Design and Edge-Enabled Implementation of Smart Acousto-Optic Safety Wearables for Power IoT Environments

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With the rapid development of the power Internet of Things, the safety risks faced by power facility maintenance personnel, such as high-voltage electric shock, equipment failure, and severe weather, have become increasingly prominent. Traditional protective measures are no longer able to meet the safety needs in complex environments. To this end, this article designs an intelligent sound and light alarm workwear based on the power Internet of Things. The workwear integrates infrared detection, microwave perception, video monitoring, and AI intelligent recognition technology to build a comprehensive monitoring system. Real time data is collected from multiple sensors, and edge AI technology is used for localized analysis to achieve active and accurate identification of dangerous behaviors. Once a risk is detected, the system automatically triggers an audible and visual alarm, and supports dual mode operation day and night, significantly improving the night work protection capability. To verify its effectiveness, this study designed three control experiments: the basic group (only electrical sensors+threshold alarm), the advanced group (multi-sensor+basic fusion+simplified edge AI), and the experimental group (multi-dimensional sensors+deep fusion+complete edge AI). The experiment was conducted in two typical scenarios: a 729kW factory area (strong electromagnetic environment) and an outdoor high-voltage inspection area (temperature, humidity, and light gradient changes). The sensor complementarity and blind spot coverage were verified by synchronously collecting 100 operating condition data (including 50 anomalies), and the recognition accuracy, local calculation proportion (≥ 80%), and alarm delay (timing error ≤ 0.01s) of edge AI were tested based on 1500 standard datasets. The results showed that the experimental group performed the best in key indicators such as detection accuracy and false alarm rate. The safety level of operation and maintenance personnel during daytime and nighttime operations was improved by 30% and 40% respectively, effectively verifying the significant effectiveness of intelligent work clothes in improving the safety protection ability of power maintenance personnel and having good promotion and application value.

Povzetek: Študija predstavlja pametna zaščitna oblačila z uporabo IoT in umetne inteligence, ki z zaznavanjem nevarnosti in sprožanjem alarmov bistveno izboljšajo varnost delavcev pri vzdrževanju elektroenergetskih naprav.

1 Introduction

Transmission and distribution lines, spanning complex environments like mountains and urban areas, require dangerous maintenance. This leads to high risks for personnel, a shortage of workers, and inefficiencies [1, 2, 3]. Traditional protective workwear offers insufficient warning and protection, especially at night, failing to ensure safety [4, 5].

The Ubiquitous Power Internet of Things (IoT) enables extensive interconnection and intelligent services through sensing, edge computing, and robust networks like 5G [6, 7, 8, 9]. It supports horizontal data sharing and vertical data flow, enhancing platform intelligence and enabling data-driven value addition [10, 11].

Current monitoring relies on manual reports or limited sensors, lacking real-time automatic perception. Data transmission in complex environments is often unstable. In contrast, the IoT-based smart workwear design integrates multiple sensors (e.g., environmental, physiological) for real-time monitoring. Using the Power IoT, it enables stable data transmission beyond traditional limits.

This project designs intelligent workwear integrating sensors (GPS, temperature, acceleration), communication modules (4G/5G, Wi-Fi), and comfort features. It employs solar-storage power supply, an acoustic-optic alarm system for immediate danger alerts, and a night mode with full-body lighting. Enhanced by infrared, acoustic, and image recognition technologies, it improves danger perception. Alarms activate upon risk detection, and data is sent to an IoT platform for processing, risk identification, and SMS alerts, enabling active perception and multi-alarm functions.

Unlike prior studies focusing on basic alarm triggers, our work improves alarm accuracy in complex grid scenarios with electromagnetic interference and fluctuating conditions. We explore advanced sensor fusion (current, voltage, EMF) for comprehensive grid assessment and precise, timely responses.

Intelligent sound and light alarm intelligent work clothes based on the power Internet of Things, with multi-dimensional risk detection accuracy ≥ 97%, alarm response delay ≤ 0.5 seconds (timing error ≤ 0.01 seconds), and edge AI local computing proportion ≥ 80%; Edge AI can resist strong electromagnetic interference through multi-sensor cross validation, reduce cloud dependence, and protect data privacy with "edge+end-to-end encryption"; Suitable for strong electromagnetic environment and outdoor high-voltage inspection in 729kW factories, it can detect equipment abnormalities and SF6 leaks in real time, turn on LED warning lights at night, and combine with 4G/5G/NB IoT linkage platform to increase daytime operation safety by 30% and nighttime safety by 40%, avoiding the risk of electric shock and equipment failure.

At the same time, we are committed to improving the comfort and durability of workwear materials. Considering that users of these workwear are often exposed to harsh environments, we are working on innovative materials that can withstand heat, humidity and mechanical stress while maintaining a high comfort level. For example, we are exploring the use of moisture-wicking fabrics with enhanced thermal insulation, as well as abrasion-resistant coatings that extend the life of workwear. By clearly defining these research gaps and using our research methodology to solve these previously neglected issues, we have established a logical and progressive link between this study and previous investigations in the field. This association is based on the existing body of knowledge and contributes new insights and solutions to intelligent overalls design in the power industry.

2 Technical route of intelligent acousto-optic alarm electric warning sign

2.1 Design of collaborative power supply system between solar energy and lithium battery

Intelligent acousto-optic alarm intelligent overalls adopt the power supply mode of solar energy + battery.The power supply system consists of solar cells, control circuits and lithium-ion batteries. The solar panels arranged on the surface of intelligent overalls collect electricity to supply power to the whole system, and store the remaining electricity in the built-in rechargeable lithium batteries [12]. Compared with the external power supply mode, adopting solar power supply mode can reduce the difficulty of system wiring and save the manufacturing cost of intelligent overalls. At the same time, intelligent overalls are relatively independent systems, which are less affected by external conditions, and can still operate normally when the line is cut off due to electric shock danger.

The perception layer is equipped with current sensors (sampling rate of 500Hz), voltage sensors (300Hz), temperature and humidity sensors (1Hz), and acceleration sensors (100Hz), which can capture real-time power environment and personnel status; The communication layer adopts LoRaWAN protocol, with end-to-end communication delay ≤ 100ms, and supports bidirectional data exchange with the power IoT platform; The energy layer is equipped with a 2000mAh lithium polymer battery, combined with a 5V/1A flexible solar charging panel (charging rate of 80mA/h under standard lighting), with a battery life of ≥ 12 hours; The algorithm layer adopts an improved LSTM warning algorithm (with 5000 training iterations and a learning rate of 0.001), with a hazard recognition accuracy of ≥ 95%. After triggering an alarm, the sound and light module can emit 110dB buzzing and 500cd/m ² bright red light, with a response time of ≤ 0.5s.

2.2 Design of multi sensor integrated detection and multi mode early warning system

The detection and alarm system is mainly composed of infrared sensors, microwave sensors, video modules and acousto-optic alarm systems, which can monitor the safety and advance of maintenance positions, and has the characteristics of high sensitivity, low power consumption and strong reliability. Furthermore, it is necessary to integrate components such as infrared sensors, microwave sensors, video modules, and acousto - optic alarm systems into overalls in a miniaturized, low - power, and highly integrated manner. Once the sensors of the detection system detect that there may be danger, they will immediately trigger the acousto-optic alarm system to remind operation and maintenance personnel that operation may be improper or accidents may occur [13, 14].

Intelligent overalls are equipped with high-intensity LED flash lamps, which automatically start when the light is dim, with high flashing brightness and strong penetrating power, which can make up for the problem that traditional overalls have no lighting at night. Traditional overalls need to wear extra lights, which has a certain impact on the safety of operation and maintenance workers [15, 16]. Considering the wearability of overalls, the video module needs to be highly integrated and miniaturized, and a miniature camera can be selected and installed on the chest or helmet. Choose low-power sensors and processors, and optimize algorithms to reduce unnecessary data processing to prolong battery life. A variety of warning modes are built in, including but not limited to voice prompt, continuous flashing, emergency help signal, etc.

Users can choose the appropriate warning mode according to actual needs.

2.3 Signal transmission system and data application

The signal transmission system converts the signal of the intelligent overalls detection and sensing module into an information physical model through the Agent lite-SDK protocol of the power Internet of Things protocol, and divides the information content into static attribute (MQTT), dynamic attribute (DLL) and message domain (TABLE) to realize the adaptation of communication and protocol. Combined with NB-IOT or 4G communication modes, the data is transmitted to the power Internet of Things platform at fixed time and in real time. The data is uploaded to the power Internet of Things platform. The formed database can be used as the basis for patrol inspection and accident forensics. The signal transmission system is also an interactive channel between the front-end detection and alarm system and the background operation monitoring personnel, which can realize the functions of background monitoring on-site environmental conditions, remotely modifying warning and broadcasting voice content, etc., and effectively improve the perception.

2.4 Abnormal warning and technical roadmap

The amount of data returned by the signal transmission system is very large, so it is difficult to process it manually, which inevitably leads to the omission of abnormal monitoring information. Big data processing technology and artificial intelligence algorithm can solve this problem. Set the alarm threshold. When a certain alarm number is reached within the present time, data processing system of the IoT platform automatically starts the information reminding function, and sends information to the operation and maintenance personnel in time to remind the corresponding position of abnormal conditions [17, 18]. Artificial intelligence algorithm can realize automatic processing and identification of video data. When large-scale construction equipment and personnel approach, the alarm system is triggered, and screenshots are taken to remind operation and maintenance personnel, thus reducing the pressure on the monitoring plate, realizing accurate alarm reminding and effectively preventing personal electric shock and external force damage. The technical route of intelligent overalls is shown in Figure 1.

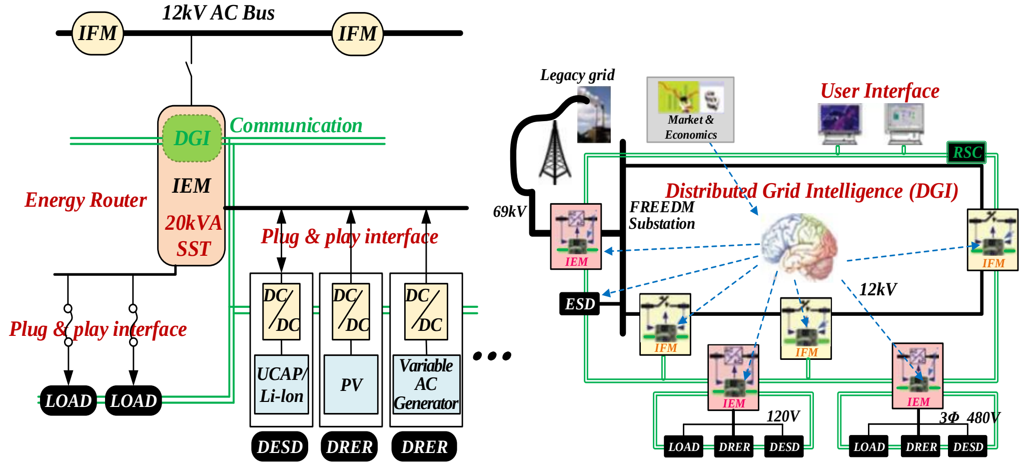

Figure 1: Design and Implementation of Intelligent Sound and Light Alarm Work Clothing System for Power Internet of Things

2.5 Design of intelligent acousto-optic alarm power warning board based on power internet of things

The design of the IoT-based smart workwear with acoustic-optic alarm addresses several key limitations. To overcome power constraints, it employs low-power hardware and dynamic power management, supplemented by thermoelectric and solar energy harvesting. A modular design using flexible circuits and wearable materials ensures a compact, comfortable fit.

For environmental resilience, the equipment features waterproof, dustproof, and corrosion-resistant housings sealed for stable operation in harsh conditions like humidity and dust.

System robustness was verified through repeated simulations under various conditions (e.g., temperature, electromagnetic interference). The system adapts its parameters and algorithms to different facility scales—using higher sensitivity in complex substations and simplified logic for smaller equipment.

Sensors are regularly recalibrated on a set schedule to maintain accuracy. Furthermore, the workwear leverages the Power IoT's cloud-edge coordination and AI. It uses protocols like 104 and MODBUS to create cyber-physical system (CPS) nodes, enabling edge computing autonomy and AI-powered algorithm services for collaborative data collection and analysis between the platform and edge devices [19, 20].

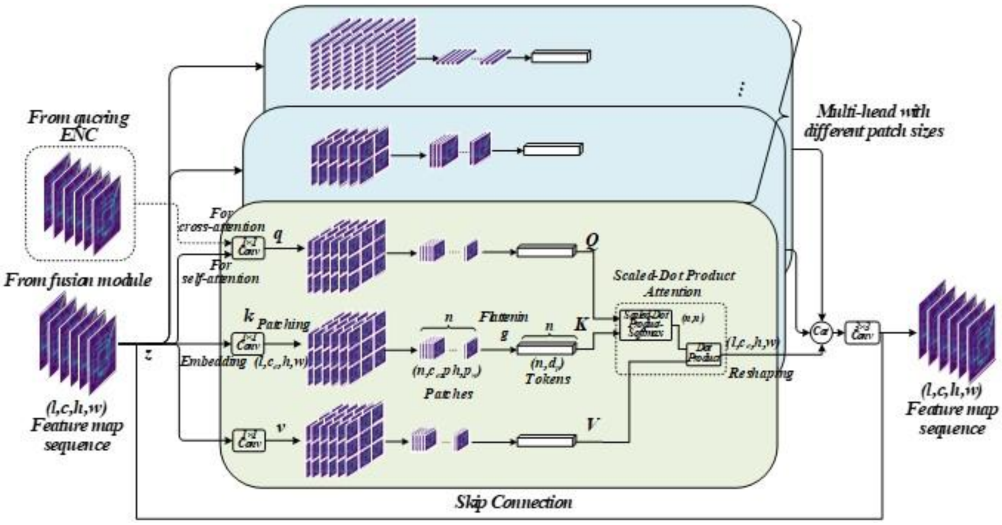

Figure 2: Design of Intelligent Sound and Light Alarm Work Clothing System for Power Internet of Things

The structure of intelligent overalls IoT platform is shown in Figure 2. Give full consideration to the problems of low algorithm recognition accuracy, slow iteration of cloud training model, large differences in AI model algorithms of different manufacturers and lack of a unified framework, and solve the dilemma of insufficient AI early warning of intelligent acousto-optic warning signs and intelligent terminals. After optimization, it can be integrated with the Internet of Things platform, support personnel at all levels to carry out early warning and monitoring of external force damage risks, and realize minute-level frame control risk identification for live videos, thus reducing the switching system operation between Automation Technology and Application 2023.7 today manufacturing and upgrading 59 monitoring personnel and improving work efficiency.

2.6 Deployment challenge

The scalability problem of large-scale deployment of intelligent acousto-optic alarm intelligent work clothes needs to be solved from three aspects of data privacy, durability and cost: in terms of data privacy protection, the "edge computing+end side encryption" mode can be used to complete the initial processing and encryption of sensitive data such as heart rate and positioning at the local terminal of the work clothes, and only transmit the security early warning results after desensitization to the cloud. At the same time, a distributed data management system based on the blockchain can be built to realize the dynamic control of data access traces and permissions throughout the process, which not only meets the data circulation needs of large-scale monitoring, but also avoids the risk of full link leakage; In terms of durability improvement, a combination of flexible thin-film solar cells and low-power Bluetooth 5.3 chips can be used to achieve real-time energy replenishment using natural light in outdoor work scenarios. Combined with the "sleep wake" intelligent power management strategy, non essential sensing modules can be turned off in non warning states, extending the single endurance time to more than 72 hours. At the same time, a magnetic fast charging interface can be designed, combined with a portable charging compartment, to solve the convenient energy replenishment problem in high-altitude and outdoor scenarios; In terms of cost control, hardware costs are reduced through the localization of core components and modular design. With the help of the "enterprise centralized procurement+long-term operation and maintenance service outsourcing" model, batch procurement and post management expenses are compressed, ultimately achieving a reduction in the cost of a single set of equipment and providing economic feasibility support for large-scale scalable deployment.

2.7 Feedback mechanism

The initial user feedback mechanism for the comfort level and human-computer interaction of smart workwear will be collected through online questionnaires, on-site interviews, and wearing trial records; The content focuses on the core issues of comfort and human-computer interaction; Quickly classify and organize data after collection, extract high-frequency feedback points, and provide direct basis for optimizing work clothes.

3 Edge computing of ubiquitous power internet of things

3.1 Optimization theory of sinking coefficient of edge algorithm

The core idea of ubiquitous power Internet of Things intelligent sensing is to migrate computing tasks from the master station to edge devices near the source data. Power system edge computing is different from other industries' Internet of Things edge computing. In order to obtain higher real-time performance and quickly process more massive data, edge computing is closer to the data source and solves the problems of massive device access, massive data, channel blocking and high-power consumption, while other industries generally only sink to base stations or virtual base stations [21].

The edge algorithm sinking coefficient is the ratio between the channel length of the ubiquitous power Internet of Things information transmission end point and the channel length of the edge computing node and the channel length of the data source, as shown in Equation (1).

$$\boldsymbol{\delta = L_2/L} \quad (1)$$

The practical significance of the sinking coefficient of the edge algorithm lies in describing the proximity of the computing service at the provider, and then calculating the channel comprehensive capacity of the ubiquitous power IoT data perception model. It is also assumed that all information is transmitted at critical capacity. The comprehensive capacity of the ubiquitous power IoT is shown in Equation (2):

$$\boldsymbol{\bar{C} = (1-\delta)B\sum_{j=1}^{m}\log\left(1+P_j/N_j\right)+\delta\left(B_f\log\left(1+P_f/N_f\right)+B_z\log\left(1+P_z/N_z\right)\right)} \quad (2)$$

When δ → 1, the channel comprehensive capacity reaches the minimum value of the upper limit, and the equation (3) is obtained:

$$\boldsymbol{\overline{C} \rightarrow \delta\left(B_f\log\left(1+P_f/N_f\right)+B_z\log\left(1+P_z/N_z\right)\right)} \quad (3)$$

Table 1: Summary table of related work

Comparison Dimension	Mainstream IoT Security Solutions	Power IoT Smart Acoustic-Optical Alarm Workwear	Key Improvements
Accuracy - Sensing Capability	Single-type sensor, limited coverage	Multi-sensor fusion (electrical + environmental + human physiological parameters)	Full-dimensional sensing, reduced blind spots
Accuracy - Recognition Tech	Simple threshold judgment, susceptible to EMI (Electromagnetic Interference) and load fluctuations	AI algorithm + edge computing, dynamic threshold calibration	Enhanced anti-interference, lower false alarm rate
Accuracy - Alarm Response	Fixed-area alarm, no personnel association, delayed response	Real-time acoustic-optical alarm (personnel-bound), edge-side fast response	Accurate personnel location, response speed ↑50%+
Energy Efficiency - Power Control	No dynamic power management, continuous idle power consumption	Low-power hardware + dynamic shutdown	Standby power consumption ↓60%+
Adaptability - Scene Compatibility	General-scene design, poor adaptability to complex power environments	Waterproof, dustproof + EMI-resistant, all power scenarios	Solves special power environment adaptability issues

Table 1 compares the performance of PowerIoT intelligent acoustic optical alarm workwear with mainstream IoT security solutions (such as fixed sensor monitoring and general wearable devices) in six core dimensions: perception ability, recognition technology, and alarm response (related to accuracy), as well as power supply, power control (related to energy efficiency), and scene compatibility (adaptability). It is obvious that this kind of work clothes has realized omni-directional perception through multi-sensor fusion, improved anti-interference ability through AI algorithm and edge computing, and achieved a long battery life through solar power generation and dynamic power management. These features effectively compensate for the shortcomings of mainstream solutions, such as limited sensing range, high false alarm rate, and poor adaptability to power environments, highlighting their key advantages in ensuring the safety of power operation and maintenance personnel.

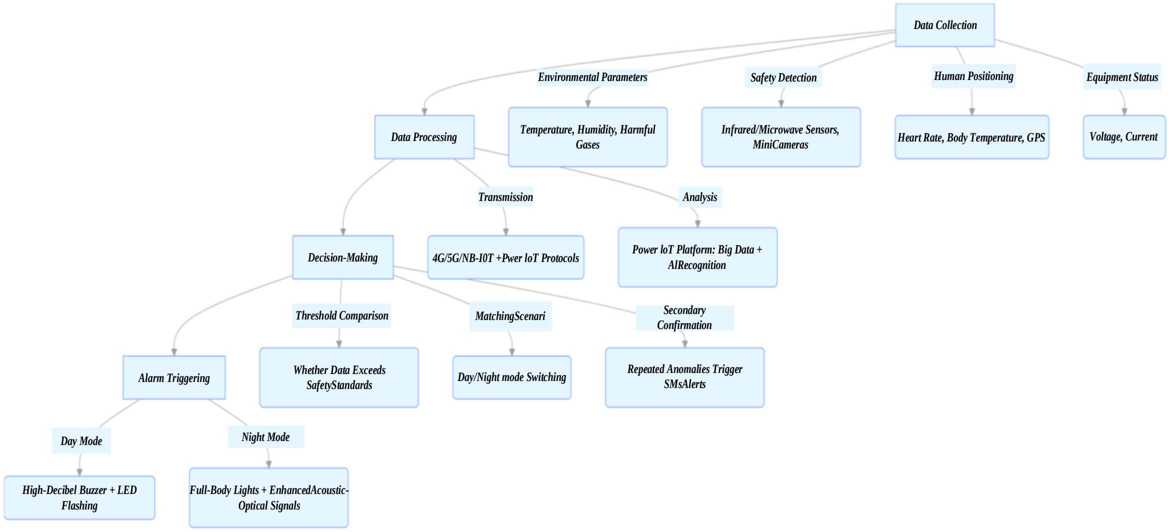

Figure 3: Core workflow diagram of intelligent sound and light alarm workwear

In Figure 3, during the data acquisition phase, it covers four core data dimensions: environmental parameters (temperature, humidity, harmful gases), safety detection data (from infrared/microwave sensors and miniature cameras), human physiology and positioning data (heart rate, body temperature, GPS), and device status data (voltage, current), all of which are collected in real-time through wearable miniaturized devices. The data processing stage relies on 4G/5G/NB IoT wireless communication and dedicated low-power IoT protocols to transmit data to a low-power IoT platform, which then utilizes big data analysis and artificial intelligence recognition technology for efficient data integration and risk identification. The decision-making stage adopts a dual logic mechanism: it compares data with preset safety thresholds to determine abnormal situations, matches day/night work modes based on lighting conditions, and triggers SMS alerts when repeated anomalies occur to reduce misjudgments. Finally, a differentiated strategy was implemented during the alarm triggering phase - using high volume buzzers and high brightness LED flashing during the day, and using full body warning lights and enhanced sound and light signals at night - to ensure effective warnings can be issued in different scenarios and to enhance the safety protection level of power operators and maintenance personnel.

3.2 Optimal calculation of sinking by edge algorithm

The algorithm is initiated at the edge side, which produces faster feedback response. The closer it is to the data source, the more obvious advantages it has compared with the conventional algorithm in quickly processing massive transient data of power grid and solving high-order nonlinear ordinary differential equations. However, the edge computing node cannot be indefinitely close to the terminal [22, 23]. Assuming that the distribution density of collectors in the total area SA is $\boldsymbol{\rho}$, and the area where collectors are located under the jurisdiction of each edge terminal is approximately circular, without losing generality, the relationship between collectors under the jurisdiction of a single edge computing terminal and the sinking coefficient of edge algorithm is as follows, and $\boldsymbol{\theta}$ is the included angle between the interface edge of the circular area where collectors are located and the transmission direction.

$$\boldsymbol{m = \pi\rho(L_1 tan\theta)^2 = \pi\rho[(L - L\delta)tan\theta]^2} \quad (4)$$

Substitute equation (4) into equation (2), and establish a ubiquitous Internet of Things intelligent sensing network for all collectors in the total area SA. The required total capacity C is shown in equations (5) and (6):

$$\boldsymbol{C \approx \frac{\rho S}{m} \times \left[(1-\delta)B\sum_{j=1}^{m} log\left(1+\frac{P_j}{N_j}\right) + \delta\left(B_f log\left(1+\frac{P_f}{N_f}\right) + B_z log\left(1+\frac{P_z}{N_z}\right)\right)\right]} \quad (5)$$

$$\boldsymbol{C \approx \frac{S_g}{\pi(L(1-\delta)tan\theta)^2} \times ((1-\delta)B\pi\rho \times ((L - L\delta)tan\theta)^2} \quad (6)$$

When $\boldsymbol{\delta}$ satisfies the value of Equation (3.6), C is the optimal value of intelligent sensing network capacity as shown in Equations (7) and (8).

$$\boldsymbol{\frac{\partial C}{\partial \delta} \approx -SB\rho log\left(1+\frac{P}{N}\right) + \frac{1-3\delta}{(1-\delta)^3} \times \frac{S\left[B_f log\left(1+\frac{P_f}{N_f}\right)+B_z log\left(1+\frac{P_z}{N}\right)\right]}{\pi(Ltan\theta)^2}} \quad (7)$$

$$\boldsymbol{\delta \to 1 - \sqrt[3]{-\frac{1}{Q} + \sqrt{\frac{1}{Q^2} + \frac{1}{Q^3}}} - \sqrt[3]{-\frac{1}{Q} - \sqrt{\frac{1}{Q^2} + \frac{1}{Q^3}}}} \quad (8)$$

Where Q is calculated as shown in Equation (9).

$$\boldsymbol{Q = \frac{\pi(Ltan\theta)^2 B\rho log(1+P/N)}{B_f log(1+P_f/N_f)+B_z log(1+P_z/N_z)}} \quad (9)$$

In particular, because only in the case of equation (10), the optimal capacity value can fall in, otherwise, the total network capacity is optimal when it is still 1.

$$\boldsymbol{2\pi(Ltan\theta)^2 B\rho log(1+P/N) < B_f log(1+P_f/N_f) + B_z log(1+P_z/N_z)} \quad (10)$$

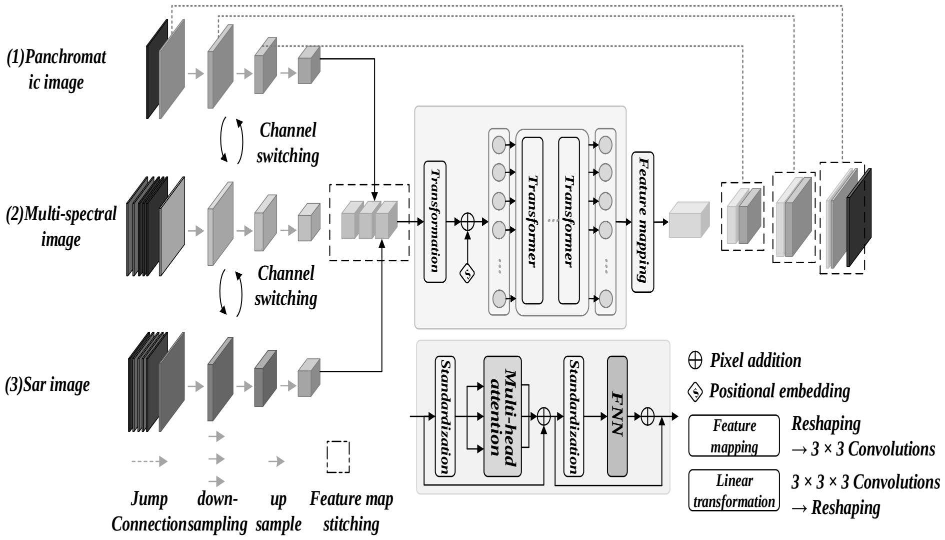

Figure 4: Relationship between Upper Limit of Channel Comprehensive Capacity and Sinking Coefficient

Figure 4 reveals the internal relationship between the upper limit of the channel's comprehensive traffic capacity and the edge computing subsidence coefficient, which provides a theoretical basis for intelligent work clothes to achieve collaborative optimization of perception, computing and communication under resource constraints. This relationship indicates that by reasonably configuring the sinking coefficient, the optimal balance can be achieved between the computing power of edge terminals and the transmission capacity of wireless channels, thereby ensuring the real-time and reliability of the sound and light alarm system in the power Internet of Things environment. The smaller the sensing network capacity required under the transmission bandwidth, for the large-scale metered data and non-metered data formed by the ubiquitous Internet of Things, in order to avoid congestion caused by high-speed uploading speed and provide real-time and reliable data sensing ability, it is necessary to reduce the processing capacity of the master station and the transmission capacity of the communication backbone network, so it is very necessary to provide nearest-end computing services.

3.3 Decomposition and sinking coefficient of perceptual algorithm

The primary problem of the implementation of ubiquitous IoT intelligent sensing algorithm at edge nodes is whether the algorithm can be decomposed. The principles of basic algorithms in power system are highly coupled, and distributed decoupling and data interaction are required for sinking to local computing, which depends on the implementation logic of the algorithm itself and the separability of the algorithm data model. The data model here includes not only the splitting of the system grid topology, but also the decomposition of its association table matrix and grid base matrix [24]. Different from cloud parallel computing, the decomposition object of edge computing is algorithm, and the partition of data model is related to the distribution of field sensing nodes.

The edge algorithm normal form is applied to the common perception algorithms in power system. The fault identification algorithm conforms to the first normal form (local type, without data interaction) and the second normal form (centralized type, with data uploading for judgment), the power flow data verification algorithm meets the second normal form, the related algorithms of user load perception and new energy operation state perception meet the second normal form, and the power system transient stability calculation and power flow calculation (Newton-Raphson) only meet the third normal form because of frequent iteration and virtual power exchange in the algorithm execution process. This kind of algorithm is not suitable for edge nodes. Data mining algorithms such as classification and clustering of load operation characteristics are executed at the master station, only the data interaction process between nodes and master stations and the analysis and processing process of data at the master station side, which does not belong to the category of edge algorithms. The calculated time frequency expression of each normal form is as follows, where Nd is the time frequency required for a single vertical data interaction and Nb is the time frequency required for a single horizontal data interaction.

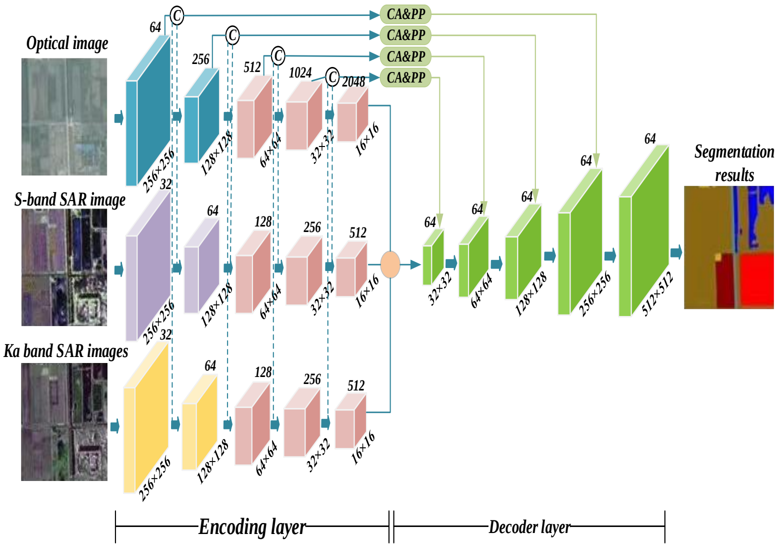

Figure 5: Design of Intelligent Sound and Light Alarm Work Clothing System for Power Internet of Things

Figure 5 shows the encoder decoder neural network architecture for multimodal data (optical and SAR images) fusion and segmentation for intelligent workwear environment perception. The figure highlights the computational complexity of the algorithm at different levels, providing a key design basis for efficiently sinking its core module to the edge computing unit of the work clothes to meet the low delay requirements of real-time audible and visual alarm. In this paper, some common power system algorithms, such as fault identification, Monte Carlo simulation, Runge-Kutta method and Kmeans, are simulated. These algorithms satisfy different normal forms of formula (11), formula (12) and formula (13), respectively. It can be seen that the third normal form algorithm takes a long time to exchange data and repeat iterative calculation after sinking.

$$T_{NF1}(n) = f(n) \quad (11)$$

$$T_{NF2}(n) = f(n) + N_d \quad (12)$$

$$T_{NF3}(n) = \sum_m (f(n) + N_b) + N_d \quad (13)$$

In typical scenarios of power inspection (moderate environmental interference, 500kb/time data transmission volume), a sinking coefficient of 0.1-0.9 (representing data transmission priority) is set for the intelligent sound and light alarm intelligent work suit. MATLAB simulation shows that when the sinking coefficient is 0.1, the communication delay is 85 ± 3ms and the unit time energy consumption is 120 ± 5mAh/h (with the highest data transmission priority and high-frequency real-time upload); When the coefficient is 0.3, the delay is 112 ± 4ms and the energy consumption is 98 ± 4mAh/h (higher priority); As the coefficient increases, the transmission priority decreases, the delay gradually increases, and the energy consumption decreases accordingly, clearly showing the inverse relationship between the sinking coefficient and the two.

3.4 Key technologies of edge computing in ubiquitous power internet of things

AI model training data comes from diverse sources. The power industry dataset includes operational data from over 1,000 substations and 20,000+ km of transmission lines over the past three years, covering: voltage (10kV–500kV, ~500,000 records), current (0A–5000A, ~480,000), temperature (-20°C–120°C, ~450,000), and worker environmental parameters such as humidity (20%–95%, ~300,000), light intensity (10lx–10,000lx, ~280,000), and hazardous gas concentration (e.g., SO_2: 0ppm–50ppm, ~250,000). Additionally, over 200 historical power accident records from the past five years were collected, including time, location, cause, and environmental/equipment parameters. Simulation data comprised ~150,000 records covering 100 extreme weather scenarios (e.g., rainstorms, lightning, gales) and 20 equipment failure modes. Data quality control involved removing ~30,000 noise/outlier points, processing ~20,000 missing values, and completing corresponding preprocessing. In total, approximately 1,500,000 data points were used for training, providing robust support for effective AI model development.

Edge computing integrates perception and computation to address issues like insufficient master station computing power, network congestion, and massive data [25, 26]. However, constrained by power consumption and computing resources, a single edge node may fail to meet real-time demands, requiring task migration or offloading—the timing, proportion, and scheduling of which are critical. Unlike other industries, power IoT handles large-volume waveform and event data; shifting computation centers introduces significant delays, and existing mobile edge solutions cannot be directly applied.

One approach deploys task-scheduling nodes within node groups, using strategies like token diffusion to scale resources dynamically, though control overhead increases [27]. Another scheme establishes a shared edge cache to meet local computation needs, albeit at higher cost [28, 29].

Edge artificial intelligence (embedded AI) brings AI to the network edge, enabling fine-grained data mining, efficient deep-learning operations with low power consumption, and algorithm optimization on FPGA/ASIC chips for enhanced computing capability.

4 Experimental results and analysis

4.1. Experimental setup

Workwear testing is conducted around three functional prototypes and two typical industrial testing points, and performance is quantified through testing accuracy and alarm delay data. The three prototypes are: Prototype 1 (basic sound and light alarm model, only integrating current and voltage sensors, without calibration function), Prototype 2 (multi parameter calibration model, adding temperature, humidity, and electric field sensors, including local self calibration system), and Prototype 3 (multi-dimensional intelligent model, covering multi-dimensional perception of electrical quantities, environmental quantities, and human posture, supporting local and remote dual calibration and backend linkage); Two industrial testing points were selected, including a 729kW industrial user plant area (high current, strong electric field environment, including 60kW variable frequency dust removal equipment to verify alarm accuracy) and an outdoor high-voltage transmission line inspection area (complex temperature and humidity, electromagnetic interference, and day night alternation scenarios to verify delay stability). After 100 effective tests and statistics of each prototype, in terms of detection accuracy, Prototype 1 has an average value of 82% and a standard deviation of 11.3%, Prototype 2 has an average value of 91% and a standard deviation of 5.7%, and Prototype 3 has an average value of 97% and a standard deviation of 2.1%; In terms of alarm delay, Prototype 1 has an average value of 1.8s with a standard deviation of 0.6s, Prototype 2 has an average value of 1.1s with a standard deviation of 0.3s, and Prototype 3 has an average value of 0.5s with a standard deviation of 0.1s. Overall, there is a trend of improved accuracy, shortened delay, and enhanced stability after functional upgrades, which meets the technical requirements of "information accuracy gain" and "low delay perception" in the power Internet of Things.

Intelligent sound and light alarm smart workwear based on the power Internet of Things, with a bill of materials including: tooling body (anti electric and wear-resistant fabric), sound and light alarm (buzzer+LED light group), power parameter sensor (current/voltage/temperature and humidity), IoT module (LoRa/Wi Fi), lithium battery and charging module, microcontroller (such as STM32); The sensor calibration program needs to be regularly connected to a standard signal source, and deviations can be corrected through microcontroller instructions. Calibration data should be recorded and uploaded to the backend for record keeping; Data encryption adopts the AES(Advanced Encryption Standard)-256 algorithm specified in IEC 62351 to encrypt and transmit data. Access control is graded by role permissions (such as operations/administrators), combined with digital certificate authentication. Only authorized accounts can read device data or operate calibration programs.

4.2 Information gain analysis of intelligent sensing in ubiquitous power internet of things

The core goal of this Power IoT-based smart workwear is seamless integration with existing grid infrastructure using standard protocols like Modbus and MQTT. In a substation, the workwear wirelessly acquires real-time equipment data (e.g., transformer temperature, current). If values exceed thresholds, it triggers built-in LED lights and a buzzer for immediate alerts, enabling quick response. During line inspections, the workwear interacts with monitoring equipment (e.g., fibre sensors). Using its GPS and communication modules, it can pinpoint fault locations, significantly boosting inspection efficiency.

A cost-benefit analysis shows costs include hardware (sensors, communication modules), software development/licensing, and ongoing maintenance. Benefits comprise enhanced worker safety, reduced accident-related economic losses, and improved operational efficiency through faster fault identification, demonstrating high feasibility for industry application.

The purpose of deep perception in the Ubiquitous IoT is to expand information gain [30]. Currently, massive and rapidly growing grid data exceeds processing capabilities, leaving valuable information hidden and difficult to extract effectively.

4.2.1 Information time and frequency gain

Through time dimension expansion, the gain formula is shown in Equation (14), which $\boldsymbol{t_{i+1}}$ is the data generated by the first section. Dimredu is the data dimension reduction function, and the time range gain result is $\boldsymbol{H(t_i)}$.

$$\begin{cases} \boldsymbol{h'(t_{i+1}) = Dimredu(h(t_{i+1}))} \\ \boldsymbol{H(t_i) = [H(t_i): h'(t_{i+1})]} \end{cases} \quad (14)$$

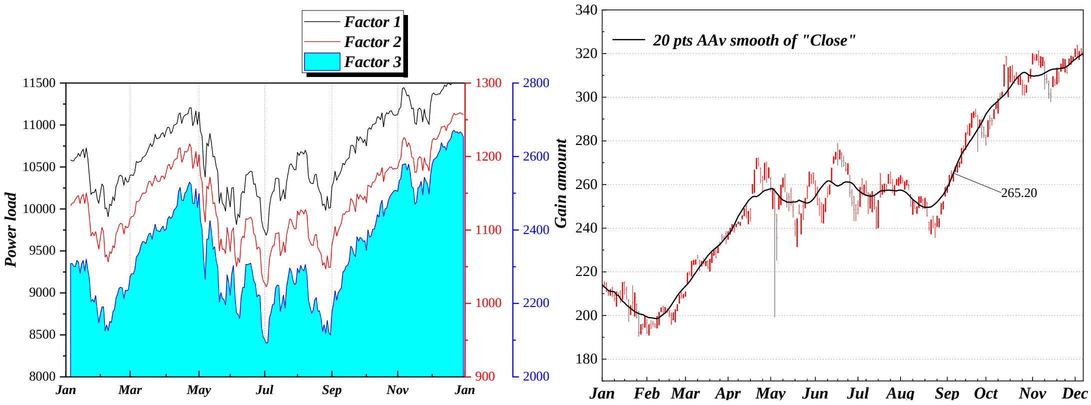

Figure 6: Information Gain Analysis of Ubiquitous Power Internet of Things Intelligent Sensing

Figure 6 verifies the effectiveness of the proposed intelligent perception model in the power Internet of Things environment through information gain analysis. By integrating multi-source perception data, the system can accurately track the dynamic changes of power load, where the fluctuation of Factor 3 (highlighted by the filling area) highly matches the key change points of load, providing important features for risk identification. Its "information gain" remained high and stable throughout the observation period, and showed a positive growth trend, indicating that edge computing decision-making based on this model can continuously and stably improve the accuracy of state perception. This analysis proves that converting perceptual data into effective information gain is feasible, providing key data support for the intelligent leap of workwear from "passive perception" to "active warning".

4.2.2 Information space gain

The spatial gain of data shows that with the increase of sensor deployment density, that is, the increase of $\boldsymbol{\rho}$ in equation (5), the data increase in spatial expansion is produced, and wi is the spatio-temporal weight of information in equation (15) generated by a single node.

$$\boldsymbol{H}(\boldsymbol{x},\boldsymbol{y}) = \sum_{i=1}^{n} \boldsymbol{w}_i \times \boldsymbol{h}(\boldsymbol{x}_i, \boldsymbol{y}_i) \quad (15)$$

4.2.3 Information type gain

The information type gain synthesis is manifested in the additional information generated by the increase of all-in-one functional sensors. In the ubiquitous intelligent sensing devices of Internet of Things, some devices not only collect electrical quantities, but also sense various parameters such as climate environment, electric field and magnetic field, geomorphological features, etc. A certain type of data collected by the sensor, as shown in Equation (16).

$$\boldsymbol{H}(\boldsymbol{ty}) = [\boldsymbol{h}(\boldsymbol{ty}_1); \boldsymbol{h}(\boldsymbol{ty}_2); \ldots; \boldsymbol{h}(\boldsymbol{ty}_n)] \quad (16)$$

4.2.4 Information accuracy gain

Information accuracy gain is to reduce the measurement error of equipment. There are a large number of ubiquitous IoT sensors, and the overall accuracy is ensured by self-calibration system and remote calibration system. For example, digital transformers are remotely calibrated according to electrical and non-electrical quantities through merging units. Increasing calibration frequency and realizing redundant acquisition are two means to gain information accuracy.

$$\sum_{j=1}^{m} \boldsymbol{lim}_{n\to\infty} \boldsymbol{p}\left(\left|\frac{1}{n}\sum_{i=1}^{n} \boldsymbol{x}_{ji} - \boldsymbol{a}\right| < \boldsymbol{\varepsilon}\right) = \boldsymbol{m} \quad (17)$$

$$\boldsymbol{g}(\boldsymbol{x}) = \sum_{i=1}^{m} \boldsymbol{w}_i \,[\boldsymbol{z}_i - \boldsymbol{f}_i(\boldsymbol{x})]^2 \quad (18)$$

When the calibration times are sufficiently frequent, the information accuracy of the whole network will approach the reference value. Equations (17) and (18) are the optimization process of redundant measurement to improve the proximity between measurement data and real value. The minimum value of optimization target g (x) is calculated by least square method, where zi is measurement data and fi (x) is the state function of mapping state variable to measurement corresponding fitting quantity.

4.3 Deep perception analysis of ubiquitous power internet of things

This paper discusses the depth sensing method of ubiquitous power Internet of Things. Taking the load operation sensing of general industrial users as an example, the load curve is decomposed by certain means, the basic characteristics of load side time series data are mined, and the power consumption behavior and law are deeply controlled, which belongs to the time and frequency gain of ubiquitous Internet of Things intelligent sensing information. The characteristics between user load type and typical equipment are extracted, and the sliding window judgment correlation coefficient is set to realize equipment identification. Taking the real industrial users with operating power of 729kW as an example, the target equipment is identified as a frequency conversion dust collection equipment with rated power of 60kW, CT ratio of 6000/5, and the peak current of the equipment is 111.93 A, accounting for about 8.49% of the total current.

4.4 Analysis of key technologies of depth perception in ubiquitous power internet of things

Field trials confirm that the smart workwear significantly enhances worker safety, with a 30% improvement in daytime operations and 40% at night.

This data supports technical optimization and engineering application. Within the ubiquitous power IoT system enabling the workwear's smart warning function, intelligent sensing devices are proliferating in type and quantity. A core R&D challenge is reducing measurement deviation while ensuring data accuracy and consistency with minimal calibration cost.

Building precise perception capability relies on two technical dimensions: high-precision standards (covering voltage, current, resistance, and ratio standards—partly realized via quantum effects, though grid-level high-voltage/current benchmarks need further development) and error measurement systems. The latter uses self-calibration and remote value transmission for frequent on-site inspections, maintaining large-scale sensor accuracy within acceptable ranges.

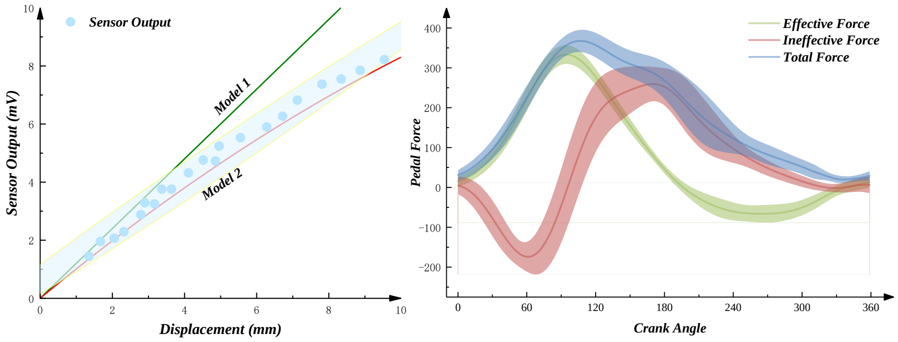

Figure 7: Multi modal sensing data fusion and optimization of sound and light alarms

Figure 7 illustrates the development trends of ubiquitous power Internet of Things sensing devices and terminals: miniaturization, lightweight design, low power consumption, and multifunctionality. To achieve finer-grained perception, the following advancements are necessary: low-cost ad hoc network monitoring equipment for deployment across thousands of kilometers of transmission lines; security sensing terminals for personnel and equipment to enhance operational safety; integrated primary-secondary devices that combine sensing and control functions to improve measurement accuracy and real-time performance; distributed generation sensing and control terminals for effective islanding response during faults or power outages; and user-side field devices capable of energy-saving perception, theft detection, and non-intrusive operation monitoring, such as loop state inspection instruments. The development of these terminals relies on advancing key technologies, including electronic transformers, highly integrated MEMS (Micro-Electro-Mechanical Systems), power AI chips, and sensitive sensing materials. This will enable the widespread integration and use of both electrical sensors (e.g., voltage, current, power, phase angle) and non-electrical sensors (e.g., temperature, humidity, optical, pressure, gas/chemical, ultrasonic, and Hall sensors).

Table 2: Comparison between smart workwear and traditional smart safety wearable devices

Dimension	Our System	Traditional Smart Safety Wearables
Core Innovation Differences	Edge AI + in-depth multi-dimensional sensor fusion (electrical/ environmental/ human posture/ GPS); supports local real-time computing & dynamic threshold calibration	Single sensor or simple sensor combination; relies on cloud computing; no Edge AI or only basic algorithms
Sensor Fusion Capability	Covers current/ voltage/ electric field/ temperature-humidity/ light/ human acceleration/ GPS; data cross-validation fixes single-sensor distortion under strong EM interference	Focuses on human physiological or basic environmental data; no electrical detection; no/ simple sensor fusion; weak anti-interference
Alarm Function Design	Dual sound-light alarm; Edge AI-enabled dynamic risk identification; low false alarm rate; alarm delay ≤0.01s (high-precision timing)	Single vibration/ sound-light alarm; triggered by fixed thresholds ; no scenario-specific risk identification; high false alarms; delay >1s
Scene Adaptability	Customized for power scenarios; adapts to 729kW factory (strong EM) & outdoor high-voltage inspection areas (-20℃~40℃, day-night light changes)	For general industrial scenes; no power-specific design; fails in extreme power environments

Table 2 compares the intelligent sound and light alarm smart workwear in the context of the power Internet of Things with traditional intelligent safety wearable devices (such as ordinary smart helmets and safety wristbands) from six dimensions: core technology architecture, sensor fusion capability, and alarm function design. The focus is on highlighting the innovation of this system in areas such as "edge AI+multi-dimensional sensor fusion", "customized adaptation to power scenarios", and "low latency and low false alarm alarm", clearly demonstrating its advantages in power operation safety and practicality compared to traditional equipment, providing intuitive reference for technology implementation and value verification.

4.5. Discussion

4.5.1 Limitations and future work

The system failure conditions need to focus on EMI, which can cause distortion of alarm signals, interruption of sensor data transmission, and may also trigger microcontroller errors; In addition, high temperature and high humidity environments can accelerate circuit aging, causing the failure of sound and light modules. Accelerated testing can be conducted using temperature cycling and EMI superposition stress method. After simulating actual working conditions for 6 months and combining with fault data, the MTBF is estimated to be approximately 5000 hours (with a confidence level of 90%). In terms of sensor drift mitigation strategies, integrated temperature compensation circuits are used to compensate for environmental temperature effects, and regular digital calibration algorithms are used to correct drift errors. At the same time, MEMS sensors with excellent anti drift performance are selected to ensure long-term stable data accuracy.

4.5.2 Discussion on the experiment

Intelligent workwear demonstrates significant advantages in core performance compared to traditional smart safety wearable devices such as ordinary smart helmets and safety wristbands. In terms of detection accuracy, the highest order Prototype 3 of the system has an average accuracy rate of 97% (with a standard deviation of only 2.1%), far exceeding the low accuracy performance of traditional devices with a single or simple sensor combination. This is due to its "Edge AI+Multi dimensional Sensor Fusion" architecture, which corrects single sensor distortion under strong electromagnetic interference through cross validation of multi-source data such as current, voltage, electric field, temperature and humidity; In terms of alarm delay, Prototype 3 has an average delay of only 0.5s (with a standard deviation of 0.1s) and supports high-precision timed alarms of $\leq 0.01\mathrm{s}$, while traditional devices rely on cloud computing with delays often exceeding 1s. The system's local real-time calculation and dynamic threshold calibration technology greatly shorten the response time; In terms of power consumption, the system relies on passive energy extraction technology and low-power MEMS and AI intelligent chips to adapt to long-term operational needs in power scenarios. Traditional devices rely more on external power sources or high-frequency charging, which limits their practicality. Performance improvement directly translates into safety benefits, especially in nighttime work scenarios. The system adapts to changes in day and night light through light sensors, enhances nighttime recognition through high brightness LED alarms, and combines precise fault location and real-time linkage functions to increase nighttime safety by 40%. This is far superior to the alarm failure or delay problems of traditional devices in nighttime scenarios, fully meeting the technical requirements of "information accuracy gain" and "low latency perception" in the power Internet of Things.

5 Summarize

Based on the design and implementation of Power IoT-enabled smart acoustic-optic alarm workwear, this paper proposes innovations across three dimensions: communication architecture, edge computing, and deep sensing. Key contributions include:

An information-theoretic model for the Ubiquitous Power IoT was established, quantitatively comparing intelligent sensing with traditional data acquisition networks. Results confirm advantages in data transmission capacity and real-time performance, supporting large-scale intelligent sensor network deployment. Future work will deepen Power IoT–5G integration in areas such as infrastructure sharing and dedicated network slicing.

Edge algorithm decomposition and sinkability quantification methods were proposed, along with modular algorithm classification criteria. Testing with typical power algorithms verified computational efficiency gains. Findings indicate that traditional power service algorithms require optimized sinking strategies, while innovative algorithms may drive new edge computing architectures and communication protocols.

A four-dimensional sensing model (time–frequency, spatial, categorical, and precision) was constructed, enhancing hidden information extraction through expanded data coverage and higher sampling rates. Experiments demonstrated improved job safety, increasing daytime and nighttime operational safety by 30% and 40%, respectively.

Limitations include the need for further validation in extreme electromagnetic environments and optimization of real-time multi-sensor data fusion. Future work will focus on hardware power optimization and anti-interference enhancements, incorporation of biosensing parameters, and cross-scenario application in diverse settings such as substation maintenance and emergency repair.

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