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Intelligent Flink Framework Aided Real-Time Voltage Computing Systems in Autonomous and Controllable Environments

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Abstract

Motivated by the progress in artificial intelligence such as deep learning and IoT networks, this paper presents an intelligent flink framework for real-time voltage computing systems in autonomous and controllable environments. The proposed framework employs machine learning algorithms to predict voltage values and adjust them in real-time to ensure the optimal performance of the power grid. The system is designed to be autonomous and controllable, enabling it to adapt to changing conditions and optimize its operation without human intervention. The paper also presents experimental results that demonstrate the effectiveness of the proposed framework in improving the accuracy and efficiency of voltage computing systems. Simulation results are provided to verify that the proposed intelligent flink framework can work well for real-time voltage computing systems in autonomous and controllable environments, compared with the conventional DRL and cross-entropy methods, in terms of convergence rate and estimation result. Overall, the intelligent flink framework presented in this paper has the potential to significantly improve the performance and reliability of power grids, leading to more efficient and sustainable energy systems.

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1. Introduction

Deep learning is a subfield of machine learning that has gained significant attention in recent years due to its outstanding performance in a wide range of applications, such as image and speech recognition, natural language processing, and autonomous vehicles [1–4]. Basically, deep learning techniques are based on artificial neural networks (ANNs), which are inspired by the structure and function of the human brain [5–7]. The earliest forms of ANNs were developed in the 1940s and 1950s, but they were limited by the lack of computing power and data. In the 1980s and 1990s, researchers made significant progress in developing more sophisticated ANNs, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [8–10]. However, it was not until the mid-2000s that deep learning became a mainstream research topic, thanks to the availability of large datasets and powerful GPUs [11–14].

One of the most influential works in deep learning is the AlexNet model, developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in 2012 [15–17]. AlexNet won the ImageNet large scale visual recognition challenge (ILSVRC) by a significant margin, and its success demonstrated the potential of deep learning for image recognition tasks. AlexNet is a deep CNN that consists of eight layers, including five convolutional layers and three fully connected layers. It also introduced the use of Rectified Linear Units (ReLUs) as activation functions, which significantly improved the convergence speed of the model. Another important contribution to the field of deep learning

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is the development of the long short-term memory (LSTM) architecture by Sepp Hochreiter and J ¨¹rgen Schmidhuber in 1997. LSTM is a type of RNN that is designed to overcome the vanishing gradient problem, which occurs when the gradients of the error function become too small to be useful for learning [18, 19]. LSTM achieves this by introducing a gating mechanism that allows it to selectively remember or forget previous inputs. LSTM has been widely used in natural language processing tasks, such as language translation and speech recognition. In recent years, deep learning has also made significant progress in reinforcement learning, which is a subfield of machine learning that involves learning how to make a sequence of decisions that maximize a cumulative reward. The AlphaGo program developed by DeepMind in 2016, which defeated the world champion, is one of the most famous examples of the success of deep reinforcement learning.

Flink is a distributed computing framework that is used for processing large-scale, real-time data streams [20–23]. Real-time voltage computing systems are systems that are used to monitor and analyze voltage data in real-time. The combination of these two technologies has enabled the development of efficient and effective real-time voltage computing systems [24–26]. One study explored the use of flink in a real-time voltage computing system for the purpose of voltage quality assessment, where an architecture that utilized flink to process and analyze voltage data was designed from multiple sources in real-time. The results showed that the use of Flink significantly improved the performance and efficiency of the system. In addition, flink could be used to develop a real-time voltage prediction system. The system was designed to predict the voltage of a power grid in real-time using data from multiple sources. The use of flink enabled the system to handle large amounts of data and perform real-time analysis with a low latency.

In this paper, an intelligent flink framework is introduced for real-time voltage computing systems operating in autonomous and controllable environments. The framework utilizes machine learning algorithms to predict voltage values and dynamically adjust them to ensure the optimal performance of the power grid. This autonomous and controllable system is designed to adapt to changing conditions and optimize its operation without requiring human intervention. Experimental results are presented to demonstrate the effectiveness of the proposed framework in improving the accuracy and efficiency of voltage computing systems. Simulation results are also provided to compare the proposed intelligent flink framework with the conventional DRL and cross-entropy methods in terms of convergence rate and estimation result. The intelligent flink framework presented in this paper has the potential to significantly enhance the performance and reliability of power grids, ultimately leading to more efficient and sustainable energy systems.

2. Proposed Intelligent Flink Framework

A feasible solution is to adopt a learning based intelligent algorithm for voltage computing , which can accurately estimate the complete voltage state within the current coherent time by reviewing incomplete voltage state observation sequences from multiple coherent time periods in the past and fully exploring the correlation of wireless voltage in the spatio-temporal domain. Specifically, as shown in Fig. 1, the incomplete observation of the current voltage state $H_t(\rho)$ is obtained by estimating the current voltage state H_t using pilot signals based on the significance coefficient ρ of the transmitted parameters at each coherence time. After that, with a length T_p adaptively determined by the algorithm, the retrospective sequence of past incomplete observations is build by

$$\Phi_t(\rho) = \{H_{t-T_p-1}(\rho), \cdots, H_{t-1}(\rho), H_t(\rho)\}. \tag{1}$$

With the retrospective sequence, the internal voltage state distribution estimator $f_{est}(H_t|\Phi(\rho))$ is capable of extracting the spatio-temporally relevant characteristics of the voltage state to estimate the distribution of the voltage state, so as to perform real-time voltage computing . Compared with traditional voltage estimators, this estimator can adaptively measure only part of the voltage state at each coherence time according to the significance of the transmitted parameters [27–29], thereby significantly reducing the voltage computing delay in heterogeneous edge networks. Specifically, the deep conditional normalizing flow (DCNF) model is feasible for implementing the conditional distribution estimation model $H_t \sim f_{est}(H_t|\Phi_t(\rho))$. Based on the theory of invertible distribution transformations in the latent variable space, the real-time voltage state H_t can be modeled as an observed variable that depends on an unknown random latent variable Z_t, where the distribution of the random latent variable Z_t is determined by the retrospective sequence $\Phi_t(\rho)$. In this case, the generation process of the $f_{est}(H_t|\Phi_t(\rho))$ is represented by

$$Z_t \sim f_{est}(Z_t|\Phi_t(\rho)), \tag{2}$$

$$H_t = f_{inv}\big(Z_t\big), \tag{3}$$

where $f_{inv}(Z_t)$ represents invertible transformation function, i.e., $Z_t = f_{inv}^{-1}(H_t)$. Specifically, for the case where the latent variable space is a multivariate complex Gaussian distribution, i.e., $Z_t \sim \mathcal{CN}(Z_t|\mu_t(\rho), \sum_t(\rho))$, its distribution parameters can be inferred from the retrospective sequence $\Phi_t(\rho)$ by two deep CNNs (DCNNs) using the characteristics

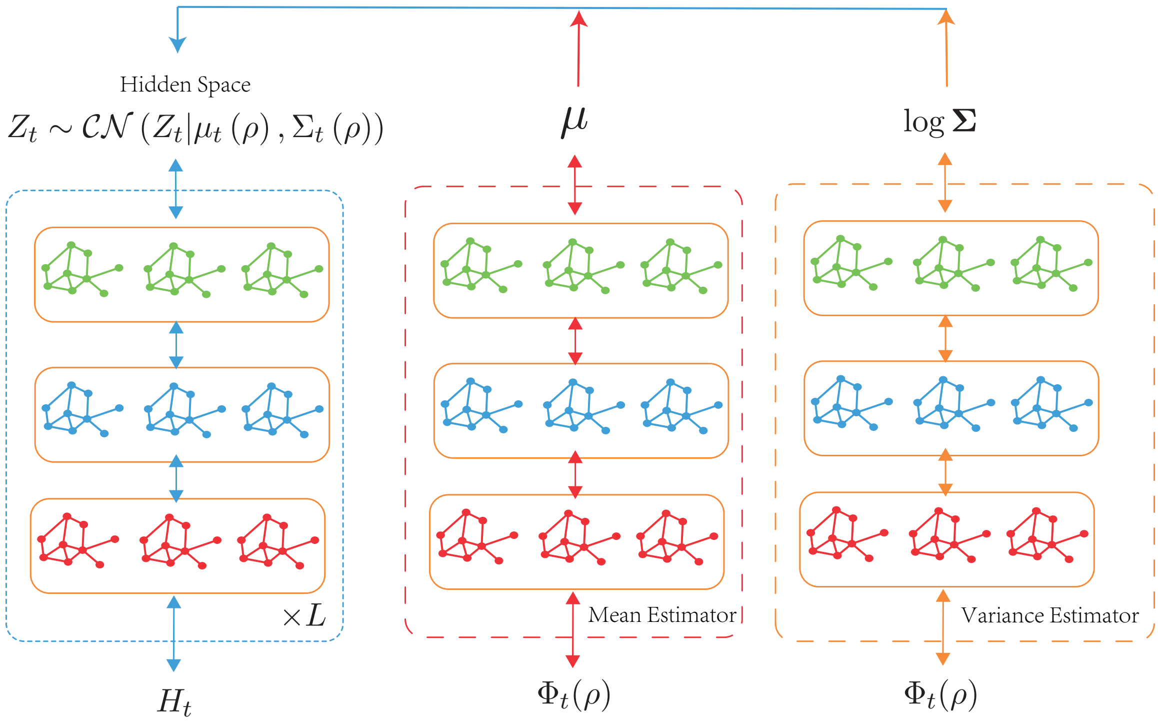

Figure 1. Diagram of the learning based intelligent algorithm for voltage computing.

of the spatio-temporal correlation of the voltage state, represented as

$$\mu_t(\rho) = CNN_\mu(\Phi_t(\rho)), \tag{4}$$
$$\Sigma_t(\rho) = CNN_\Sigma(\Phi_t(\rho)). \tag{5}$$

From this, the analytical expression for the distribution $f_{est}(Z_t|\Phi_t(\rho))$ of the latent variable space can be determined. Furthermore, the invertible transformation function can be decomposed into a sequence of invertible transformation functions, represented by

$$f_{inv}(Z_t) = f_1(Z_t) \odot f_2(Z_t) \cdots \odot f_{L_C}(Z_t), \tag{6}$$

to significantly enhance the robustness of the model. Finally, a complete estimation of the current voltage state can be inferred from the retrospective sequence of past incomplete observations, given by

$$Z_t \sim \mathcal{CN}(Z_t|\mu_t(\rho), \Sigma_t(\rho)), \tag{7}$$
$$H_t = f_{inv}(Z_t). \tag{8}$$

In conclusion, the proposed algorithm can adaptively and selectively measure partial voltage states in real-time according to the significance of the transmitted parameters, thereby effectively reducing the voltage computing delay for massive users in heterogeneous edge networks while meeting the reliability requirement.

In addition, we also intend to design a deep learning based elastic detection framework by comprehensively considering the multi-dimensional characteristics of heterogeneous edge networks, such as the significance coefficient of the transmitted parameter ρ, wireless voltage state H, and complex dynamic noise and interference n_I. One feasible approach is to combine a deep heuristic tree search algorithm with a convolutional neural network into iteration, and to adaptively determine the maximum number of iterations and the breadth and depth during search according to the significance of the transmitted model, so as to iteratively eliminate the impact of complex dynamic noise and interference, and to significantly improve the efficiency of voltage detection. Specifically, as shown in Fig. 2, the proposed framework adaptively determines the maximum number of external iterations I_p and the maximum number of visited nodes N_p for the internal tree search algorithm based on the significance coefficient ρ of the transmitted model. The received voltage is given by

$$y = Hx + n_I, \tag{9}$$

where H is the voltage state and n_I is the complex dynamic noise and interference. For the t-th round of iteration, the initial estimate of the voltage to be detected $\hat{x}_t$ is obtained using the above-mentioned deep heuristic tree search algorithm based on N_p, and the estimate value of the complex dynamic noise and interference n_I is obtained by

$$\hat{n}_{It} = y_t - H\hat{x}_t, \tag{10}$$

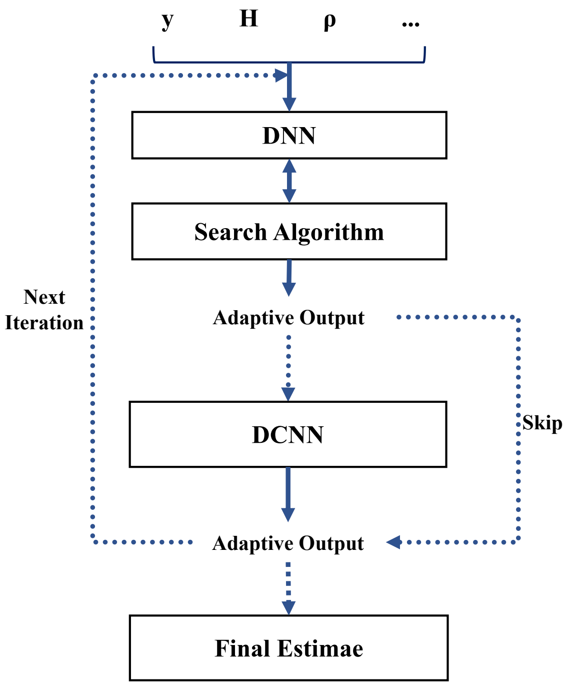

Figure 2. Diagram of the learning based elastic detection framework.

where $y_0 = y$. In this process, the deep convolutional neural networks $CNN(\hat{n}_{It})$ are used to extract features of $\hat{n}_{It}$ in the temporal and spatial domains, which enables having a further estimate of $\hat{n}_{It} = CNN(\hat{n}_{It})$ and corresponding noise reduction to obtain $y_{t+1} = y_t - \hat{n}_I$. Through multiple rounds of iteration, the signal-to-noise ratio of the system can be effectively improved, thereby significantly improving the performance of the internal detection algorithm. Specifically, when the maximum number of iterations is reached, the detection result of that round is output as the final estimate of the transmitted voltage.

At the same time, the internal deep heuristic tree search algorithm, compared with traditional heuristic search algorithms, can estimate the near-optimally heuristic values by mining the relevant characteristics of wireless voltage and complex dynamic noise and interference, thereby significantly improving the search speed without compromising detection accuracy. Specifically, the deep heuristic tree search algorithm models the maximum likelihood voltage detection problem as a shortest path search problem on a perfect multiway tree through QR matrix decomposition. For the shortest path search problem, the speed and accuracy of the search can be significantly improved by calculating the heuristic value of each node as precisely as possible. However, traditional heuristic search algorithms are affected by problem scale and complex noise and interference, and their heuristic value estimation is difficult to reach the optimal. Therefore, we plan to adopt a memory-adaptive best-frist search strategy as the basis. When accessing the node x^v at v-th level on the tree, the search algorithm accurately estimates the cost of the shortest path from the node x^v to the subtree rooted at that node by using a deep neural network $\mathcal{H}(x^v)$ to mine the characteristics of wireless voltage s and complex noise and interference. Then, combined with the cumulative cost $\mathcal{G}(x^v)$ from the global root node x^0 to the node x^v, the heuristic value of node x^v can be calculated by

$$\mathcal{F}(x^v) = \mathcal{G}(x^v) + \mathcal{H}(x^v). \tag{11}$$

At this point, it is only necessary to select the node with the smallest heuristic value $\mathcal{F}(x^v)$ among the nodes to be explored during each search to achieve fast voltage detection while minimizing the bit error rate and improving the system's reliability. In particular, we can also achieve a dynamic balance between voltage detection latency and reliability by considering the significance coefficient ρ of the transmitted parameters, and the maximum number N_p of nodes to be visited to be adaptively determined.

3. Simulations

In this part, we present some simulation results to verify the proposed intelligent voltage estimation method, by using several voltages in different noise environments. Without loss of generality, we consider the practical voltage of 5V or 10V, with the noise variance $\sigma^2 =$

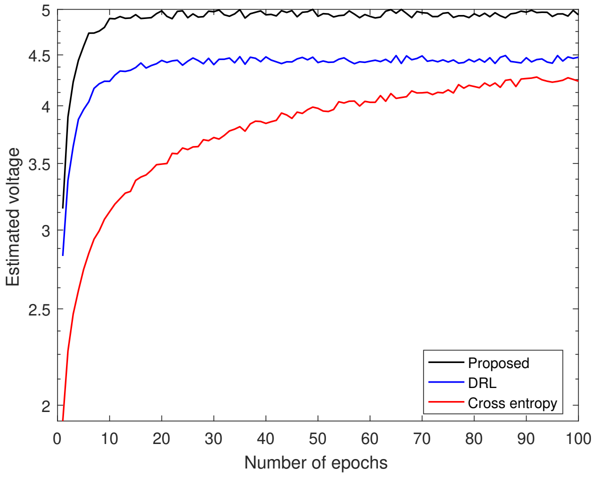

Figure 3. Estimated voltage for $x = 5$V and $\sigma^2 = 0.02$.

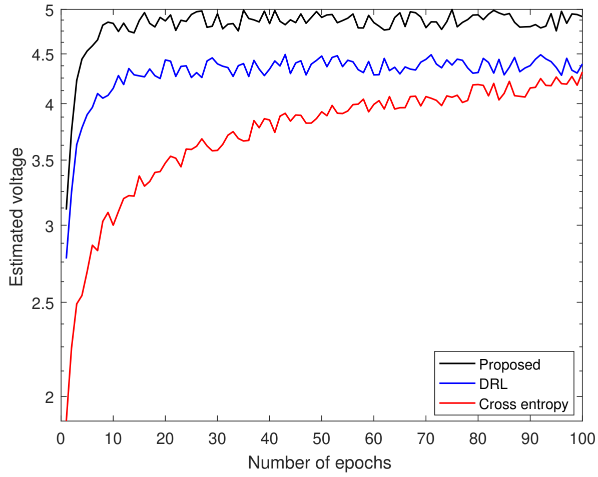

Figure 4. Estimated voltage for $x = 5$V and $\sigma^2 = 0.05$.

$0.02, 0.05, 0.08$, in order to reveal the impact of noise on the intelligent voltage estimation. For comparison, we consider two competitive methods on the intelligent voltage estimation. One is the deep reinforcement learning [30], while the other is based on the cross-entropy method [31].

Fig. 3 shows the estimated voltage versus the number of epochs, where the true voltage is 5V and the noise covariance is 0.02. The number of epochs varies from 0 to 100. From Fig. 3, one can observe that the proposed method can converge to 5V very quickly. In particular, about only 10 epochs are needed in the proposed scheme. In contrast, about 20 epochs and 100 epochs are needed in the DRL method and cross-entropy method. Moreover, the proposed method can accurately estimate the value of voltage, while the DRL and cross entropy methods fail. In particular, the DRL can only obtain the estimate of 4.4V, while the cross entropy method can only obtain the estimate of 4.1V.

In Fig. 4, the estimated voltage is plotted against the number of epochs, ranging from 0 to 100, with a true voltage of 5V and a noise covariance of 0.05. The proposed method exhibits rapid convergence to 5V, requiring only 15 epochs. By contrast, the DRL and cross-entropy methods require 30 and 100 epochs, respectively, to converge. In further, the proposed method accurately estimates the voltage, while the DRL and cross-entropy methods fail to do so. Specifically, the DRL method produces an estimate of only 4.3V, and the cross-entropy method produces an estimate of only 3.9V.

We plot the estimated voltage against the number of epochs ranging from 0 to 100 in Fig. 5, with a true voltage of 5V and a noise covariance of 0.08. It can be observed that the proposed method quickly converges to 5V, requiring only about 20 epochs. In comparison,

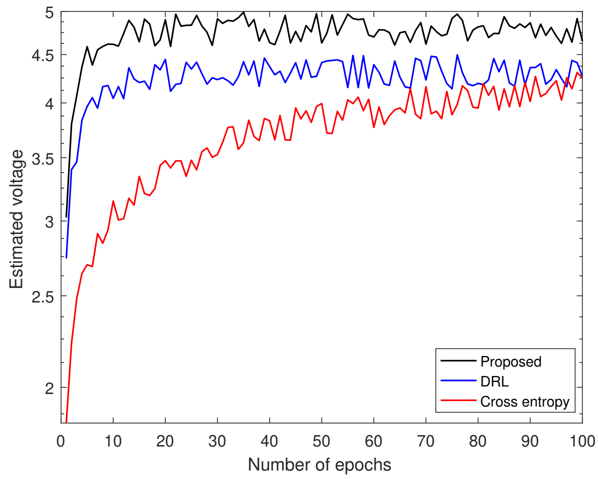

Figure 5. Estimated voltage for $x = 5$V and $\sigma^2 = 0.08$.

the DRL and cross-entropy methods require 50 and 100 epochs, respectively, to converge. Additionally, the proposed method accurately estimates the voltage, while the DRL and cross-entropy methods do not. Specifically, the DRL method produces an estimate of only 4.1V, and the cross-entropy method produces an estimate of only 3.6V.

In Fig. 6, the estimated voltage is plotted against the number of epochs ranging from 0 to 100, with a true voltage of 10V and a noise covariance of 0.02. It can be observed that the proposed method rapidly converges to the voltage of interest, requiring only about 8 epochs. In contrast, the DRL and cross-entropy methods require 20 and 100 epochs, respectively, to converge. Additionally, the proposed method accurately estimates the voltage, while the DRL and cross-entropy methods do not. Specifically, the DRL method produces

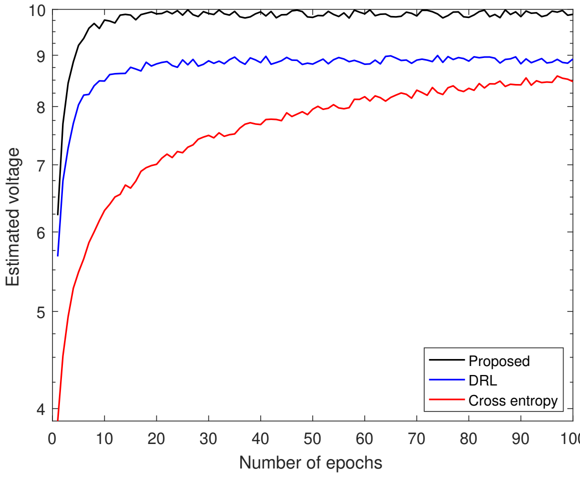

Figure 6. Estimated voltage for $x = 10$V and $\sigma^2 = 0.02$.

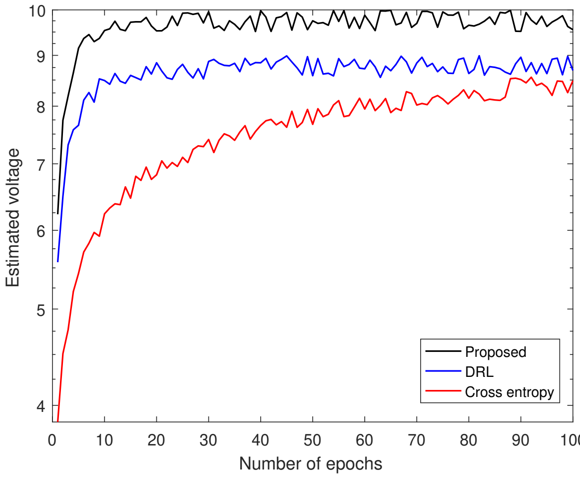

Figure 7. Estimated voltage for $x = 10$V and $\sigma^2 = 0.05$.

an estimate of only 8.6V, and the cross-entropy method produces an estimate of only 8.1V.

The graph in Fig. 7 illustrates the estimated voltage across epochs, with a noise covariance of 0.05, where the actual voltage is 10V. The range of epochs examined is from 0 to 100. As demonstrated in Fig. 7, the proposed approach can swiftly converge to 10V with just 10 epochs. Conversely, the DRL and cross-entropy methods necessitate around 25 epochs and 100 epochs, respectively. Moreover, the proposed technique can precisely determine the voltage value, whereas the DRL and cross-entropy methods fail. Specifically, the DRL can only yield an estimate of 8.5V, while the cross-entropy method can only produce an estimate of 7.9V.

The graph presented in Fig. 8 displays the estimated voltage against the number of epochs, with a noise covariance of 0.08, where the actual voltage is 10V. The range of epochs considered is from 0 to 100. As

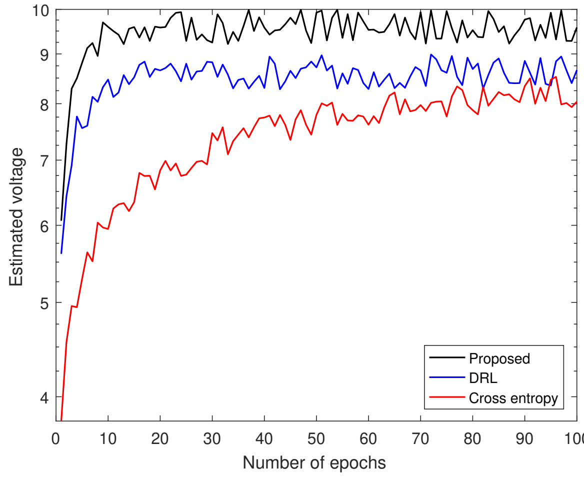

Figure 8. Estimated voltage for $x = 10$V and $\sigma^2 = 0.08$.

indicated in Fig. 8, the proposed method can promptly converge to 10V, requiring only 15 epochs. Conversely, the DRL and cross-entropy methods necessitate around 30 epochs and 100 epochs, respectively. Additionally, the proposed method can precisely determine the voltage value, whereas the DRL and cross-entropy methods fail. Specifically, the DRL can only yield an estimate of 8.2V, while the cross-entropy method can only produce an estimate of 7.6V.

4. Conclusions

This paper introduced an intelligent flink framework that could be used for real-time voltage computing systems in autonomous and controllable environments. By utilizing machine learning algorithms, the proposed framework predicted voltage values and dynamically adjusted in real-time to ensure the optimal performance of the power grid. The autonomous and controllable design of the system allowed it to adapt to varying conditions and optimize its operation without requiring human intervention. Simulation results were finally presented to validate that the intelligent flink framework could effectively operate for real-time voltage computing systems in autonomous and controllable environments when compared with conventional DRL and cross-entropy methods in terms of convergence rate and estimation result. This work in this paper had the potential to significantly enhance the performance and reliability of power grids, ultimately leading to more efficient and sustainable energy systems. In future works, we will consider some other intelligent networks such as graph neural networks into the considered system, to further enhance the estimation performance and distributed computing.

4.1. Copyright

4.2. Acknowledgements

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