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# OPGW State Evaluation Method Based on MSIF and QPSO-DQN in Icing Scenarios

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## ABSTRACT

A new OPGW state evaluation method based on Multi-Source Information Fusion (MSIF) and Quantum Particle Swarm Optimization & Deep Q-learning (QPSO-DQN) is proposed. Firstly, using MSIF to integrate and unify historical data and real-time monitoring data of OPGW, more comprehensive and accurate OPGW status information was obtained. Then, utilizing the advantages of deep reinforcement learning (DRL) algorithm DQN in handling highly nonlinear problems, various influencing factors related to the operation of OPGW were addressed. Finally, DQN was improved by introducing the QPSO optimization algorithm, which transformed the Q-value function solving in DQN into a function fitting problem and used QPSO as an intelligent agent to fit the function, achieving accurate evaluation of the OPGW operating status. The simulation experiment results show that the proposed method has the highest accuracy in ice weight detection, temperature detection, frequency detection, and optical power detection on the same dataset, reaching 98.85%, 98.97%, 98.13%, and 98.97%, respectively.

## KEYWORDS

OPGW, State Assessment, QPSO, DQN, Multi-Source Information Fusion

## OPGW STATE EVALUATION IN ICING SCENARIOS BASED ON MSIF AND QPSO-DQN

With the rapid development of modern society and the explosive growth of information, communication networks have become an important component of national infrastructure. In this field, optical ground wire (OPGW), as a unique type of optical cable, has attracted much attention due to its dual functions of both overhead ground wire for power lines and fiber optic communication (Xia et al., 2023; Sun et al., 2021; Marie et al., 2020). OPGW is a composite optical cable that wraps optical fibers in overhead ground wires. It uses power overhead ground wires as external protection for optical cables, while providing grounding protection and electromagnetic interference resistance for power lines (Nguyen & Nguyen, 2020; Mohammed & Daham, 2021; Wang et al., 2022). Due to its unique structure, OPGW has many advantages:

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1. Due to their structural characteristics, OPGW optical cables are highly reliable and can effectively avoid communication line failures caused by lightning strikes and short-circuit currents in traditional power communication systems (Peng et al., 2022; Xu et al., 2020).
2. OPGW optical cables are suitable for installation on power lines of various voltage levels and are easy to construct and install (Zhang et al., 2022; Wang & Li, 2022).
3. OPGW optical cables can withstand large stresses and have strong resistance to strong winds, ice, and other factors (Wang et al., 2020a; Wang et al., 2020b).
4. OPGW optical cables have a long service life, generally ranging from 25 to 30 years, often more (Martín-López et al., 2021; Qin et al., 2021).

OPGW is generally designed and installed simultaneously with overhead ground wires of transmission lines and can be installed in one go. On the premise of maintaining all the performance and functions of the original overhead ground wire unchanged, optical fibers are added to open up high-performance optical transmission channels, making it both lightning protection and communication functions (Wang et al., 2022; Lalam et al., 2021). As seen above, OPGW has good electrical, mechanical, and optical transmission performance and has been widely used in power grids in recent years. Most newly built transmission lines use OPGW as overhead ground wire, which undertakes important tasks in power communication (Lin et al., 2021; Rao et al., 2021). Compared to overhead transmission lines, OPGW towers are higher than transmission lines, closer to thunderstorms, and more susceptible to lightning strikes. During normal operation, OPGW has no load current, and the wire diameter is smaller than that of the conductor, which makes OPGW more severely covered with ice under the same meteorological conditions. Due to the lower mechanical strength of OPGW compared to conductors, it is more susceptible to damage and more severe (Ding et al., 2021; Wang et al., 2023; Zhu et al., 2022).

Due to the complexity of its working environment, the state assessment of OPGW has become an important and challenging issue. At present, the state assessment of OPGW mainly focuses on the following aspects (Wang et al., 2022; Zhang et al., 2021; Liu et al., 2023):

1. **Fiber optic performance evaluation.** Changes in parameters such as attenuation, dispersion, and PMD of optical fibers to evaluate the performance of fiber optic communication.
2. **Mechanical performance evaluation.** Changes in mechanical properties, such as tension, bending, and torsion, of optical cables to evaluate their mechanical strength and durability.
3. **Environmental factor assessment.** Environmental factors in the area where the optical cable is located, such as temperature, humidity, wind, rain, ice, and snow, that impact the cable.

However, existing evaluation methods still have some problems and challenges, such as the complex working environment of OPGW, making it difficult to obtain comprehensive status information and conduct accurate status assessments. In addition, existing evaluation methods often only focus on a certain aspect of performance and cannot comprehensively evaluate the overall performance of OPGW (Zhou et al., 2023; Li et al., 2022). Through in-depth research on the performance changes of OPGW and the development of comprehensive evaluation methods, it is expected to achieve an accurate evaluation of OPGW status, providing strong guarantees for the safe and stable operation of the national power communication system.

The current OPGW state evaluation methods are usually based on limited test data and simple statistical analysis, which makes it difficult to reflect the true state of OPGW fully. Most of these methods require human intervention and involvement, with low levels of automation and intelligence. This not only increases the cost and time of evaluation but may also lead to inaccurate and inconsistent evaluation results due to human factors. In order to overcome these shortcomings, it is necessary to advance research and develop more accurate, reliable, automated, and intelligent OPGW state assessment methods to improve the safety and reliability of power transmission and optimize the operation and maintenance of power facilities. In response to the above issues, this article proposes an OPGW state evaluation method based on MSIF and QPSO-DQN in icing scenarios. Compared with traditional methods, the innovation of the proposed method lies in:

1. Based on MSIF, multiple sources of information are integrated, including historical data on power transmission lines, real-time monitoring data, meteorological data, geographic information, etc. This information is integrated to reflect the status of OPGW more comprehensively.
2. In evaluating OPGW's operational status, the DQN algorithm, which can effectively handle highly nonlinear, non-deterministic, and complex problems, was adopted to accurately reflect the impact of various factors, including environment, climate, and equipment performance, on OPGW's operational status.
3. Based on QPSO, DQN has been optimized to jump out of local optima and find global optima more effectively. This helps DQN avoid falling into local optima during the optimization process, thereby optimizing for better network parameters.

## RELATED RESEARCH

OPGW is an important component of the power system, and its state directly affects the safety and stable operation of the power system. By evaluating the status of OPGW, potential safety hazards can be identified and addressed in a timely manner, thereby avoiding or reducing the occurrence of power system failures and improving the reliability of the power system. And after evaluation, the health condition and performance level of OPGW can be understood, so as to develop a reasonable maintenance and repair plan and extend its service life. This can not only reduce the cost of replacing equipment but also reduce the impact on the environment. In addition, by monitoring and analyzing the status of OPGW, it is possible to predict its future performance changes and maintenance needs, thereby formulating reasonable budgets and plans to avoid unnecessary economic losses.

At present, researchers have conducted relevant research on OPGW state evaluation methods. Based on the weak fiber Bragg grating (WFBG) array as the basic theoretical basis, Feng et al. (2022) proposed a new method for temperature monitoring of OPGW, which can, to some extent, locate the lightning strike point through abnormal temperature conditions. However, this method focuses more on the key monitoring of temperature and cannot comprehensively evaluate the health status of OPGW. Sun et al. (2021) used the Brillouin optical time-domain reflectometer (BOTDR) as the basic theoretical basis to measure the temperature of OPGW. They proposed a method for monitoring the thickness of the ice layer covering the surface of OPGW. The relationship between ice thickness and surface temperature was analyzed using finite element analysis. However, this method is limited by testing conditions and environmental limitations, and the evaluation results may have certain errors and uncertainties. Meng et al. (2020) established an online monitoring system for strain of OPGW optical cables. By comparing the measurement results of long-distance Brillouin optical time-domain analysis (BOTDA) and BOTDR sensing systems, it was found that the measurement accuracy of BOTDA sensing systems is higher at shorter distances. When the distance is longer, BOTDR is more optimal, and line measurements can continue after the fiber optic before the disconnection point is disconnected. However, this method may not be suitable for OPGW state assessment in different working environments, and there are significant differences in the accuracy and reliability of the assessment results.

Zhang et al. (2021) developed a distributed fiber optic sensing device based on various parameters, which can be used for monitoring the status of power OPGW. This device has minimal loss in single parameter sensing and can achieve fusion and sensing of different parameters related to OPGW. It has a promoting effect on the application of distributed fiber optic sensing technology in the power industry. However, this method requires the comprehensive analysis of multiple parameters and a large amount of computation. In order to prevent power accidents caused by ice cover on OPGW in extremely cold weather, Hai and Huang (2022) used BOTDR as the basic theoretical basis. They introduced a finite element analysis method to achieve real-time monitoring of the surface ice thickness of OPGW. On this basis, the principle of how the thickness of the ice layer on the surface of OPGW affects its strain occurrence was obtained through modeling. However, the adaptability of this method to different environments and conditions needs to be improved.

Real-time monitoring of the temperature of optical cables used for cross-sea power transmission at the bottom of the deep sea is a very important task. In response to this issue, Chen et al. (2022) proposed a temperature monitoring system for deep-sea bottom optical cables based on BOTDA and introduced the IEC60287 thermal circuit. On this basis, the reliability of the system's calculation results was experimentally verified. However, this method can only monitor the temperature on the surface or shallow part of the optical cable, making it difficult to monitor the temperature inside and deep layers of the cable. For specific application scenarios, Lu et al. (2021) proposed a method for monitoring the status of OPGW and underground and submarine cables by combining various technical means, such as fiber optic sensing and wireless positioning. This method is based on a panoramic monitoring system and can be used for fault diagnosis and status evaluation of different types of cables and optical cables. However, this method makes it difficult to effectively predict the future development trends and potential problems of OPGW.

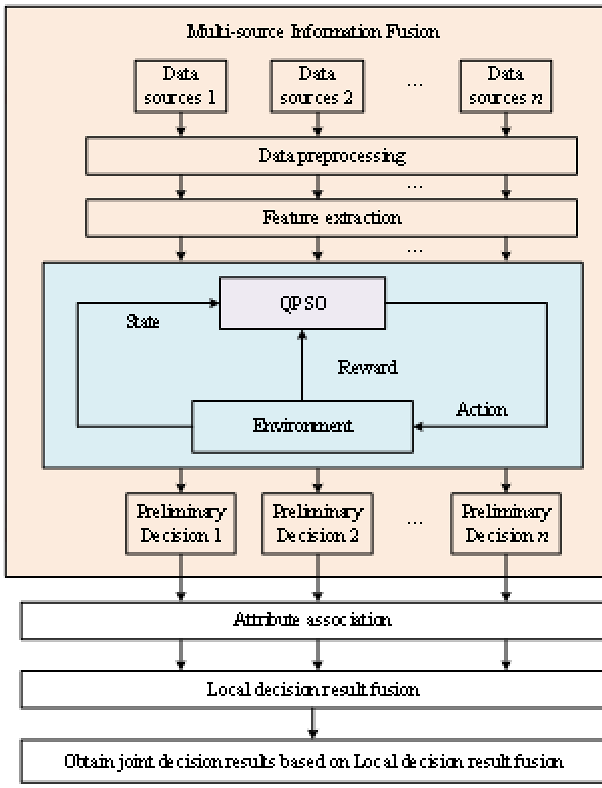
## ARCHITECTURE

A model architecture for OPGW evaluation is proposed based on two considerations. Figure 1 shows the collection of OPGW operation data of different types or dimensions using different sensors, preprocessing, extracting data features from these data, and using them as input for the QPSO-DQN model. The specific principles of the QPSO-DQN model will be explained in detail later. By utilizing data from different dimensions, corresponding preliminary judgment results can be provided separately. Based on the attribute correlation between these preliminary judgment results, the local decision results are fused, and the joint decision results are obtained.

On the one hand, considering that the OPGW state assessment needs to comprehensively consider multiple factors, including historical data of the line, real-time monitoring data, meteorological data, and geographic information. Through MSIF, these data can be integrated into a unified framework, providing more comprehensive and accurate information, which helps to evaluate the status of OPGW more accurately. In addition, there may be differences in data quality, accuracy, and reliability among different data sources. Through MSIF, the complementarity between different data sources can be utilized to reduce data uncertainty and errors, thereby enhancing data reliability and accuracy, avoiding the tedious process of repeated processing and manual integration, and improving evaluation efficiency to a certain extent.

On the other hand, considering that deep reinforcement learning (DRL) can play an important role in OPGW state evaluation, for example, DRL can use deep neural networks to automatically extract features from raw data, avoiding the cumbersome process of manually extracting features in traditional methods and improving the efficiency and accuracy of feature extraction. By utilizing the nonlinear mapping ability of deep neural networks, complex feature mapping relationships can be automatically established to describe the relationship between OPGW state and influencing factors better. Through the interaction between intelligent agents and the environment, continuously optimize decision-making strategies, and improve the accuracy and efficiency of decision-making. In OPGW state evaluation, appropriate reward functions can be designed based on real-time monitoring data and historical data to guide agents to learn better decision-making strategies.

**Figure 1. Proposed method architecture**



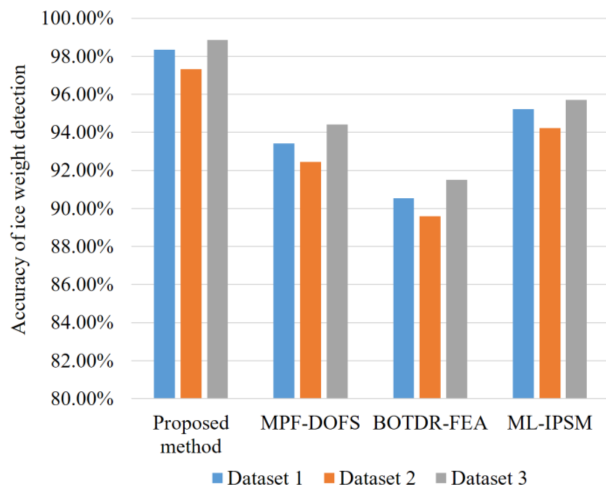

## Multi-Sensor Information Fusion

*Multi-sensor information fusion* (MSIF), or *data fusion*, comprehensively analyzes incomplete environmental information collected in local environments through various methods. MSIF was first applied in the navigation of military weapons such as airplanes, submarines, and missiles, utilizing multiple sensors to obtain on-site information. At the same time, computers were used to process and analyze the collected information automatically. At this time, MSIF technology achieved unprecedented development.

MSIF is closely related to fields such as artificial intelligence, data mining, and machine learning. These fields have interrelated and complementary parts in technology and methods, which can jointly improve the ability of information processing and analysis. MSIF is an important branch in the field of AI, aimed at improving the accuracy and reliability of decision-making by integrating information from multiple sources. AI technology provides advanced algorithms and models for MSIF, such as deep learning, and neural networks, for processing and analyzing complex multi-source data. MSIF can utilize the decision-making and reasoning capabilities of AI to make more intelligent decisions or predictions based on the fused information. Through machine learning, MSIF systems can adaptively handle changes and uncertainties between different data sources, improving the accuracy and robustness of fusion results.

In addition, in MSIF, data mining techniques can be used to analyze and mine information from different data sources, discovering correlations, trends, and anomalies between them. Data mining algorithms can be applied to MSIF systems to reveal valuable information hidden in multi-source data. MSIF is a technology that integrates data from multiple sensors, which involves fields such as pattern recognition, fuzzy mathematics, signal processing, and artificial intelligence. Compared to

Figure 2. Data layer fusion process




a single data source, MSIF can reduce the amount of data transmission by removing a large amount of redundant data, thereby reducing latency and improving the robustness of the entire system. On the other hand, improving measurement accuracy and enhancing data credibility. MSIF generally consists of four steps: collecting and organizing information source data, processing information source data, analysis and decision-making, and fusion of output results. According to the hierarchical classification of the information source to be processed, MSIF technology can be divided into data layer fusion, feature layer fusion, and decision layer fusion.

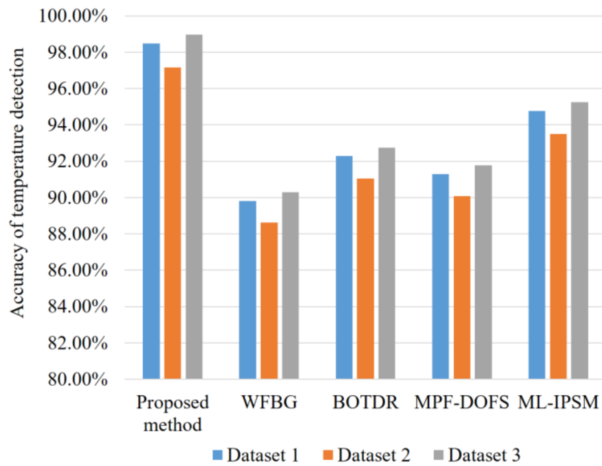
### *Data Layer Fusion*

Data layer fusion is the lowest-level fusion in MSIF, which directly processes the original data. Its advantage is that it can retain more original information with less information loss. However, its disadvantage is that fusion has significant limitations, as it can only process a single or the same type of data information, resulting in a large computational workload. The data layer fusion process is as follows. Figure 2 shows the data layer fusion process.

The main functions and processes of the data fusion layer are as follows.

- **Data preprocessing.** Clean, normalize, and extract features from data provided by multiple sources to improve its accuracy and reliability.
- **Data association and matching.** Associate and match data from multiple sources to obtain more comprehensive and accurate information. For example, the measurement data of different sensors are correlated and matched to obtain more accurate operation status information.
- **Data fusion algorithm.** Adopt appropriate data fusion algorithms to fuse data from multiple data sources. Common fusion algorithms include the weighted average, Kalman filtering, and neural network methods.
- **Data output.** Output the fused data for use by upper-level applications. In OPGW state evaluation, the fused operational state information is provided to the evaluation model for state evaluation.

Figure 3. Feature layer fusion process




### *Feature Layer Fusion*

Feature layer fusion extracts, selects, and combines feature information from different data sources to obtain more accurate and reliable feature descriptions. By extracting and selecting features from the data, it is possible to reduce the dimensionality and complexity of the data and improve processing efficiency. Figure 3 shows the process of feature layer fusion.

In Figure 3, the main steps of feature layer fusion include:

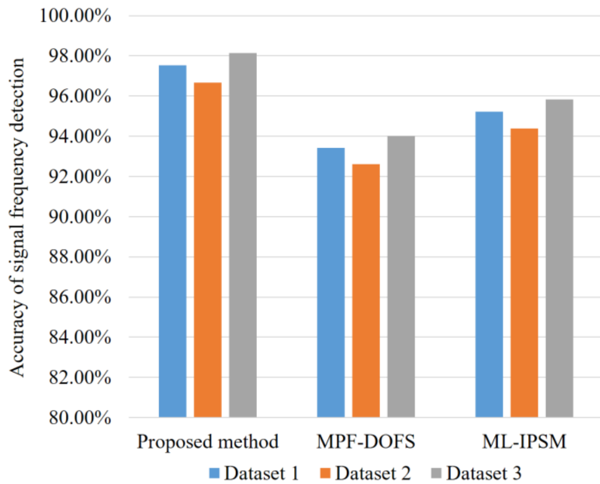
- **Feature extraction:** Extracting feature information related to the target from multiple data sources, with such features as pixel intensity, edge information, and texture, in the spatial domain, as well as dynamic behavior and velocity in the temporal domain.
- **Feature selection:** Selecting features related to the target from the extracted feature information, removing redundant and irrelevant features. The feature selection methods can, for example, be based on statistics, single-layer neural networks, or deep learning.
- **Feature combination:** Combines feature information from different data sources to obtain more comprehensive and accurate feature descriptions. The combination method could include simple weighted averaging, a combination of neural networks, or voting of decision trees.
- **Feature output:** Takes the fused feature information as output to provide for subsequent decision-making and analysis. This feature information can be in various forms, such as images, videos, and audio.

### *Integration of Decision-Making Levels*

Decision fusion is a high-level fusion method in MSIF, which improves the accuracy and reliability of decision-making by fusing decision results from different data sources. Decision fusion can adopt different decision-making methods and models based on different decision-making needs and data source characteristics, with strong flexibility. Due to the fusion at the level of decision results, it has strong anti-interference ability. Decision fusion can reduce the error rate of a single decision result by comprehensively processing multiple decision results. Figure 4 shows the fusion process of the decision-making level.

In Figure 4, the basic steps of decision layer fusion include:

Figure 4. Decision layer fusion process




- **Data preprocessing.** Preprocessing data from different sources, including data cleaning, normalization, feature extraction, and other operations, to improve the accuracy and reliability of the data.
- **Local decision-making.** Conducting decision analysis for each data source separately to obtain their own decision results.
- **Decision result fusion.** Integrating the decision results of various data sources to obtain the final joint decision result. Common methods for integrating decision results include voting, weighted average, and logistic regression.
- **Decision output.** Taking the fused decision results as output to provide for subsequent decision-making and analysis.

### *Reliable Data Handling*

Faced with the issues of uncertainty and inconsistency in handling data, MSIF mainly solves them through the following channels:

- Different data sources may use different coordinates or reference frames, so they can be converted to a unified coordinate or reference frame through data registration before conducting MSIF: This process may introduce registration errors, so compensation for these errors is necessary to minimize uncertainty and inconsistency.
- Preprocessing the data provided by each data source to eliminate noise and inconsistency
- Establishing an uncertainty model can quantify and describe data uncertainty: Methods such as probability distribution, fuzzy sets, and rough sets can be used to model uncertainty. This can consider these uncertainties in the MSIF process, thereby improving the accuracy of the results.
- In the MSIF process, uncertainty reasoning methods such as Bayesian reasoning and fuzzy reasoning can be used to handle uncertainty and inconsistency in data: These methods can comprehensively consider the information from multiple data sources and weight fusion based on their respective confidence and reliability, thereby obtaining more accurate and consistent results.

- Some optimization algorithms can be used to find the optimal fusion result. These algorithms can find the optimal solution through iterative search under certain constraints, thereby reducing uncertainty and inconsistency in the data.

### *System Design*

When evaluating and designing an MSIF system for OPGW, it is necessary to consider the requirements for real-time data, communication protocols, and data transmission mechanisms of OPGW sensor networks, computational resource limitations, scalability, and flexibility. The general design process is as follows.

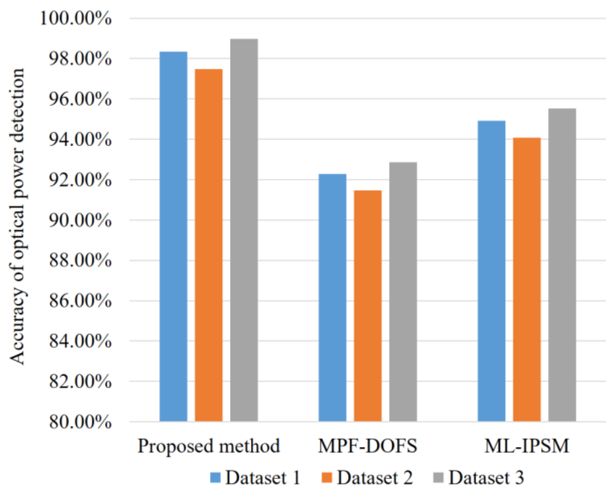
- **Define application requirements.** Gain a deep understanding of the specific application scenarios of OPGW sensor networks, including environment, sensor types, data acquisition frequency, and transmission requirements. Identify key issues the MSIF system needs to address, such as performance monitoring.
- **Data source analysis.** Analyze available sensor data and its characteristics, including data type, accuracy, reliability, and noise level. Identify which data sources are most critical to the MSIF system and evaluate their complementarity and redundancy.
- **Selection of data fusion levels.** Choose the appropriate data fusion level based on application requirements, which can be data-level fusion, feature-level fusion, or decision-level fusion. Consider the requirements of different fusion levels for computing resources, communication bandwidth, and real-time performance.
- **Data issues.** Consider how MSIF handles uncertainty and inconsistency issues in data. Modeling uncertainty in sensor data, which may include random errors, systematic errors, sensor biases, etc. Determine how to incorporate these uncertainties into the information fusion process to improve the robustness of the results.
- **Design of information fusion algorithms.** Select or develop information fusion algorithms suitable for cable sensor networks, such as weighted averaging, Kalman filtering, particle filtering, and Bayesian inference. Consider the balance between algorithm complexity, real-time performance, and accuracy.
- **System architecture and implementation.** Design the overall architecture of the MSIF system, including modules such as data acquisition, data transmission, data processing, and information fusion, to implement the designed MSIF system and test and verify the system in a practical environment.

## Deep Reinforcement Learning

The new generation of artificial intelligence methods represented by DRL have achieved disruptive breakthroughs in fields such as state assessment, solving some previously unsolvable problems and demonstrating significant advantages in dynamic decision-making applications under complex conditions. Introducing the DRL method to train artificial intelligence agents to schedule sensor resources can achieve the goal of improving the efficiency of resource scheduling systems and enhancing system automation.

From the perspective of reinforcement learning, if the decision-maker is viewed as an agent and the constructed Markov decision process model is viewed as an environment, the algorithm implementation process can be seen as the following four steps.

**Figure 5. DRL structure**



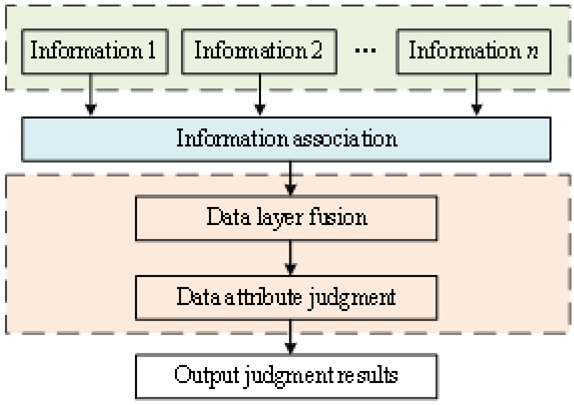

1. Based on the current operating status and environmental factors of OPGW, a state matrix *s* is formed and transmitted to the intelligent agent. The intelligent agent makes decisions and converts them into an action matrix *a*, which acts on the environment.
2. Based on the actual operation and action *a*, form a feedback state *r*.
3. The intelligent agent receives feedback state *r* to evaluate and improve the current strategy and makes new decisions based on the updated strategy.
4. Actions and feedback repeat until the trained strategy meets the requirements.

Reinforcement learning can enable agents to interact with the environment and learn how to make optimal decisions. It should be clear that reinforcement learning is not about learning patterns or relationships from large amounts of data but rather about acting in the environment and learning from the results to make decisions. In reinforcement learning, agents learn how to act in a given situation to obtain maximum rewards by interacting with the environment. Intelligent beings take a series of actions and receive a series of rewards and punishments for these actions. The goal of an intelligent agent is to learn how to take action in various situations to achieve maximum rewards. Figure 5 shows the structure of DRL that combines deep learning and reinforcement learning.

In Figure 5, the functions undertaken by the neural network include three aspects. The first is to abstractly extract key features from the multi-dimensional detection state data provided by the environment through the neural network's perceptual ability. The second approach is to replace nonlinear parameters by treating deep networks as intelligent agents that make direct decisions, determining the actions to be executed based on the obtained states, and applying them to the environment. The third one is based on the feedback obtained after the action is executed, which is incorporated into the algorithm objective. By optimizing network parameters, the final algorithm objective is maximized or minimized. Figure 6 shows the DRL training model.

In Figure 6, the network structure used in the DRL training model can be improved according to the actual situation. During the training process of the neural network, optimization objectives need to be given, and the left network plays the role of an operator in the entire structure. After obtaining the scene state features, decisions are made directly. The optimization objective is to find a parameter to improve future performance.

**Figure 6. Training model for DRL**




## Deep Q-Network

The *deep Q-network* (DQN) is a special neural network that combines deep learning and Q-learning and is a type of DRL. *Q-learning* is a method that allows machines to learn how to make the best decisions by trying different actions and observing the results. Therefore, the task of DQN is to assist machine learning in making the best decisions in specific situations. It can be imagined as an algorithm that can make machines smarter. It can enable machines to learn to make optimal decisions when facing various complex situations. Similar to how humans try different methods when learning new things, they compare and select the most effective method and remember it. In the future, when encountering similar situations, they can use this method to solve problems.

In addition, the DQN algorithm adds a target network on top of the original estimation network due to the inherent instability of the data. Therefore, if the same neural network is used to update the actual output and the network's output, there will be certain fluctuations during each iteration, and as the iteration progresses, the fluctuations will become larger, affecting the stability of the system. After joining the target network, the target output is calculated using the target network for each iteration, while the actual output is calculated using the estimation network. This allows for allocating tasks for calculating the target output and actual output to two different networks, reducing data fluctuations and enhancing system stability.

In the DQN algorithm, a neural network is used as the carrier of the value function to obtain an approximate Q value:

$$Q(s_t, a_t) = F(s_t, a_t, \omega) \tag{1}$$

where $s_t$ and $a_t$ represent the state and action taken at time $t$, respectively, and $\omega$ represents the weight values of each node in the neural network.

In DQN, there are two networks, namely the estimation network and the target network. The structure of the two networks is completely identical, with the difference being that the estimated output of the network in the network parameters is $Q(s, a, \omega)$, which is used to estimate the value function of the current state action. The output of the target network is represented as $Q(s_t, a_t, \omega_0)$. By introducing an untrained target network, it is possible to ensure that the target Q value remains stable for a certain period. In addition, the target network also has its own update mechanism, which directly assigns the estimated weights in the network to the target network after a preset time step.

In a neural network, the input is the current state S, and the output is a sequence of Q-values corresponding to a series of actions. In this way, Q-learning can make it more convenient to select actions and update Q-values. The update formula and loss function of Q-learning are as follows:

$$q(s_t, a_t) + \lambda \begin{bmatrix} \delta maxq(s_{t+1}, a_t) \\ +r_{t+1} - q(s_t, a_t) \end{bmatrix} \rightarrow q(s_t, a_t) \tag{2}$$

$$LOSS = E\left[r_{t+1} + \delta maxq(s_{t+1}, a_t, \omega_0) - q\,(s_t, a_t, \omega)^2\right] \tag{3}$$

where $\lambda$ is the learning rate, $\delta$ is the discount factor, and $r$ is the feedback value. Apply the above formula to correct the parameters of the Q sequence obtained from the Q-network.

## Quantum-Behaved Particle Swarm Optimization

*Particle swarm optimization* (PSO) is an optimization algorithm that originated from studying bird foraging behavior. It shares information with other members of a bird flock through one member, allowing the movement of the entire flock to evolve from chaotic to orderly movements in spatial pursuit. It can find the optimal solution by simulating the movement of particles in the search space within a population. In PSO, each particle has a certain velocity and position. They will adjust their speed and position based on the current position and velocity, as well as information such as historical and global optimal positions, in the hope of finding a better solution. Specifically, the position of each particle can be represented as an $n$-dimensional vector, representing a solution vector, and its velocity is also an $n$-dimensional vector. Each particle must update its velocity and position to approach the optimal solution gradually. There are many variations and improvements in PSO, such as adaptive weights, multi-objective PSO, constraint processing PSO, and QPSO, among others. Different variant algorithms may have different ways of updating particles and maintaining group information.

*Quantum-behaved particle swarm optimization* (QPSO) is an advanced optimization algorithm that combines the ideas of quantum computing and particle swarm optimization. In PSO, each particle has two attributes: velocity and position. In QPSO, the position of particles is represented by the principle of quantum superposition, which allows particles to be in a superposition state of multiple positions, thereby increasing the diversity of search. QPSO utilizes the principle of quantum entanglement to achieve information sharing and collaboration between particles. When two particles are in an entangled state, their position information will affect each other, which enables the particle swarm to converge to the optimal solution faster. QPSO also introduces quantum gate operations to adjust the velocity and position of particles.

By selecting quantum gates reasonably, the search strategy of particles can be dynamically adjusted during the search process, improving the search efficiency of the algorithm. QPSO ensures its convergence because the particles will converge to the local attractor, and the local attractor, current position, individual, and global optimal total will converge to the same position. By applying the delta potential well model in quantum mechanics to constrain particles, if the particle exhibits quantum behavior, it can be obtained that the quantum potential well of the local attractor absorbs the quantum state of the particle. In classical mechanics, during the convergence process, the particle tends towards the local attractor until it stops moving. In quantum mechanics, to quantitatively describe the state of microscopic particles, the wave function $\varnothing = \varnothing(r, t)$ is commonly used. If a particle is in a non-rotating state, it is known from the wave function that the particle's state is not related to velocity but to its position. Assuming a particle swarm consisting of $M$ particles searches in $N$-dimensional space, and at time $t$, the specific position of the $u$th particle in the $v$th dimension is $x_u(t)$ :

$$x_u(t) = \left[x_{u,1}(t), x_{u,2}(t), \ldots, x_{u,N}(t)\right] \tag{4}$$

The optimal position of individual particles can be expressed as:

$$p_{be,u}(t) = \left[p_{be,u,1}(t), p_{be,u,2}(t), \ldots, p_{be,u,N}(t)\right] \tag{5}$$

The optimal position of global particles can be expressed as:

$$g_{be}(t) = \left[g_{be,1}(t), g_{be,2}(t), \ldots, g_{be,N}(t)\right] \tag{6}$$

The minimization problem $p_{u,v}(t)$ can be expressed as:

$$p_{be,u}(t) = \begin{cases} x_u(t), f\left[x_u(t)\right] < f\left[p_{be,u}(t-1)\right] \\ p_{be,u}(t-1), f\left[x_u(t)\right] \geq f\left[p_{be,u}(t-1)\right] \end{cases} \tag{7}$$

where $u = 1, 2, \ldots, M, f\left[x_u(t)\right]$ represents the fitness value of particle $u$ at time $t$, and E represents the fitness value of particle $u$ at its individual optimal position at time $t-1$. In QPSO, the condition of particles is determined by the wave function, so particles search throughout the entire spatial range, thus possessing global search capability. In quantum mechanics, the position of particles in space can be solved by the Schrödinger equation to obtain the probability density equation of particle occurrence. The random position function of particles is:

$$p_r(t) = p \pm \frac{1}{2}\ln\left(\frac{1}{\lambda}\right) \tag{8}$$

$$L_p(t+1) = 2\alpha\left|B_{be} - x(t)\right| \tag{9}$$

where $\lambda$ is a random coefficient, $\lambda \epsilon (0,1)$, $L_p$ represents the length of the potential well, and $\alpha$ represents the contraction and expansion coefficient in the algorithm, which can be manually set. The value can be fixed or variable and is generally determined by the following equation.

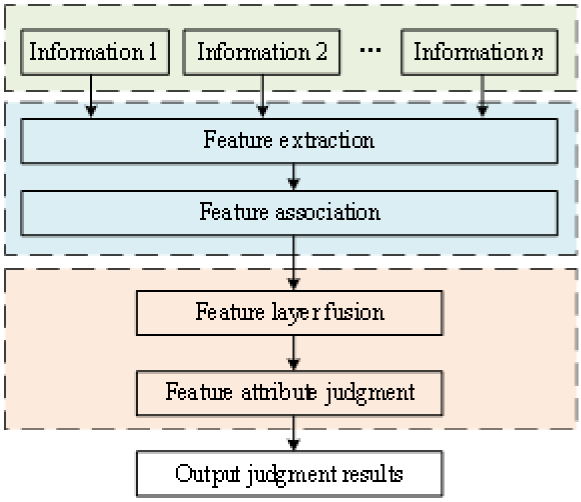
$$\alpha = a - (a-b)\frac{t}{E_{max}} = 1 - \frac{0.5t}{E_{max}} \tag{10}$$

As the iteration linearly decreases from $a$ to $b$,, $a = 1$, $b = 0.5$, $E_{max}$ is usually the maximum number of iterations, $t$ is the current number of iterations, and the average of local optimal positions represents the next iteration variable $B_{be}$; $M$ represents the average optimal position of the $t$th iteration, and its solution is as follows.

$$\begin{gathered} B_{be}(t) = \frac{1}{M}\sum_{u\text{-}1}^{M} p_{be,u}(t) \\ = \left[\frac{1}{M}\sum_{u\text{-}1}^{M} p_{be,u,1}(t), \frac{1}{M}\sum_{u\text{-}1}^{M} p_{be,u,2}(t), \ldots, \frac{1}{M}\sum_{u\text{-}1}^{M} p_{be,u,N}(t)\right] \end{gathered} \tag{11}$$

$$p_{u,d}(t) = \mu p_{u,d}(t) + (1-\mu) p_{g,d}(t) \tag{12}$$

Figure 7. QPSO implementation steps




$$r_{u,d}(t) = p_{u,d}(t) \pm \alpha\left|B_{be} - r_{u,d}(t)\right| \bullet \ln\frac{1}{\lambda} \tag{13}$$

where$\mu$ and $\mu$ are random coefficients, taken from 0 to 1, and $p_{u,d}(t)$ is the random point between position $u$ and the optimal position $g$. Figure 7 shows the implementation steps of QPSO.

## The DQN Optimized Based on QPSO

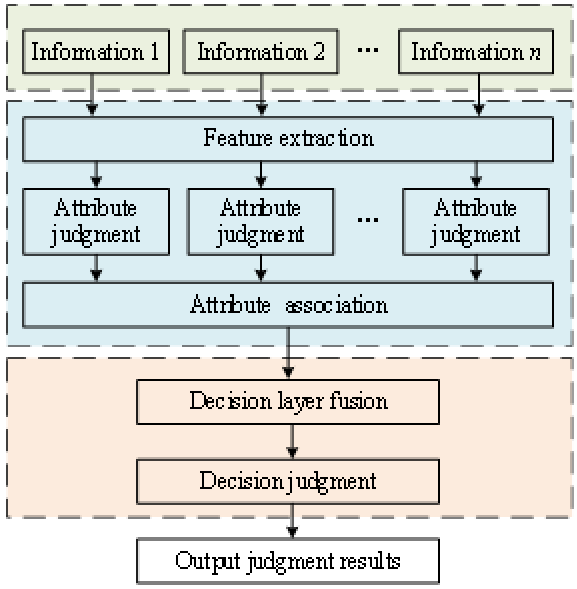
The application of QPSO in the exploration and development of DQN mainly involves balancing the following aspects.

1. In QPSO, a particle swarm represents a set of candidate solutions. In the context of DQN, a particle swarm can be initialized as a set of different strategies or action selection methods.
2. The fitness function is used to evaluate the quality of each particle in the particle swarm. In DQN, the fitness function can be defined as the performance of an agent in the environment under a given policy or action selection method, such as cumulative rewards or task completion rate.
3. Based on the evaluation results of the fitness function, use the update rules of QPSO to update the position and velocity of particles. In DQN, this is equivalent to adjusting the balance between exploration and development. For example, if a particle has poor fitness, the probability of exploration can be increased to explore more states and actions. If the fitness is good, the probability of development can be increased to make optimal decisions using known information.
4. During DQN's training process, QPSO can be continuously used to balance exploration and development. As the training progresses, the intelligent agent's performance will continue to improve, and QPSO will also continuously optimize the position and velocity of particles to find better strategies.

Figure 8 shows the overall structure of DQN based on QPSO optimization.

In Figure 8, the DQN based on QPSO optimization treats the entire particle swarm as the agent of the DQN, with the environment representing the operating environment of OPGW and the state representing the current position information of the entire particle swarm. An action is defined as the current running state of a particle, which includes conventional, exploratory, particle explosion, random mutation, or fine-tuning. Conventional actions are used to make the algorithm converge,

**Figure 8. The DQN optimized based on QPSO**




exploration, particle explosion, and random mutation are used to improve the algorithm's global search ability, and fine-tuning operations are used to improve the accuracy of the algorithm's final results.

A multi-layer feedforward neural network was constructed in a QPSO-optimized DQN, with an input layer consisting of seven-dimensional data containing particle swarm position information and an output layer consisting of five-dimensional action data. The network has two hidden layers in the middle, each with six neurons, achieving mapping from state to action. On this basis, DQN adaptively selects a behavior based on the current state of the particles, causing the particle swarm to change its position and receive a certain reward. This process is repeated until the maximum number of iteration steps is met. The reward value of the algorithm in each generation is as follows:

$$r(t) = \begin{cases} -1, f\left[x_u(t)\right] \geq f\left[p_{be,u}(t-1)\right] \\ \sigma \bullet \left[f\left[p_{be,u}(t)\right] - f\left[p_{be,u}(t-1)\right]\right], other \end{cases} \tag{14}$$

where $\sigma$ is the fine-tuning damping coefficient, which is used to balance the global search ability of the algorithm and avoid falling into local optima too early due to excessive reliance on the rewards brought by fine-tuning operations in the early stage of the search.

During the algorithm's operation, each iteration passes a seven-dimensional information representing the current state information of the particle population to the neural network. Derive the optimal action through neural network operations, update the particle population information, and calculate the reward value $r(t)$. Then, train through the data sequence $\left[s(t), a(t), r(t), s(t+1)\right]$ in the data experience pool. When the accumulated data reaches a certain amount, the neural network can be trained to have better decision-making ability.

## OPGW Status Evaluation Process

Next is to construct a network model for OPGW state evaluation based on the proposed QPSO-optimized DQN combined with MSIF. Figure 9 shows the process of using this model to evaluate the status of OPGW.

**Table 1. Experimental environment**

| Parameters | Configuration |
|---|---|
| OS | Linux |
| CPU | Intel(R) Xeon(R) Gold 5118 CPU |
| CPU memory | 32G @ 2.30GHz |
| GPU | Tesla V100 |
| Programming language | Python 3.8.13 |
| Programming environment | PyTorch 1.12.1 |

**Table 2. QPSO parameter settings**

| Parameters | Value |
|---|---|
| Particle swarm size | 200 |
| Learning factor | 1.5 |
| Compression–expansion coefficient | 1.0 |
| Random factor | 0.5 |
| Iteration number | 100 |

# ANALYSIS

## Experimental Environment and Parameters

Table 1 shows the specific experimental environment information for this experiment, Table 2 shows the parameter settings for the QPSO optimization algorithm, and Table 3 shows the parameter settings for the DQN algorithm.

**Figure 9. The state evaluation process of OPGW**

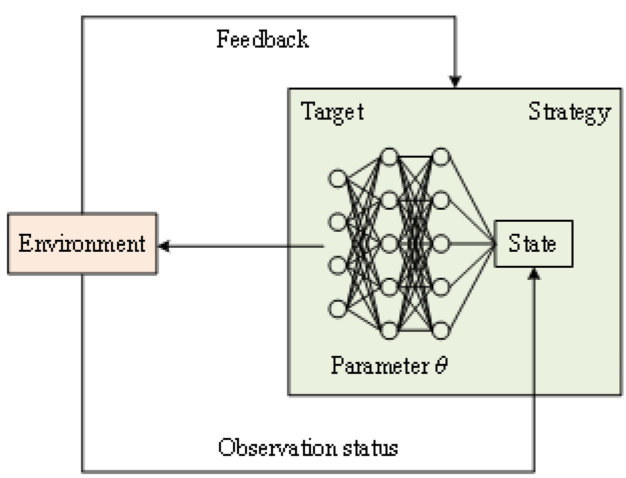


**Table 3. DQN parameter settings**

| Parameters | Value |
|---|---|
| Learning rate | 0.001 |
| Discount factor | 0.95 |
| Initial exploration rate | 1.0 |
| The decreasing rate of exploration rate | 0.01 |
| Mini-batch size | 32 |

## Construction of Evaluation System

In order to verify the effectiveness of the proposed OPGW state evaluation method, the following four different evaluation indicators are adopted to evaluate the experimental results.

1. **Accuracy of ice weight detection (E1).** By detecting the icing weight of the optical fiber, its performance under different conditions can be evaluated, which can reflect the quality of the material, structure, and processing technology of the optical fiber and provide a reference for the design and operation of the power system. In addition, ice weight detection can optimize the design and use of optical cables in low-temperature or ice-covered environments, timely identify potential problems with optical fibers, and take corresponding maintenance measures.
2. **Temperature detection accuracy (E2).** The abnormal increase in fiber optic temperature may indicate equipment malfunction or problem. Accurately detecting temperature can prevent equipment overheating and ensure equipment safety. In addition, temperature changes can affect the transmission quality and stability of optical signals. Detecting the temperature of optical fibers can promptly detect temperature anomalies, take measures to adjust and optimize system parameters, and improve communication quality.
3. **Frequency detection accuracy (E3).** By detecting the frequency of optical signals in optical fibers, the quality and stability of optical signals can be evaluated. The frequency instability or offset of optical signals can increase the error rate of communication systems, affecting communication quality. In addition, changes in fiber optic frequency may be related to equipment failures or abnormal wiring. By monitoring the frequency of optical fibers in real time, equipment faults or abnormal circuit conditions can be detected in a timely manner, and corresponding maintenance measures can be taken to ensure the normal operation of the communication system.
4. **Accuracy of optical power detection (E4).** By detecting the optical power of optical fibers, the quality of optical signals during transmission can be evaluated. The stability and intensity level of optical power are directly related to the reception quality and error rate of optical signals. When the optical power is too low, it may cause signal reception failure or errors. When the optical power is too high, it may have a negative impact on the transmission quality and lifespan of the optical signal. Therefore, detecting the optical power of optical fibers can timely detect and solve problems during optical signal transmission. In addition, changes in optical power may indicate equipment failures or abnormal situations, and timely detection of changes in optical power can prevent and solve potential equipment problems.

By detecting the above four evaluation indicators and overlaying them with different weights, the health status of OPGW is scored:

$$FH = \omega_1 E_1 + \omega_2 E_2 + \omega_3 E_3 + \omega_4 E_4 \tag{15}$$

**Table 4. Health status classification of OPGW**

| FH | Health grade | Operational status |
|---|---|---|
| $80 \leq FH \leq 100$ | 1 (Health) | Operate normally |
| $60 \leq FH \leq 80$ | 2 (Sub health) | Small fluctuation |
| $40 \leq FH \leq 60$ | 3 (Critical fault) | Large fluctuation |
| $20 \leq FH \leq 40$ | 4 (Fault) | Unable to operate |

Table 4 shows different FH correspond to different levels of health status.

## Experimental Data and Preprocessing

To improve the evaluation accuracy of the model, the algorithm model requires a large number of data training samples as support. Here, online monitoring devices for OPGW deployed in Jiangsu Province, Hebei Province, and Inner Mongolia are used for data collection. Due to the significant geographical differences among the three OPGWs, their data is highly representative. We collected monitoring data on the operational status characterization of OPGW under 7500080000 and 100000 on-site time series and divided them into three datasets. Firstly, the data of each dataset is fused to obtain data fusion labels. Then, the monitoring data and data fusion labels are divided into training, testing, and testing sets in an 8:1:1 ratio.

In the dataset used for health assessment, different feature quantities have different dimensions. For example, the temperature and environmental temperature and humidity of OPGW vary greatly in order of magnitude. Direct calculation not only increases the complexity of the algorithm but also leads to a decrease in the accuracy of the assessment results. Normalization is used here to preprocess the data.

$$y = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{16}$$

where $x_{max}$ is the maximum value in the sample data and $x_{min}$ is the minimum value in the sample data.

## Comparative Experiment

Using the same experimental data, comparative experiments will be conducted for different evaluation indicators. For the accuracy of ice weight detection, the proposed method will be compared and analyzed with MPF-DOFS in (Zhang et al., 2021), BOTDR-FEA in (Hai & Huang, 2022), and ML-IPSM in (Lu et al., 2021). For the accuracy of temperature detection, the proposed method will be compared and analyzed with WFBG in (Feng et al., 2022), BOTDR in (Sun et al., 2021), MPF-DOFS in (Zhang et al., 2021), and ML-IPSM in (Lu et al., 2021). For the accuracy of frequency detection and optical power detection, the proposed method will be compared and analyzed with the MPF-DOFS method (Zhang et al., 2021) and the ML-IPSM method (Lu et al., 2021). Figure 10 shows the experimental results of the accuracy of ice weight detection using different methods, Figure 11 shows the experimental results of OPGW temperature detection using different methods, and Figure 12 shows the experimental results of the frequency accuracy of OPGW signal transmission using different methods. Figure 13 shows the experimental results of OPGW optical power accuracy using different methods, and Table 9 shows the error between the HF obtained by different methods and the actual HF.

The experimental results of different evaluation indicators show that the overall results of different methods using three different OPGW operation data for the experiment are relatively small. When using three different datasets, the proposed method achieved the best results, with the highest accuracy

Figure 10. Results on the accuracy of ice weight detection

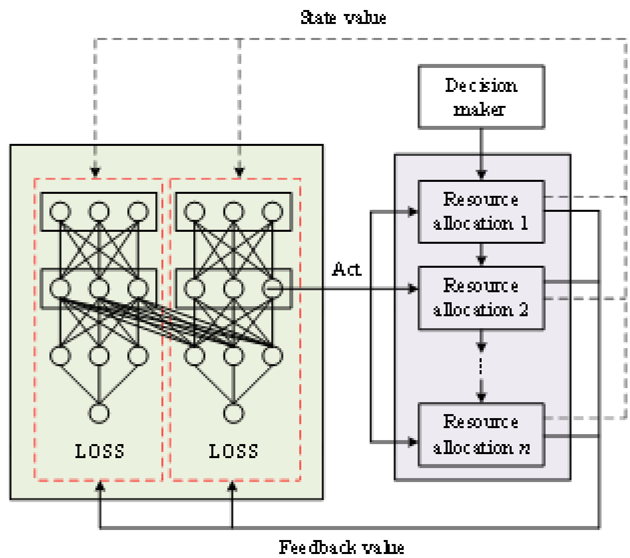



Table 5. Results on the accuracy of ice weight detection

| Method | Accuracy of ice weight detection (%) | | |
|---|---|---|---|
| | Dataset 1 | Dataset 2 | Dataset 3 |
| Proposed method | 98.35 | 98.35 | 98.35 |
| MPF-DOFS (Zhang et al., 2021) | 93.42 | 93.42 | 93.42 |
| BOTDR-FEA (Hai & Huang, 2022) | 90.53 | 90.53 | 90.53 |
| ML-IPSM (Lu et al., 2021) | 95.22 | 95.22 | 95.22 |

rates for ice weight detection, temperature detection, frequency detection, and optical power detection, reaching 98.85%, 98.97%, 98.13%, and 98.97%, respectively. The accuracy of ice weight detection has increased by 4.43%, 7.35%, and 3.15% compared to other comparative methods, respectively. The accuracy of temperature detection has increased by 8.69%, 6.22%, 7.22%, and 3.72% compared to other comparison methods, respectively. The accuracy of frequency detection has increased by 4.13% and 2.31% compared to other comparison methods, respectively. The accuracy of optical power detection has increased by 4.96% and 3.15% compared to other comparison methods, respectively. This means that the proposed method has greater advantages in different performance aspects than other comparative methods and can more accurately obtain the operating status of OPGW. This is because the multi-source data fusion method can obtain more comprehensive and accurate OPGW status information by fusing data from different sources and types. The complementarity and correlation between various data can help to describe the current state of OPGW more accurately, thereby improving the accuracy of state evaluation. In addition, the QPSO optimization algorithm has been used to optimize DQN, which can improve the performance and stability degradation of traditional DQN when dealing with complex tasks. This helps to improve the global search ability of the DQN algorithm, enabling it to find more globally optimal solutions when dealing with complex problems. This greatly improves the accuracy of conducting state assessments on OPGW.

Table 6. Results on the accuracy of temperature detection

| Method | Accuracy of temperature detection (%) | | |
|---|---|---|---|
| | Dataset 1 | Dataset 2 | Dataset 3 |
| Proposed method | 98.47 | 98.47 | 98.47 |
| WFBG (Feng et al., 2022) | 89.82 | 89.82 | 89.82 |
| BOTDR (Sun et al., 2021) | 92.28 | 92.28 | 92.28 |
| MPF-DOFS (Zhang et al., 2021) | 91.29 | 91.29 | 91.29 |
| ML-IPSM (Lu et al., 2021) | 94.77 | 93.51 | 95.25 |

## Ablation Experiment

In order to further verify the importance and differences of each module in the model, a model ablation experiment was designed to compare the impact of different modules on the overall performance of the model. The model design is as follows:

- **Model 1 (without MSIF).** Remove MSIF-based data collection and processing from the complete model.
- **Model 2 (without QPSO).** Remove the QPSO module from the complete model and directly use the OPGW running state as the intelligent agent.
- **Model 3 (without DQN).** Remove the DQN module from the complete model.

Figure 11. Results on the accuracy of temperature detection

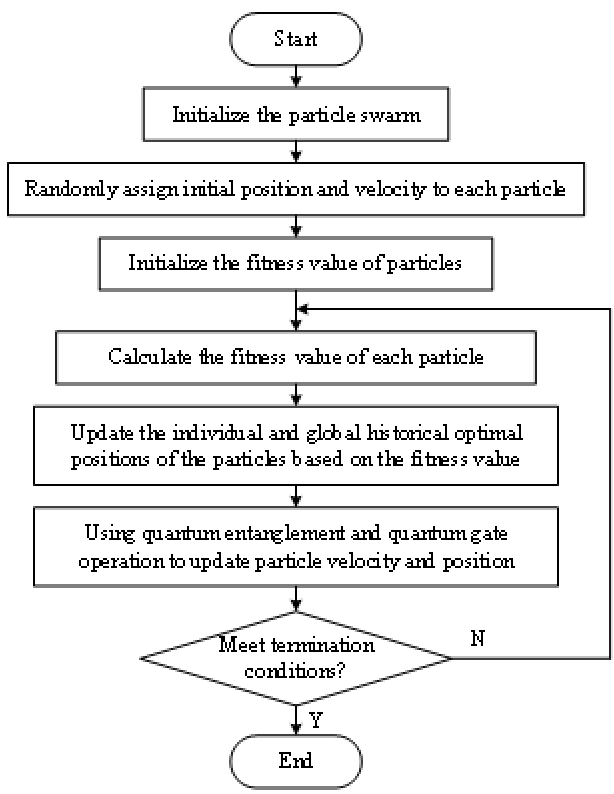


**Figure 12. Results on the accuracy of signal frequency detection**

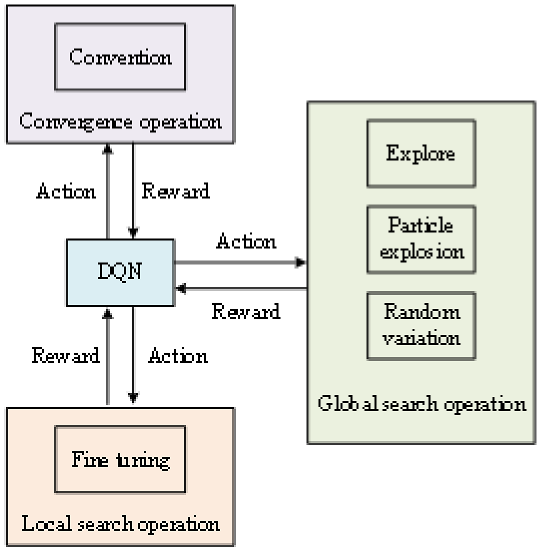



**Table 7. Results on the accuracy of signal frequency detection**

| Method | Accuracy of signal frequency detection (%) | | |
|---|---|---|---|
| | Dataset 1 | Dataset 2 | Dataset 3 |
| Proposed method | 97.52 | 97.52 | 97.52 |
| MPF-DOFS (Zhang et al., 2021) | 93.42 | 93.42 | 93.42 |
| ML-IPSM (Lu et al., 2021) | 95.22 | 95.22 | 95.22 |

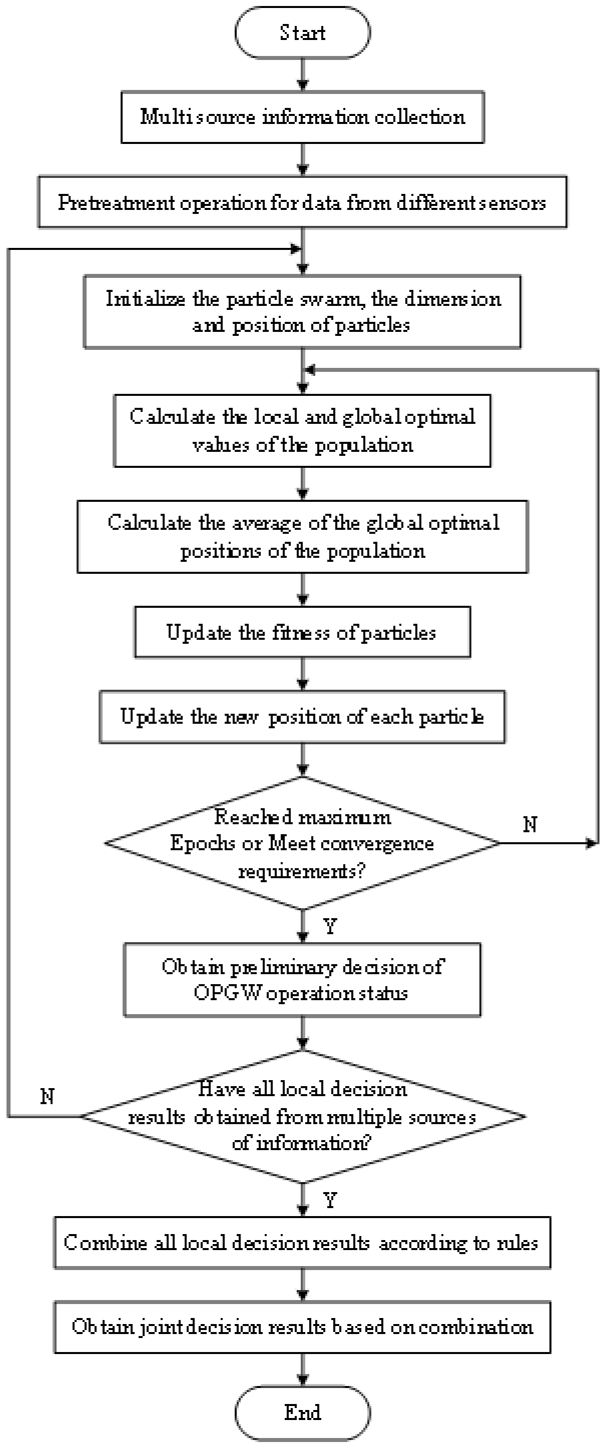
Table 10 shows the final model ablation experiment results, using the OPGW operation dataset collected within Hebei Province as an example.

In Table 8, the experimental results on this dataset show that regardless of the removal of any module in the model, it will cause a decrease in the accuracy of the four evaluation indicators and an increase in FH error in the OPGW operation status evaluation. Therefore, removing modal-related or unique features will affect the overall performance of the model. When the three features are fused simultaneously, the model can more accurately evaluate and discriminate the OPGW operation status. At the same time, this also fully verifies the necessity of each module in this article's model to achieve the best experimental results.

## CONCLUSION

A state evaluation method for OPGW based on MSIF and QPSO-DQN in icing scenarios is proposed to address the issues of low accuracy and susceptibility to missed detections or misjudgments in traditional OPGW state evaluation methods. The performance of this method was validated through experiments. These experiments include model testing experiments, model ablation experiments, and comparison experiments with other models on three different datasets for ice weight detection, temperature detection, frequency detection, and optical power detection accuracy. According to experimental data, it can be concluded that integrating OPGW operational data based on MSIF technology can more comprehensively reflect the operational status of OPGW. The use of DQN to

**Figure 13. Results on the accuracy of signal frequency detection**




evaluate the operational status of OPGW can accurately and comprehensively reflect the various factors

**Table 8. Results on the accuracy of optical power detection**

| Method | Accuracy of optical power detection (%) | | |
|---|---|---|---|
| | Dataset 1 | Dataset 2 | Dataset 3 |
| Proposed method | 98.35 | 98.35 | 98.35 |
| MPF-DOFS (Zhang et al., 2021) | 92.27 | 92.27 | 92.27 |
| ML-IPSM (Lu et al., 2021) | 94.92 | 94.92 | 94.92 |

**Table 9. HF error of different methods**

| Method | Accuracy of ice weight detection (%) | | |
|---|---|---|---|
| | Dataset 1 | Dataset 2 | Dataset 3 |
| Proposed method | 2.68 | 2.72 | 2.59 |
| WFBG (Feng et al., 2022) | 4.43 | 4.50 | 4.28 |
| BOTDR (Sun et al., 2021) | 5.26 | 5.34 | 5.08 |
| MPF-DOFS (Zhang et al., 2021) | 3.87 | 3.93 | 3.74 |
| BOTDR-FEA (Hai & Huang, 2022) | 4.72 | 4.79 | 4.56 |
| ML-IPSM (Lu et al., 2021) | 5.59 | 5.67 | 5.40 |

**Table 10. Model ablation experimental results**

| Model | Indicator (%) | | | | |
|---|---|---|---|---|---|
| | E1 | E2 | E3 | E4 | E5 |
| Model 1 | 92.93 | 92.93 | 92.93 | 92.93 | 92.93 |
| Model 2 | 90.16 | 90.16 | 90.16 | 90.16 | 90.16 |
| Model 3 | 88.54 | 88.54 | 88.54 | 88.54 | 88.54 |
| Proposed method | 97.33 | 97.33 | 97.33 | 97.33 | 97.33 |

that affect the operational status of OPGW. Using QPSO to improve DQN can solve the difficulties of the DQN algorithm in dealing with complex, large-scale, and high-dimensional problems, improve its stability and applicability, enhance its global search ability and dependence on policies, and thus better apply it to practical problem-solving.

Future work will further explore the applicability of digital twin technology in evaluating OPGW operation status. By establishing a digital twin model of OPGW, real-time monitoring and prediction of OPGW operation status will be achieved, providing decision support for maintenance and management.

## CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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## REFERENCES

Chen, Y., Wang, S., Hao, Y., Yao, K., Li, H. Z., Jia, F., Yue, D. L., Shi, Q. Y., Cheng, Y. H., & Huang, X. W. (2022). Temperature monitoring for 500 kV oil-filled submarine cable based on BOTDA distributed optical fiber sensing technology: Method and application. *IEEE Transactions on Instrumentation and Measurement*, *71*(3), 132–140. 10.1109/TIM.2021.3136182

Ding, Z., Zhang, X., Zou, N., Xiong, F., Song, J., Fang, X., Wang, F., & Zhang, Y. (2021). Phi-OTDR based on-line monitoring of overhead power transmission line. *Journal of Lightwave Technology*, *5*(9), 142–152. 10.1109/JLT.2021.3078747

Feng, X. B., Hou, J. Y., Yu, Q. S., Li, X., Wu, J., Liu, L., & Chen, W. Q. (2022). Research on optical fiber composite overhead wire (OPGW) lightning monitoring technology based on weak fiber Bragg grating array. *Journal of Nanoelectronics and Optoelectronics*, *17*(1), 170–176. 10.1166/jno.2022.3182

Hai, S., & Huang, Z. T. (2022). OPGW cable icing status monitoring based on BOTDR. *Proceedings of the Third International Conference on Advances in Materials, Machinery, and Electronics*, Wuhan, China, 65–70.

Lalam, N., Ng, W. P., Dai, X., Wu, Q., & Fu, Y. Q. (2021). Performance improvement of Brillouin ring laser based BOTDR system employing a wavelength diversity technique. *Journal of Lightwave Technology*, *36*(4), 1084–1090. 10.1109/JLT.2017.2766765

Li, Z., Tong, Y., Fu, X., Wang, J., Guo, Q., Yu, H., & Bao, X. (2022). Simultaneous distributed static and dynamic sensing based on ultra-short fiber Bragg gratings. *Optics Express*, *26*(13), 174–184.30119555

Lin, R., Zhu, Y., Tian, L., Zhou, L., Liu, W., & Cheng, L. (2021). On-situ monitoring of sleet-thawing for OPGW based on long distance BOTDR. *Optoelectronics Letters*, *17*(4), 329–338. 10.1007/s11801-021-0067-9

Liu, T., Wang, F., Zhang, X., Yuan, Q., Niu, J., Zhang, L., & Wei, T. (2023). Interrogation of ultra-weak FBG array using double-pulse and heterodyne detection. *IEEE Photonics Technology Letters*, *30*(8), 677–680. 10.1109/LPT.2018.2811411

Lu, L. D., Bu, X. D., & Wang, Q. S. (2021). An optical fiber composite power cable panoramic state monitoring system for typical scene application. *Proceedings of the 2021 International Conference on Power System Technology*, Haikou, China, 17–21. 10.1109/POWERCON53785.2021.9697772

Marie, T. F., Han, D., An, B., & Chen, X. (2020). Research and software design of an Φ-OTDR-based optical fiber vibration recognition algorithm. *Journal of Electrical and Computer Engineering*, *2020*(5), 1–13.

Martín-López, S., Corredera, P., Filograno, M. L., Frazão, O., & González-Herráez, M. (2021). Phase-sensitive optical time domain reflectometer assisted by first-order raman amplification for distributed vibration sensing over > 100 km. *Journal of Lightwave Technology*, *32*(8), 1510–1518. 10.1109/JLT.2014.2308354

Meng, X., Xiaohui, T., Ying, W., Shulin, Z., Hui, J., & Yongkang, D. (2020). Comparative analysis of strain monitoring of the installed optical fiber composite overhead ground wire using BOTDA/R. *Acta Optica Sinica*, *40*(15), 252–261.

Mohammed, H. J., & Daham, H. A. (2021). Analytic hierarchy process for evaluating flipped classroom learning. *Computers, Materials & Continua*, *66*(3), 2229–2239. 10.32604/cmc.2021.014445

Nguyen, T., & Nguyen, T. D. (2020). Calculation of parameters for altering the ship's course at sea using artificial neural network (ANN). *IOP Conference Series. Materials Science and Engineering*, *862*(3), 85–97. 10.1088/1757-899X/862/3/032097

Peng, F., Wu, H., Jia, X., Rao, Y. J., Wang, Z., & Peng, Z. (2022). Ultra-long high-sensitivity Φ-OTDR for high spatial resolution intrusion detection of pipelines. *Optics Express*, *22*(11), 138–147.24921572

Qin, Z., Zhu, T., Chen, L., & Bao, X. (2021). High sensitivity distributed vibration sensor based on polarization-maintaining configurations of phase-OTDR. *IEEE Photonics Technology Letters*, *23*(15), 1091–1093. 10.1109/LPT.2011.2157337

Rao, Y. J., Wang, Z., Wu, H., Ran, Z., & Han, B. (2021). Recent advances in phase-sensitive optical time domain reflectometry (Φ-OTDR). *Photonic Sensors*, *11*(1), 1–30. 10.1007/s13320-021-0619-4

Sun, J., Zhang, Z., Li, Y., Yan, Z., Zhai, T., Li, L., & Xiao, Z. (2021). Distributed transmission line ice-coating recognition system based on BOTDR temperature monitoring. *Journal of Lightwave Technology*, *9*(4), 13–21. 10.1109/JLT.2021.3063267

Sun, J. X., Zhang, Z. G., Li, Y. M., Yan, Z. H., Zhai, T., Li, L. M., & Xiao, Z. Y. (2021). Distributed transmission line ice-coating recognition system based on BOTDR temperature monitoring. *Journal of Lightwave Technology*, *39*(12), 3967–3973. 10.1109/JLT.2021.3063267

Wang, B., Dong, Y., Ba, D., & Bao, X. (2020a). High spatial resolution: An integrative review of its developments on the Brillouin optical time and correlation-domain analysis. *Measurement Science & Technology*, *31*(5), 52–62. 10.1088/1361-6501/ab5f85

Wang, B., Hua, Z., Pang, C., Zhou, D., Ba, D., Lin, D., & Dong, Y. (2020b). Fast Brillouin optical time-domain reflectometry based on the frequency agile technique. *Journal of Lightwave Technology*, *38*(4), 946–952. 10.1109/JLT.2019.2950451

Wang, C., Shang, Y., Liu, X., Wang, C., Yu, H., Jiang, D., & Peng, G. (2022). Distributed OTDR-interferometric sensing network with identical ultra-weak fiber Bragg gratings. *Optics Express*, *2*(6), 48–57.26561173

Wang, J., Pang, W., Wang, L., Pang, X., & Yokoyama, R. (2022). Synthetic evaluation of steady-state power quality based on combination weighting and principal component projection method. *CSEE Journal of Power and Energy Systems*, *3*(2), 160–166. 10.17775/CSEEJPES.2017.0020

Wang, J. J., & Li, Y. Q. (2022). Progress on distributed optical fiber sensing technology in OPGW monitoring. *Study on Optical Communications*, *207*(3), 29–38.

Wang, Y., Gong, J., Dong, B., Wang, D. Y., Shillig, T. J., & Wang, A. (2023). A large serial time-division multiplexed fiber Bragg grating sensor network. *Journal of Lightwave Technology*, *30*(17), 2751–2756. 10.1109/JLT.2012.2205897

Wang, Z., Zeng, J., Li, J., Fan, M., Wu, H., Peng, F., Zhang, L., Zhou, Y., & Rao, Y. (2022). Ultra-long phase-sensitive OTDR with hybrid distributed amplification. *Optics Letters*, *39*(20), 53–63.25361105

Xia, M., Tang, X. H., Wang, Y., Li, C., Wei, Y., Zhang, J. J., Jiang, T. F., & Dong, Y. K. (2023). OPGW positioning and early warning method based on a Brillouin distributed optical fiber sensor and machine learning. *Applied Optics*, *62*(6), 1557–1566. 10.1364/AO.47977236821317

Xu, Z. L., Zeng, Y. H., & Guo, S. (2020). Application of intelligent monitoring system for transmission lines based on image recognition technology. *Computer Systems and Applications*, *29*(1), 67–72.

Zhang, X., Guo, Z., Shan, Y., Sun, Z., Fu, S., & Zhang, Y. (2021). Enhanced Φ-OTDR system for quantitative strain measurement based on ultra-weak fiber Bragg grating array. *Optical Engineering (Redondo Beach, Calif.)*, *55*(5), 54–63.

Zhang, X. P., Wu, J. L., & Shan, Y. Y. (2022). On-line monitoring of power transmission lines in smart grid based on distributed optical fiber sensing technology. *Optoelectronic Technology*, *37*(4), 221–229.

Zhang, Z. P., Shuo, C., Niu, X. C., Jie, H., Sun, S. H., & Jie, L. (2021). Application of multi parameter coherent distributed optical fiber sensing technology in power OPGW condition monitoring. *Proceedings of the Second International Conference on Computing and Data Science*, 98–104. 10.1145/3448734.3450828

Zhou, C., Pang, Y., & Fan, D. (2023). Demodulation of a hydroacoustic sensor array of fiber interferometers based on ultra-weak fiber Bragg grating reflectors using a self-referencing signal. *Journal of Lightwave Technology*, •••, 2568–2576.

Zhu, F., Zhang, Y., Xia, L., Wu, X., & Zhang, X. (2022). Improved Φ-OTDR sensing system for high-precision dynamic strain measurement based on ultra-weak fiber Bragg grating array. *Journal of Lightwave Technology*, *33*(23), 4775–4780.

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