[1]Ming Ma

[1]Shujie Xu

[1]Yingfang Miao

[1]Shilong Chen

[1] *Xu Liu

Research on Data-Driven Fault ScenarioSimulation Model of Distribution Network

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Abstract: - Distribution lines are critical components of today's power system, and can directly impact on power supply security and stability. An effective power system protection system should detect any faults as soon as they occur. There are two steps in fault diagnosis. One is defect classification, which has already achieved excellent accuracy rates. As a result, this study concentrates on the opposite objective, which is fault location. This research introduces a War Strategy Water Wave Optimization (WSWWO) based Deep Q Network for radial distribution networks using synchronous generators for Distributed Generation (DG). The algorithm estimates the fault site by analyzing voltage and current samples at the main feeder head, and scheduled active and reactive power injections by network synchronous generators. A full-ordersynchronous machine model was utilized to analyze the dynamic behavior of DG plants during fault transients. Here, the Deep Q Network is trained by WSWWO, and hybridized by two optimization algorithms, War Strategy Optimization (WSO) and Water Wave Optimization (WWO). Furthermore, the experimental results revealed that the WSWWO-Deep Q Network outperformed state-of-the-art models in terms of Accuracy and Error, with values of 0.997 and 0.141, respectively.

Keywords: Distribution Network, Fault location, Water Wave Optimization, Water Wave Optimization, War Strategy Optimization.

1. Introduction

Distribution line failures can result in electromagnetic transients that can have significant repercussions, including disruptions to power supplies, degradation of the grid, and disturbances to power quality [9][7]. As a result, it is critical to find problems in distribution lines rapidly and adequately [7]. The distribution systemis responsible for providing subscribers with the energy required while minimizing the frequency and extent of power outages. This issue is critical because fault location is difficult due to the size of these networks and the extent of blackouts in the distribution network, among other parts of the power system. The system reliability index and its efficiency are increased by pinpointing the fault's precise location in the shortest time and with the most significant degree of accuracy [10] [1].

When a fault develops in a distribution network, a diagnosis procedure is necessary to detect fault spots quickly and precisely to restore power supply as soon as possible. Thus, efficiently reduces the scope of power line inspection and improves the efficiency of emergency repair [11][3]. However, because distribution networks typically have a complicated architecture with several branches and significant amounts of equipment spread across a vast area, precisely identifying fault branches and locating fault locations is difficult [12]. Fault finding in distribution networks with DG is more challenging owing to the loss of effective protective coordination in the presence of DG. Most fault location algorithms for distribution networks focus on typical radial distribution systems, whereas fault location in distribution networks with distributed generation has received less attention until recently [5].

[1]Yunnan Power Grid Co. , Ltd. . Yuxi Power Supply Bureau, Yunnan, Yuxi, 653100, China

*Corresponding author's e-mail: 18869754714@163.com

Ming Ma: 120212306099@ncepu.edu.cn

Shujie Xu: 1067546657@qq.com

Yingfang Miao: 709445661@qq.com

Shilong Chen：chenshilong7777@163.com

Impedance methods, time domain methods, traveling wave methods, and intelligent algorithms are all used to locate faults in distribution networks. However, each of these approaches has disadvantages. Traveling wave-based approaches may encounter issues such as complex structure, high sampling frequency, and requirement for a database [13]. In contrast, intelligent methods may need help due to their complex structure and the requirement for an accurate and vast database [14][1]. As a result, extensive research has been conducted on the location of faults in distribution networks. Many approaches have been presented, including those based on impedances [15], fault indicators [8], signal injection [15][16], traveling waves [17], matrix algorithms [18], and artificial intelligence algorithms [19][3]. As a result, typical traveling wave-based methodologies make it difficult to identify wave heads at nodes of refraction and reflection efficiently [20][3].

This work proposes an automated deep learning-based WSWWO technique for power distribution. The voltage measured at a substation is considered as the available data. The recorded three-phase voltage signal is converted to its alpha component or aerial mode to simplify a training procedure. The suggested data-driven approach combines smart meters in Low Voltage (LV) networks and RFIs with directional components in Medium Voltage (MV) networks to locate faults in distribution systems with DGs quickly and accurately. In addition, the fault is situated using the Deep Q Network is a popular deep learning algorithm. Here, the Deep Q Network is trained by WSWWO, and WSO and WWO are hybridized. WSO devised two war strategies: the first is an attack plan, and the second is a defense strategy. This method uses a unique (soldier) update procedure in which the war strategy determines the soldier's current position. In WWO, the propagation operator directs high-fitness waves to search small areas, while low-fitness waves explore larger areas. The fraction operator helps waves avoid search stagnation, increasing diversity and reducing premature convergence.

The key contributions of this study are:

- The WSWWO was developed by combining WSO with WWO to locate flaws in the electrical Distribution Network. This method uses offline and internet data banks to accurately identify the defective portion and its precise position in two steps.
- For determining problematic line sections, a Deep Q Network is developed that takes into account incomplete and incorrect data from RFIs and includes directional features. The result is a robust method for locating faults in distribution networks using DGs, allowing for faster service restoration and improved system reliability.

The remaining sections are arranged as follows: Section 2 describes a conventional fault location in the Distribution Network algorithm, Section 4 explains the WSWWO- Deep Q Network fault location. Section 5 compares WSWWO- Deep Q Network efficiency to classical techniques. Section 6 includes the conclusion.

2. Literature survey

Using smart meters at remote fault indicators (RFIs) and low voltage (LV) networks at an MV, Yazhou Jiang *et al.* [1] have introduced a data-based approach for a fault location in the distribution systems with the use of Distributed Generations (DGs). The discovered fault location helps system operators restore services more quickly, boosting system dependability and resilience. An improved escalation approach was introduced to anticipate the outage zone using outage notifications from smart meters to detect a malfunction promptly. The method has achieved outstanding performance and robustness, making it suitable for industrial applications. The problem of determining the actual fault site in distribution systems with substantial DG penetration remains unresolved.

Masoud Dashtdar *et al.* [2] have devised an optimization-based fault-location structure for distribution networks. The two objective functions were created by applying voltage variations to locate the defect and identify its faulty area. The method combines the Phasor Measurement Units (PMU) with the Power System Status Estimation (PSSE) issue to estimate current and voltage at branch points and network nodes following a fault. The method has several benefits: ease of use, step-by-step execution, efficiency under varying branch specifications, use for multiple faults, such as series and short-circuit, and optimal accuracy compared to alternative techniques. However, the method is not applicable for series faults.

Liang Cheng *et al.* [3] have developed a cost-effective method for accurately locating faults in distribution networks using a time matrix of traveling waves and optimal device setup. It works well in both ideal and optimal configuration scenarios. The time determination matrix is created by extracting beginning wave head data from moving waves, allows for distance calculation and identification of fault section. The method accurately locates faults under various scenarios. The technique needed to have been able to identify faults in distribution networks with a high concentration of DGs to fulfill new power grid requirements.

Sandhya Chandran *et al.* [4] devised a fault location technique for both single-source and multi-source distribution networks. In addition, a two-step algorithm was introduced that uses apparent impedance values from the measured synchro phasors. Data from remote PMUs were used to determine the actual fault location to eliminatepseudo-fault spots derived by the impedance method. The method effectively detects shunt problems anywhere inthe network. However, the demand for extensive data capability in conjunction with high-quality measurements may be a substantial problem.

S. Jamali and V. Talavat [5] have introduced a new fault location algorithm for distribution networks with synchronous devices for DG. Here, the time-domain numerical analysis and a data window were used that spans from pre-fault to post-fault, considering the dynamic behavior of synchronous machines during faults. During initialization, line section currents, node voltages, capacitive and load charging currents, and synchronous generator parameters were evaluated using pre-fault voltages and scheduled injected active and reactive powers from DG plants. Then, the numerical fault location technique was applied to shift the data window from pre-fault to the post-fault. The fault location algorithm has excellent accuracy, but failed to determine the fault point.

J. Faig *et al.* [6] employed impedance-based algorithms to identify single-phase faults in power distribution systems with distributed generating. This method relies on measuring voltages and currents at a single place, which might lead to inaccurate location estimates due to scattered generation. Here, the error achieved was minimal, but more sophisticated models were not introduced for DG-units and evaluating the effectiveness of fault location approaches.

Yang Yu *et al.* [7] have introduced a signal-to-image convolutional neural network (SIG-CNN) for estimating the location of distribution line faults. The SIG-CNN technique converts signals from the time domain to the image domain and builds the feature cubic. It correlates to the real power system and carries physics implications. SIG-CNN's well-trained network requires less memory than other networks, but it takes more time to predict the location of faults.

Ziyang Yin *et al.* [8] have introduced the Distribution Network Reconfiguration (DNR) approach, which is proposed to minimize power loss, bus voltage variance, and increasing reliability. Moreover, a dataset that meets the specifications of the data drive model was obtained. Next, the DNR dataset was trained using the enhanced Convolution Neural Network (CNN). The technique shortens the reliability calculation time, but still needs to include Structural neural networks to enhance the accuracy and generalization of DNR problems.

The following are the problems encountered in the relevant work,

Distribution systems have seen significant changes in recent years due to on-site generation offered by various distributed energy resources (DERs), such as small hydropower, solar power, biomass, wind power, and a fuel cell, among other alternatives. Distributed generation (DG) in either grid-connected can considerably increase supply security while also lowering environmental effects. However, the complex network configuration with bidirectional current flow poses major obstacles for situational awareness.

3. Distribution Network model

The Meter Data Management System (MDMS) in the distribution operations center receives and compiles smart meter outage reports that occur downstream of the activated protective device in the event of a power loss. Due to restricted transmission capacity and other issues such as hardware failures, improper firmware settings, and impediments in the line of sight in communication networks, utility providers typically receive fewer than half of planned outage reports. Retracing the distribution transformer and protective devices from the meter to the substation is necessary if smart meters at the LV network detect an outage. The outage reports are collected in a

bottom-up manner, and the top protective device that receives the most outage complaints is judged open for fault isolation. It is important to note that the distribution system may face missed protection coordination and multiple faults. How escalation is handled could cause complex fault scenarios to escalate excessively. Using smart meters, the following logic is introduced for an improved outage escalation: a) If a DT is linked to a single smart meter downstream and detects a power outage, the outage will escalate, b) When a DT is linked to multiple smart meters downstream, the power outage becomes more severe if at least two intelligent meters detect it. Depending on the capacity and system setup, a DT can serve from one to tens of consumers. Using the logic, power outages grow for distribution transformers T9, T11, T8, T13, and T12. Moreover, if any DT downstream of a fuse is located in the outage region, the outage will escalate, if there are many fuses downstream of a single fuse, the outage will escalate if at least two of them are located in the outage region, according to the escalation process. These logics indicate that fuses F3, F4, F8, and F10 are in the outage region. Figure 1 shows a simplified distribution network.
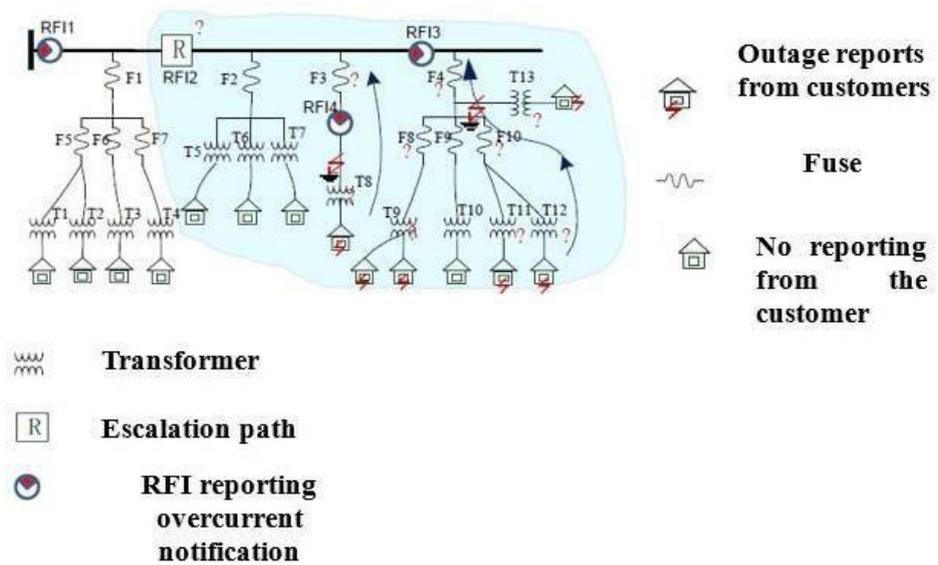

Figure 1. Simple distribution network.

3.1 Fault location using Deep Q-Network

Previous fault location algorithms for distribution networks are primarily based on steady-state solutions, which means they employ fundamental components of the steady-state current and voltage captured at the network main feeder, such as in a High Voltage/Low Voltage (HV/MV) substation. The radial distribution networks with distributed generation cannot use these technologies because of the dynamic behavior of synchronous generators. Thus, the Deep Q Network is used for fault location identification in distribution networks. Users need initial data and are not required to perform in data processing operations, like feature extraction and dimension lifting. This method is ideal for analyzing data with complicated structures and deep information that cannot be manually extracted.

Architecture of Deep Q-Net

Deep Q-Net [21] is the most popular reinforcement learning method, which uses CNN to estimate the action value function known as the Q-function. This approach is sometimes unstable due to the nonlinear function approximator representing the Q-function. Updates to Q-values and correlations in the sequence of state observations caused the instability. To circumvent these limitations, Deep Q-net employs the experience replay method. To produce an experience replay, the experiences of an agent $D_t = (b_t, d_t, l_t, b_{t+1})$ at time stamp t are saved in the dataset $B_t = (D_1, ..., D_t)$. B_t represents the dataset, also known as replay memory. In addition, the Q learning updates are made to data samples based on agent experience (b_p, d_p, l_p, b_{p+1}). This experience is

uniformly derived from the dataset B_t. Consider the count of episodes as F, the maximum number of action

steps per episode as I, the interval for updating target network parameters as U, and the loss function for Q-learning updates with iteration κ as,

$$Loss(\delta_\kappa) = \chi_\kappa \left[\left(c + \upsilon \max_{d'} \hat{P}(b', d'; \delta_\kappa^-) - P(b, d; \delta_\kappa) \right)^2 \right]$$

(1)

where, δ_κ is the network parameters of the Q-network at iteration κ, δ_κ^- is the network parameters to compute

the target $g_p = c + \upsilon \max_{d'} \hat{P}(b', d'; \delta_\kappa^-)$ at iteration κ, c is the reward, and υ is the discount factor. The TD

error, denoted by $c + \upsilon \max_{d'} \hat{P}(b', d'; \delta_\kappa^-) - P(b, d; \delta_\kappa)$, exhibits instability in convergence due to its

dependence on the network parameters δ_κ at each iteration κ. Deep Q-Net uses a neural-fitted Q-technique to

improve stability, in which τ in the target $c + \upsilon \max_{d'} \hat{P}(b', d'; \delta)$ is supposed to be fitted

$c + \upsilon \max_{d'} \hat{P}(b', d'; \delta^-)$ at a specific time step. Furthermore, δ^- is updated according to the action value

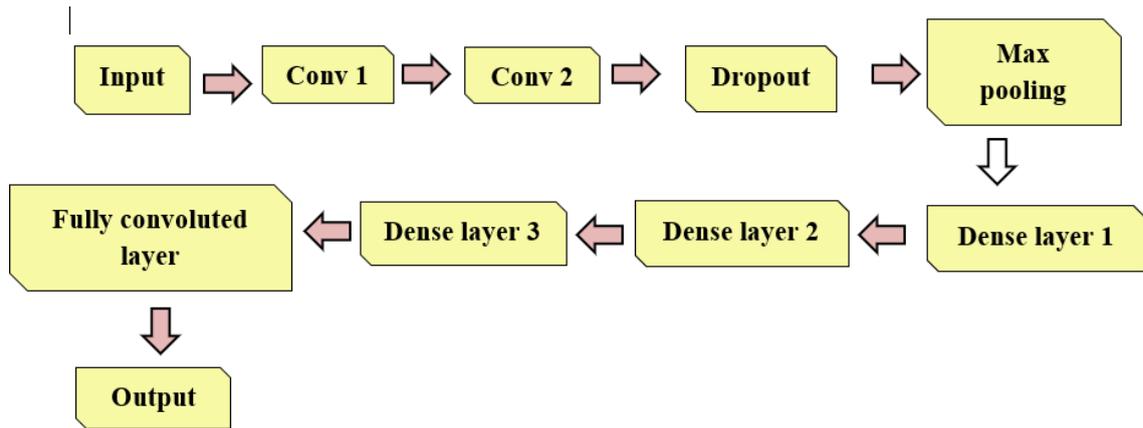function. Figure 2 shows the structure of a Deep Q Network.

Figure 2. Deep Q Network architecture

Training of Deep Q-Net using WSWWO

To detect the faulted line sections, the optimization model uses overcurrent notifications from Remote Fault Indicators (RFIs) in the Medium Voltage (MV) network and the outage zone indicated by outage reports from smart meters in the LV network. In previous works, the nonlinear logical restrictions are converted into a linear combination of decision variables. Using these concepts, this WSWWO seeks to address the issue of fault location with RFIs with directed features and smart meters. The suggested WSWWO combines the WSO [22] and WWO [23] algorithms. WSO optimizes based on the heritage of military strategy. The WSO has three population members: kings, soldiers, and commanders. Furthermore, the WSO algorithm employs two common battle strategies: defense and offensive mechanisms. To increase the value of the ideal solution, two tactics are included: weak soldier relocation and a updating the weight. This algorithm achieved a superior imbalance between exploration and exploitation. The WWO draws influence from shallow water waves to solve optimization issues. The WWO algorithmic framework is straightforward to apply, requiring a small population and minimal control

settings. The essential advantage of WWO is that it improves the algorithm's computational efficiency. As a result, the suggested WSWWO algorithm is modeled by combining the concepts of WWO and WSO algorithms, reducing time complexity. The steps of the WSWWO algorithm are discussed in the following section.

-Initialization

During the initialization step, the WSWWO algorithm's population of members, namely Commander, Soldiers and King are initialized.

-Fitness function

The fitness metric is used to determine the ideal value based on the loss function. Here, the lowest value of the loss function is regarded an ideal solution, which is given in equation (1).

Attack Strategy

Each soldier updates their position in accordance with the commander's and king's locations. The soldiers with the most offensive force are chosen as the king. In the early stages of the conflict, every soldier has a comparable rank and weight. In the later stages, each soldiers weight and rank vary according on their success performance. At the end of the attack, the commander, soldiers, and king approach the objective position, which is portrayed as,

$$p_a(q+1) = p_a(q) + 2*\beta*(g-t) + \varpi*(p_a*t - p_a(q)) \tag{2}$$

$$p_a(q+1) = p_a(q) + 2*\beta*(g-t) + \varpi*p_a*t - \varpi*p_a(q) \tag{3}$$

$$p_a(q+1) = p_a(q)[1-\varpi] + 2*\beta*(g-t) + \varpi*p_a*t \tag{4}$$

The WWO is used in the WSO position update to improve soldiers' positions. Using the concept of WWO,

$$p_a(q+1) = p_a(q) + Gaussian(0,1).\alpha.Z_b \tag{5}$$

$$p_a(q) = p_a(q+1) - Gaussian(0,1).\alpha.Z_b \tag{6}$$

Substitute equation (6) in equation (4),

$$p_a(q+1) = (p_a(q+1) - Gaussian(0,1).\alpha.Z_b)[1-\varpi] + 2*\beta*(g-t) + \varpi*p_a*t \tag{7}$$

$$p_a(q+1) - p_a(q+1)[1-\varpi] = 2*\beta*(g-t) + \varpi*p_a*t - Gaussian(0,1).\alpha.Z_b[1-\varpi] \tag{8}$$

$$p_a(q+1)[1-[1-\varpi]] = 2*\beta*(g-t) + \varpi*p_a*t - Gaussian(0,1).\alpha.Z_b[1-\varpi] \tag{9}$$

$$p_a(q+1) = \frac{1}{\varpi}[2*\beta*(g-t) + \varpi*p_a*t - Gaussian(0,1).\alpha.Z_b[1-\varpi]] \tag{10}$$

where, $p_a(q+1)$ be a new location at $q+1$ iteration, p_a is a preceding commander position g, the king's position is denoted as t and the weights be p_a. The term α is the breaking coefficient, Gaussian (0, 1) provides a Gaussian random integer with standard deviation 1and mean o. Z_b be the length of dimension at search space.

Updation of weight and rank

Each search agent's position is updated based on the rank of King, Commander, and soldier. Soldiers are ranked based on their success in war, as determined by equation (11), which influences the weighting factor. Each soldier's rank indicates their proximity to the target, also known as their fitness value. If an attack force in the newlocation G_m is lower than the prior position G_n, the soldier returns to the former position.

$$p_a(q+1) = (p_a(q+1)) \times (G_m \geq G_n) + (p_a(q)) \times (G_m < G_n) \tag{11}$$

If the soldier successfully updates their position, their rank R_a is improved.

$$R_a = (R_a + 1) \times (G_m > G_n) + R_a \times (G_m < G_n)$$ (12)

The new weight is calculated using the rank as follows:

$$L_a = L_a \times \left(1 - \frac{R_a}{X}\right)^{\gamma}$$ (13)

where, X denotes the maximum iteration, and γ be the factor.

Defense plan

The second strategic position update is made according to King's, the army chief's, and a soldier's situations,. Ranking and weight updates remain unchanged.

$$p_a(q+1) = p_a(q) + 2 * \beta * (t - p_\varpi(r)) + \varpi * p_a * (d - p_a(q))$$ (14)

This war policy expands the search space beyond the previous policy by including the location of a random soldier. Soldiers take significant moves and evaluate their position in order to achieve high values. Soldiers take smaller steps p_a when judging a site with smaller values.

Weak soldiers' replacement

Identify the weakest warriors with the worst fitness in each cycle. We tried several alternative approaches. A straightforward solution is to replace the weak soldier with a random soldier given by,

$$p_x(q+1) = E_k + \varpi \times (E_r - E_k)$$ (15)

This method improves the convergence of the WSWWO.

Fitness Re-evaluation

Following the replacement or relocation of weak soldiers, each soldier's position is changed depending on the fitness function.

Termination

All of the stages described in this approach are repeated until the optimal answer is obtained. Furthermore, the algorithmic steps of the WSWWO algorithm are described in Algorithm 1.

Algorithm 1. Pseudo code of WSWWO

Set the starting values for war space dimension, soldier size, commander location, king location, and so on.
Locate soldiers randomly in war space.
    For $1: Size\ of\ soldier$
Calculate the fitness or assault force of each soldier.
The for loop has ended
Soldiers are relocated according to the fitness value.
Choose a commander and king using attack force.
    While $q < q_{max}$

For 1: *Size of soldier*

Update each soldier's position.

Calculate every soldier's assault force.

Renew and locate soldiers using the fitness function.

The for loop has ended

Identify the vulnerable soldiers.

Replace the warriors who are weak

Renew the location of the king and commander

$q = q + 1$

The while loop has ended

Thus, the WSWWO collects outage reports from smart meters in the LV network and RFI notifications from the MV networks. The active protection device is found by analyzing outage reports from smart meters with escalation logics.

4. Results and discussion

This section provides the results and analysis of a WSWWO- Deep Q Network for fault location.

4.1. Experimental setup

Figure 3 depicts the IEEE 34-node feeder as the preferred network. This network is 28.8 kilometres long, with eight branches in a main feeder. This network is broken into 32 pieces of varied lengths. The fault type is assumed to be predetermined here. Using a real-time three-phase voltage signal, but detecting the type of fault is a simple task. This study trains five models for single, two, and three-phase grounding, as well as three-phase and phase-to-phase fault. MATLAB Simulink 2018 is the simulation environment.
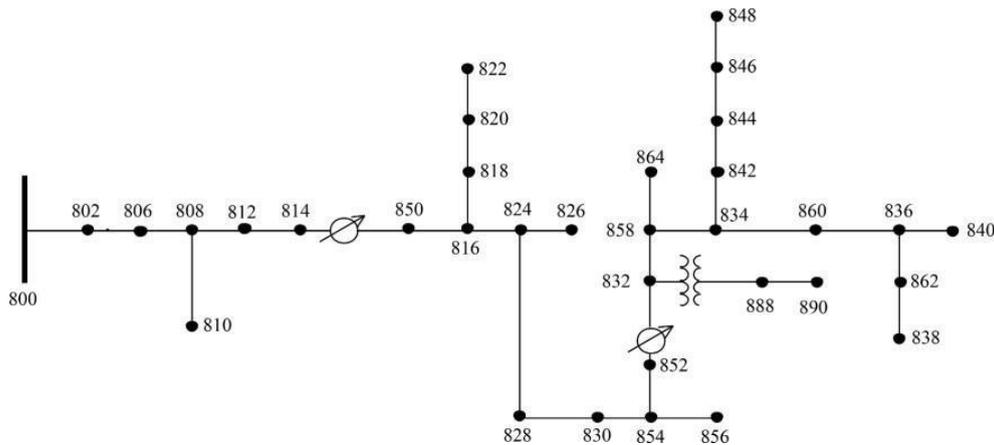

Figure 3. Single IEEE 34-node feeder

4.2 Evaluation metrics

The created WSWWO- Deep Q Network for fault location has the following performance metrics: Accuracy and Error.

Accuracy is used to measure the accuracy of the WSWWO- Deep Q Network functioning, which is characterized as

$$A = \frac{e_f + e_j}{e_f + e_j + h_f + h_j} \tag{16}$$

where, e_f and e_j denotes true positive and negative. The terms h_f and h_j be the false positive and negative.

The Error rate for fault location is defined as,

$$Err(\%) = \frac{\left| C_{actual} - C_{estimated} \right|}{K} \qquad (17)$$

where, K is the feeder length, C_{actual} is the real fault location, and $C_{estimated}$ determined fault location by Deep Q Network.

4.3. Competing methods

In terms of performance measurements, this section compares WSWWO- Deep Q Network to other methodologies, such as Improved Escalation approach [1], Impedance-based algorithm [2], and SIG-CNN [7].

4.3.1 Comparative assessment for one phase to ground fault

Figure 4 shows a comparative analysis of WSWWO-Deep Q Network based on performance metrics. Figure 4i) depicts the accuracy. The accuracy assessed by Improved Escalation approach, Impedance-based algorithm, SIG-CNN, and WSWWO-Deep Q Network is 0.821, 0.835, 0.867, and 0.887, respectively, for 80 % training data. Figure 4ii) depicts an assessment of approaches to Error. The Error values for Improved Escalation approach, Impedance-based algorithm, SIG-CNN and WSWWO-Deep Q Network are 0.288, 0.278, 0.258, and 0.212 for 2nd epoch. Furthermore, for 3rd epoch, the Error assessed by Improved Escalation approach is 0.237, Impedance- based algorithm is 0.216, SIG-CNN is 0.212 and WSWWO-Deep Q Network is 0.192. The results show that the WSWWO-Deep Q Network is nearly perfect at recognizing the defective section. This approach ensures that the model is not impacted by noise and can properly identify the faulty portion and location, allowing the maintenance staff to find and repair the fault promptly and effectively.
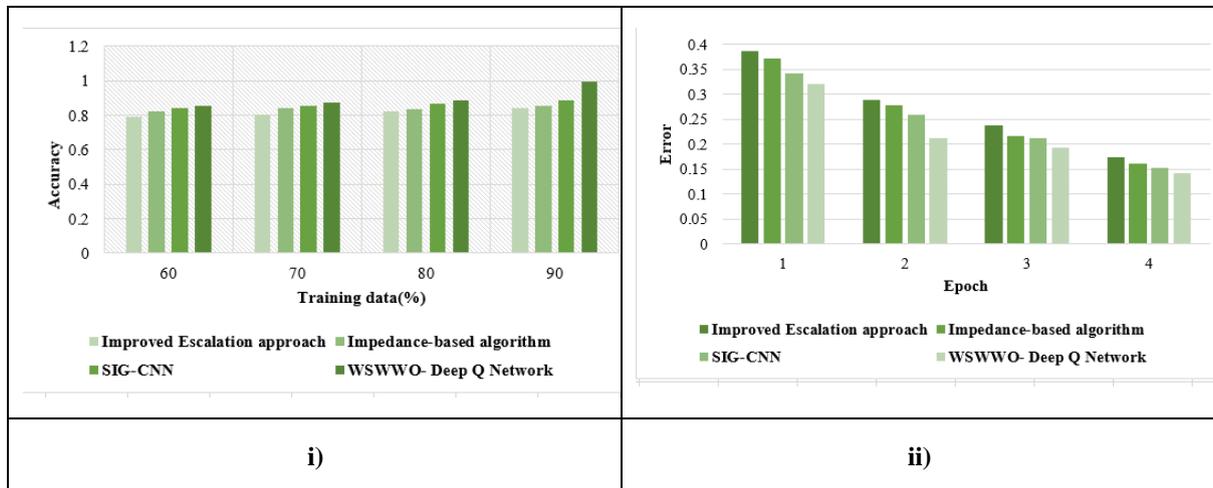

i)	ii)

Figure 4. Comparative evaluation of WSWWO-Deep Q Network for one phase to ground fault i) Accuracy, ii) Error

4.4. Comparative discussion

Table 1 shows based on accuracy and Error based on one phase to ground fault. Using 90% of training data, WSWWO-Deep Q Network have highest accuracy of 0.997, followed by Improved Escalation approach, Impedance-based algorithm, and SIG-CNN are 0.843, 0.852, and 0.884 respectively. The WSWWO-Deep Q Network has the lowest Error of 0.141, while Improved Escalation approach, Impedance-based algorithm, and SIG-CNN have Error values of 0.173, 0.161, and 0.152, respectively. Thus, from the result the WSWWO-Deep Q Network may quickly and effectively locate problems on both valid and invalid branches. The ideal setup of traveling wave detection devices with a temporal Error and increase in fault location Error rates. The proportion of DGs increases Error rates for various fault types, respectively, while being within engineering constraints. The WSWWO-Deep Q Network is resilient to temporal faults and improves engineering practicability. In addition, the WSWWO-Deep Q Network excels at detecting problematic sections and accurately locating faults. The faulty section identification approach is virtually 100% accurate in identifying faulty parts.

Table 1. Comparative analysis

Metrics	Improved Escalation approach	Impedance-based algorithm	SIG-CNN	WSWWO-Deep Q Network
Accuracy	0.843	0.852	0.884	**0.997**
Error	0.173	0.161	0.152	**0.141**

5. Conclusion

For distribution networks with a large penetration of DGs, fault location must be efficient and accurate. The ongoing distribution automation efforts and the growing emphasis on system stability and resiliency, are encouraging the installation of intelligent sensors in distribution systems to improve system monitoring. This paper uses the data from smart meters in LV networks and RFIs in MV networks are used together to locate faults efficiently and accurately. A Deep Q Network is proposed in this research to identify both the faulty portion and its exact location. Here, Deep Q Network is trained by WSWWO in which WSO and WWO are hybridized. To extract more information from deep layers, spectrogram time-frequency analysis is utilized to turn the alpha component of the voltage signal collected at the substation into an image. The WSWWO-Deep Q Network demonstrated remarkable performance, with an Accuracy of 0.997, and an Error of 0.141. Later, we'll look at the cost-benefit analysis of various intelligent sensors used for fault management.

References

[1] Yazhou Jiang,"Data Driven Fault Location of Electric Power Distribution Systems with Distributed Generation", IEEE Transactions on Smart Grid, vol.11, no.1, pp.129-137, 2019.

[2] Masoud Dashtdar, Arif Hussain, Hassan Z. Al Garni, Abdullahi Abubakar Mas'ud, Waseem Haider, Kareem M. AboRas, and Hossam Kotb, "Fault Location in Distribution Network by Solving the Optimization Problem Based on Power System Status Estimation Using the PMU", Machines, vol.11, no.1, pp.109, 2023.

[3] Liang Cheng, Tao Wang, and Yi Wang, "A novel fault location method for distribution networks with distributed generations based on the time matrix of traveling-waves", Protection and Control of Modern Power Systems, vol.7, no.1, pp.1-11, 2022.

[4] Sandhya Chandran, Ramakrishna Gokaraju, and Krish Narendra, "An extended impedance-based fault location algorithm in power distribution system with distributed generation using synchrophasors", IET Generation, Transmission & Distribution, vol.18, no.3, pp.479-490, 2024.

[5] S. Jamali, and V. Talavat,"Dynamic fault location method for distribution networks with distributed generation", Electrical Engineering, vol.92, pp.119-127, 2010.

[6] J. Faig, J. Melendez, S. Herraiz, and J. Sánchez," Analysis of Faults in Power Distribution Systems with Distributed Generation", In proceedings of International Conference on Renewable Energies and Power Quality (ICREPQ'10), Granada, Spain, 23th to 25th March, 2010.

[7] Yang Yu, Mengshi Li, Tianyao Ji, and Q. H. Wu, "Fault Location in Distribution System Using Convolutional Neural Network Based on Domain Transformation", CSEE Journal of Power and Energy Systems, vol.7, no.3, pp.472-484, 2021.

[8] Ziyang Yin, Xingquan Ji, Yumin Zhang, Qi Liu, and Xingzhen Bai, "Data-driven approach for real-time distribution network reconfiguration", IET Generation, Transmission & Distribution, vol.14, no.13, pp.2450-2463, 2020.

[9] Kunjin Chen, Caowei Huang, Jinliang He,"Fault detection, classification and location for transmission lines and distribution systems: a review on the methods", High voltage, vol.1, no.1, pp.25-33, 2016.

[10] Adly Girgis, and Sukumar Brahma, "Effect of Distributed Generation on Protective Device Coordination in Distribution System", In proceedings of LESCOPE 01 large engineering systems conference on power engineering, Theme: Powering Beyond 2001 (Cat. No. 01ex490), pp. 115-119), IEEE, July 2001.

[11] Marco Pignati, Lorenzo Zanni, Paolo Romano, Rachid Cherkaoui, Mario Paolone,"Fault Detection and Faulted Line Identification in Active Distribution Networks using Synchrophasors-based Real-Time State Estimation", IEEE Transactions on Power Delivery, vol.32, no.1, pp.381-392, 2016.

[12] Chenchen Li, Yanna Xi, Yufan Lu, Nian Liu, Liudong Chen, Li Ju and Yibin Tao, "Resilient outage recovery of a distribution system: co-optimizing mobile power sources with network structure", Protection and Control of Modern Power Systems, vol.7, no.1, pp.1-13, 2022.

[13] Fernanda C. L. Trindade, and Walmir Freitas, "Low Voltage Zones to Support Fault Location in Distribution Systems With Smart Meters", IEEE Transactions on Smart Grid, vol.8, no.6, pp.2765-2774, 2016.

[14] Myeon-Song Choi, Seung-Jae Lee, Seong-Il Lim, Duck-Su Lee, and Xia Yang,"A Direct Three-Phase Circuit Analysis-Based Fault Location for Line-to-Line Fault",IEEE Transactions on Power Delivery, vol.22, no.4, pp.2541-2547, 2007.

[15] Sadegh Jamali, Alireza Bahmanyar and Siavash Ranjbar, "Hybrid classifier for fault location in active distribution networks", Protection and Control of Modern Power Systems, vol.5, pp.1-9, 2020.

[16] Amir Mehdi Pasdar, Yilmaz Sozer, and Iqbal Husain," Detecting and Locating Faulty Nodes in Smart Grids Based on High Frequency Signal Injection",IEEE transactions on Smart Grid, vol.4, no.2, pp.1067-1075, 2013.

[17] Liwei Xie, Longfu Luo, Li, Yu Zhang, and Yijia Cao,"A Traveling Wave Based Fault Location Method Employing VMD VMD-TEO for Distribution Network", IEEE Transactions on Power Delivery, vol.35, no.4, pp.1987-1998, 2019.

[18] Yanhui Xi, Zewen Li, Xiangjun Zeng, Xin Tang, Xiaodong Zhang, and Hui Xiao, "Fault location based on travelling wave identification using an adaptive extended Kalman filter", IET Generation, Transmission & Distribution, vol.12, no.6, pp.1314-1322, 2018.

[19] A. Jamehbozorg and S. M. Shahrtash,"A Decision Tree-Based Method for Fault Classification in Double-Circuit Transmission Lines", IEEE transactions on power delivery, vol.25, no.4, pp.2184-2189, 2010.

[20] Yanhui Xi, Xiaodong Zhang, Zewen Li, Xiangjun Zeng, Xin Tang, Yonglin Cui, Hui Xiao,"Double-ended travelling-wave fault location based on residual analysis using an adaptive EKF", IET Signal Processing, vol.12, no.8, pp.1000-1008, 2018.

[21] Hikaru Sasaki, Tadashi Horiuchi and Satoru Kato,"Study on Vision-based Mobile Robot Learning by Deep Q-network",In Proceedings of the SICE Annual Conference, Kanazawa University, Kanazawa, Japan, September 2017.

[22] Ayyarao, T.S., RamaKrishna, N.S.S., Elavarasan, R.M., Polumahanthi, N., Rambabu, M., Saini, G., Khan, B. and Alatas, B., "War strategy optimization algorithm: a new effective metaheuristic algorithm for global optimization", IEEE Access, vol.10, pp.25073-25105, 2022.

[23] Zheng, Y.J., "Water wave optimization: a new nature-inspired metaheuristics", Computers & Operations Research, vol.55, pp.1-11, March 2015.