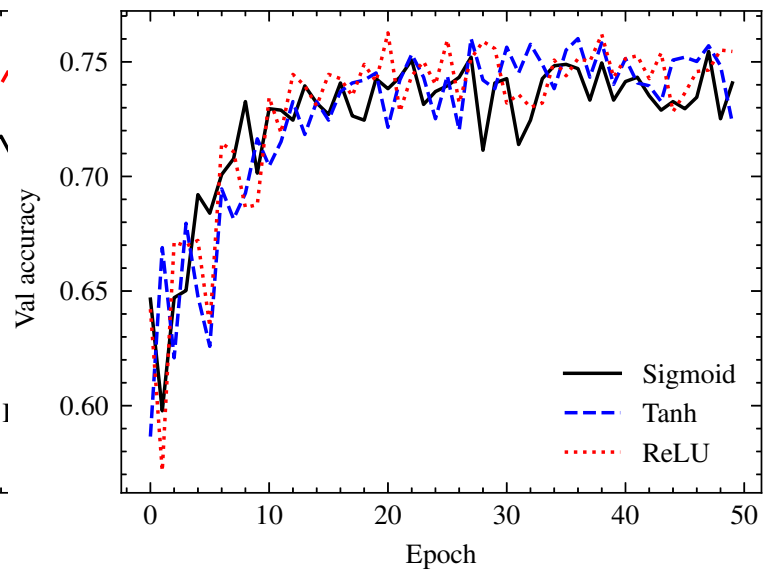
Table 3. Accuracy on the test dataset versus training epoch with several activated functions for the knowledge management based power system.

	Sigmoid	Tanh	ReLU
Test Accuracy	75.78	77.98	**78.92**

features. In addition, the 3-CNN is enough for the task, and increasing an additional layer will cause the occurrence of overfitting.

Fig. 4 shows the accuracy on validation set versus the training epoch of three activated functions for the knowledge management based power system. We can find that the three activated function can work successfully in the training processing. However, the ReLU can reach the highest accuracy performance, which demonstrates its ability of non-linear transformation. The same situation can be found in Table. 3, where the test dataset is used. In particular, the model with

ReLU function achieves the accuracy gain of 3% and 1%, compared to that of sigmoid and tanh, respectively.

4. Conclusions

With the rapid development of information technology, the power system had been developed and applied rapidly. In the power system, fault detection was very important and was one of the key means to ensure the system operation. How to effectively improve the ability of fault detection was the most important issue in the research of power system. Traditional fault detection mainly relied on manual daily inspection, and the power must be cut off during maintenance, which affected the normal operation of the power grid. In case of emergency, the equipment could not be powered off, which may lead to missed test and bury potential safety hazards. To solve these issues, in this paper, we studied the knowledge management based power system by employing the deep learning technique. Specifically, we firstly introduced the data augmentation in the knowledge management based power system and the associated activated functions. We then developed the deep network architecture to extract the local spatial features among the data of the knowledge management based power system. We further provided several training strategies for the data classification in the knowledge management based power system, where the cross entropy based loss function was used. Finally, some experimental results were demonstrated to show the effectiveness of the proposed studies for the knowledge management based power system.

4.1. Data Availability Statement

The data of this work can be obtained through the email to the authors: Zhengping Lin (zhengping_lin@hotmail.com), Jiaxin Lin (jiaxinlincsg@hotmail.com). As to this work, the authors would like to sincerely thank the following researchers for the meaningful discussions: Xiazhi Lai (xiazhilai@hotmail.com), Bowen Lu (bwlu@ieee.org), and Yinghao Guo (yinghaoguo@ieee.org).

4.2. Copyright

The Copyright was licensed to EAI.

References

[1] H. Wang and Z. Huang, "Guest editorial: WWWJ special issue of the 21th international conference on web information systems engineering (WISE 2020)," *World Wide Web*, vol. 25, no. 1, pp. 305–308, 2022.

[2] H. Wang, J. Cao, and Y. Zhang, *Access Control Management in Cloud Environments*. Springer, 2020. [Online]. Available: https://doi.org/10.1007/978-3-030-31729-4

[3] X. Hu, J. Wang, and C. Zhong, "Statistical CSI based design for intelligent reflecting surface assisted MISO systems," *Science China: Information Science*, vol. 63, no. 12, p. 222303, 2020.

[4] D. Cai, P. Fan, Q. Zou, Y. Xu, Z. Ding, and Z. Liu, "Active device detection and performance analysis of massive non-orthogonal transmissions in cellular internet of things," *Science China information sciences*, vol. 5, no. 8, pp. 182 301:1–182 301:18, 2022.

[5] N. Dahlin and R. Jain, "Scheduling flexible nonpreemptive loads in smart-grid networks," *IEEE Trans. Control. Netw. Syst.*, vol. 9, no. 1, pp. 14–24, 2022.

[6] E. Z. Serper and A. Altin-Kayhan, "Coverage and connectivity based lifetime maximization with topology update for WSN in smart grid applications," *Comput. Networks*, vol. 209, p. 108940, 2022.

[7] Z. Alavikia and M. Shabro, "A comprehensive layered approach for implementing internet of things-enabled smart grid: A survey," *Digit. Commun. Networks*, vol. 8, no. 3, pp. 388–410, 2022.

[8] S. Mishra, "Blockchain-based security in smart grid network," *Int. J. Commun. Networks Distributed Syst.*, vol. 28, no. 4, pp. 365–388, 2022.

[9] H. Wang, Y. Wang, T. Taleb, and X. Jiang, "Editorial: Special issue on security and privacy in network computing," *World Wide Web*, vol. 23, no. 2, pp. 951–957, 2020.

[10] K. He and Y. Deng, "Efficient memory-bounded optimal detection for GSM-MIMO systems," *IEEE Trans. Commun.*, vol. 70, no. 7, pp. 4359–4372, 2022.

[11] L. Chen, "Physical-layer security on mobile edge computing for emerging cyber physical systems," *Computer Communications*, vol. PP, no. 99, pp. 1–12, 2022.

[12] S. Tang and L. Chen, "Computational intelligence and deep learning for next-generation edge-enabled industrial IoT," *IEEE Trans. Netw. Sci. Eng.*, vol. 9, no. 3, pp. 105–117, 2022.

[13] X. Hu, C. Zhong, Y. Zhu, X. Chen, and Z. Zhang, "Programmable metasurface-based multicast systems: Design and analysis," *IEEE J. Sel. Areas Commun.*, vol. 38, no. 8, pp. 1763–1776, 2020.

[14] R. Zhao and M. Tang, "Profit maximization in cache-aided intelligent computing networks," *Physical Communication*, vol. PP, no. 99, pp. 1–10, 2022.

[15] J. Lu and M. Tang, "Performance analysis for IRS-assisted MEC networks with unit selection," *Physical Communication*, vol. PP, no. 99, pp. 1–10, 2022.

[16] X. Hu, C. Zhong, Y. Zhang, X. Chen, and Z. Zhang, "Location information aided multiple intelligent reflecting surface systems," *IEEE Trans. Commun.*, vol. 68, no. 12, pp. 7948–7962, 2020.

[17] X. Lai, "Outdated access point selection for mobile edge computing with cochannel interference," *IEEE Trans. Vehic. Tech.*, vol. 71, no. 7, pp. 7445–7455, 2022.

[18] S. Tang, "Dilated convolution based CSI feedback compression for massive MIMO systems," *IEEE Trans. Vehic. Tech.*, vol. 71, no. 5, pp. 211–216, 2022.

[19] R. Zhao and M. Tang, "Impact of direct links on intelligent reflect surface-aided MEC networks," *Physical Communication*, vol. PP, no. 99, pp. 1–10, 2022.

[20] L. Zhang and C. Gao, "Deep reinforcement learning based IRS-assisted mobile edge computing under physical-layer security," *Physical Communication*, vol. PP, no. 99, pp. 1–10, 2022.

[21] S. Tang and X. Lei, "Collaborative cache-aided relaying networks: Performance evaluation and system optimization," *IEEE Journal on Selected Areas in Communications*, vol. PP, no. 99, pp. 1–12, 2022.

[22] J. Liu, Y. Zhang, J. Wang, T. Cui, L. Zhang, C. Li, K. Chen, H. Huang, X. Zhou, W. Zhou *et al.*, "The intelligent bi-directional relaying communication for edge intelligence based industrial iot networks: Intelligent bi-directional relaying communication," *EAI Endorsed Transactions on Industrial Networks and Intelligent Systems*, vol. 9, no. 32, pp. e4–e4, 2022.

[23] Y. Tang and S. Lai, "Intelligent distributed data storage for wireless communications in b5g networks," *EAI Endorsed Transactions on Mobile Communications and Applications*, vol. 2022, no. 8, pp. 121–128, 2022.

[24] J. Sun, X. Wang, Y. Fang, X. Tian, M. Zhu, J. Ou, and C. Fan, "Security performance analysis of relay networks based on-shadowed channels with rhis and cees," *Wireless Communications and Mobile Computing*, vol. 2022, 2022.

[25] L. Chen and X. Lei, "Relay-assisted federated edge learning:Performance analysis and system optimization," *IEEE Transactions on Communications*, vol. PP, no. 99, pp. 1–12, 2022.

[26] J. Chen, Y. Wang, J. Ou, C. Fan, X. Lu, C. Liao, X. Huang, and H. Zhang, "Albrl: Automatic load-balancing architecture based on reinforcement learning in software-defined networking," *Wireless Communications and Mobile Computing*, vol. 2022, 2022.

[27] Y. Wu and C. Gao, "Task offloading for vehicular edge computing with imperfect CSI: A deep reinforcement approach," *Physical Communication*, vol. PP, no. 99, pp. 1–10, 2022.

[28] J. Liu, Y. Zhang, J. Wang, T. Cui, L. Zhang, C. Li, K. Chen, S. Li, and S. Feng, "Outage probability analysis for uav-aided mobile edge computing networks," *EAI Endorsed Transactions on Industrial Networks and Intelligent Systems*, vol. 9, no. 31, pp. e4–e4, 2022.