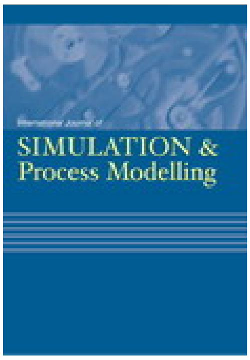

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Modelling and simulation of AI-driven operation and maintenance processes: a case study in broadcasting systems

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Modelling and simulation of AI-driven operation and maintenance processes: a case study in broadcasting systems

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Abstract: The conventional manual operation and maintenance mode has been challenging to satisfy the modern operation and maintenance needs in the radio and television sector as demand for equipment operation and maintenance efficiency and stability rises. This research thus suggests an intelligent operations and maintenance (O&M) system based on artificial intelligence (AI), hoping to increase the O&M efficiency and fault response capacity of broadcasting and television transmitters via four components. The method is based on discrete event simulation and LSTM data-driven modelling. The anomaly detection loop is implemented through isolation forest, and the large application possibility of the intelligent O&M system in terms of response timeliness and task scheduling efficiency is revealed by the trial findings. The experimental verification framework reduces response time by 38% and improves task scheduling efficiency by 42%, reflecting the value of cross domain simulation optimisation.

Keywords: AI-driven; intelligent operations and maintenance; broadcasting and television transmitters.

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1 Introduction

Radio and television have long assumed several purposes including national emergency broadcasting, government information distribution and cultural dissemination, and their social value and strategic position cannot be overlooked as among the forms of public media with the widest coverage and fastest propagation speed. Ensuring the stable transmission and efficient coverage of the signal depends mostly on the transmitter, the main output of the final kilometre of the signal, in the overall radio and television system (Aragón-Zavala et al., 2021). Particularly in rural places with quite poor communication circumstances, the transmitter is still the major signal coverage method and a crucial technical support for realising the strategic goals of village-to-village and emergency broadcasting. But with the growing amount of equipment and business complexity, the conventional means of operation and maintenance seem increasingly inadequate, mostly depending on manual inspection and empirical judgement; hence, there are a series of problems such as lagging response and incomplete detection of hidden problems, which limits the further enhancement of the operational efficiency of the transmitter system.

At this point, the operational environment of radio and TV transmitters is usually defined by high equipment density, obsolete technological systems and frequent manual intervention, which results in a long-term high load and low efficiency of O&M system. Simultaneously, the large geographical dispersion and varied environmental circumstances make it challenging for uniform and standardised management tools to offer thorough coverage (Zhang and Chui, 2018). Furthermore, challenging the industry's development needs for real-time, accuracy and high dependability is the continuous expansion of intelligent broadcasting, remote supervision and other emerging business scenarios, which calls for a different static maintenance mode and passive response system. With the aid of sophisticated information processing, this means how to increase visual management and danger prevention and control capability of the transmitter system (Shittu et al., 2018). This has become a major technological innovation breakthrough in the industry.

Data-driven intelligent technology has been extensively used in recent years to complex industrial systems including electric power, transportation, manufacturing, etc., which offers a new notion for equipment status observation, operation optimisation and maintenance strategy development. Particularly, the intelligent analysis represented by artificial intelligence has the capacity to perform adaptive modelling and knowledge reasoning on multi-source data, so extracting the possible laws from the complex operation information, and realise the functions of early fault identification and predictive maintenance, etc (Zhao et al., 2020). Apart from enhancing the scientific and prospective operation and maintenance decision making, the adoption of artificial intelligence technology is projected to solve the conventional problems of inadequate manpower and experience dependency to some extent, so improving the scientific and prospective operation and maintenance decision making. Besides expected improvements in scientific and prospective decision making, the introduction of artificial intelligence technology is expected to solve conventional challenges including manpower shortage and experience dependence to a certain extent, so encouraging the in-depth innovation of the broadcasting O&M system. The existing simulation research mainly focuses on manufacturing and logistics and has not yet established a closed-loop modelling framework for high reliability and multi constraint scheduling scenarios in broadcasting and television transmission. This paper fills this gap.

Direct application of artificial intelligence to radio and TV transmitters is not a straightforward technology migration, though. Practically, the signal processing, energy control, environment sensing, other elements of the transmitter system are quite heterogeneous and nonlinear, which complicates data modelling and algorithm deployment. Simultaneously, the long-term operation of the launch equipment in high-power, high-temperature, high humidity, and other complex environments cause challenges in sensor data collecting, missing interference, and other problems, so aggravating the difficulty of model training. Furthermore, missing established system architecture and practical expertise, the present knowledge and use of artificial intelligence O&M systems in the sector is still in the experimental stage (Zhang et al., 2023). Thus, to really realise the basic change from passive response to active prediction, an adaptive and scalable intelligent O&M solution based on the traits of broadcasting and television must be designed. This article tends to propose an intelligent operation and maintenance framework that integrates discrete event simulation and deep temporal models to solve the three major problems of delayed task scheduling, high false alarm rate, and low resource utilisation at the launch site.

This paper aims to introduce artificial intelligence technology system into the intelligent O&M system of broadcasting and TV transmitter stations in face of the above challenges and develops an intelligent platform architecture based on data-driven and knowledge-based reasoning around the central links of equipment monitoring, fault early warning, and O&M scheduling. By means of the integration of several artificial intelligence techniques, the dynamic perception and intelligent judgement of the equipment running state is attained, so enhancing the adaptive capacity and O&M system intelligence level of the transmitter. With the hope that it will serve as a reference basis and application demonstration for the intelligent transformation of the industry in the framework of the new round of technological innovation, this paper concentrates on analysing the feasibility, key technology paths and practical effect evaluation of AI in the intelligent operation and maintenance scenarios of broadcasting and television.

The remaining part of the paper is organised as follows: Section 2 reviews relevant technologies, including the system structure of broadcasting and television transmission stations and key AI technologies; Section 3 proposes core module implementation of intelligent operation and maintenance system; Section 4 conducts experimental verification; Section 5 concludes provides a review and summary of the article.

2 Relevant technologies

2.1 *O&M system for radio and television transmitters*

The main responsibility of a radio and television transmitter, as a terminal facility in the chain of radio and television signal transmission, is to amplify the modulated audio and video signals through high frequency transmitting equipment, then radiate them into the atmospheric space using an antenna system, so obtaining effective coverage of the target area. Usually, a full transmitter in terms of system structure consists of five core subsystems: the main transmitter system, the antenna feeder system, the power supply and distribution system, the environmental control system, and the monitoring and management system. The primary technological link for signal amplification is core equipment including high-frequency transmitters, frequency synthesisers, modulators, etc.; it is also the main transmitter system. Feeder lines, branchers, antenna arrays, etc. which control the angle, range, and directionality of signal coverage make up the antenna feeder system. Often fitted with dual-channel mains power input, diesel generator and UPS power switching module, the power supply and distribution system guarantee 24-hour continuous operation of the whole system, so ensure that the equipment still maintains the operation in extreme meteorological or emergency conditions.

The running of the launch pad depends much on an environmental control system. Usually equipped with industrial-grade air conditioners, fresh air systems, lightning protection devices, smoke alarms and other auxiliary facilities to ensure that the operating environment is within a safe and stable threshold, the transmitter equipment is quite sensitive to temperature, humidity and electromagnetic environment. Higher demands for environmental adaptation are shown by some transmitters in plateau, desert, and coastal locations, which also have to deal with unique environmental obstacles such limited oxygen, high temperature, high salt, etc. Technical hubs for realising unified management and centralised control of stations, the monitoring and management system are mostly responsible for equipment parameter acquisition, operation status reporting, log recording and operation order issuing (Raptis et al., 2019). Many big provincial transmitters have now set monitoring systems based on SCADA architecture to get centralised visual scheduling and status viewing of dispersed stations.

Radio and TV transmitters have amazing qualities of great availability and low fault tolerance at the operation and maintenance level. The system runs non-stop all year long, which calls for extremely high equipment stability; once an interruption occurs, it may lead to regional broadcast paralysis, with major effects (Ikram and Sayagh, 2023). Consequently, the conventional method of operation and maintenance is based on regular inspection and fault repair; the maintenance staff must thus regularly record and manually assess the operation of the core equipment, signal quality, energy consumption level, environmental parameters, and so on. Most of the grassroots stations have low staffing, and the phenomena of one person working in several roles is prevalent, therefore restricting the efficiency of operation and maintenance and the degree of risk control. Furthermore, the fast replacement of equipment causes several versions of equipment from different suppliers to coexist in the system with non-uniform interfaces and uneven maintenance criteria, therefore complicating technical administration.

Globally, transmitter simulation studies, the degree of informatisation of radio and television transmitters has been raised in recent years as the approach of intelligent broadcasting and television has been progressively encouraged. Research on the optimisation of the system structure of transmitter stations, the construction of centralised monitoring platforms, electromagnetic environment monitoring, energy-saving control strategies and other aspects has been progressively carried out by China Radio and Television, radio and television stations at all levels and research institutes. To realise the networked reporting and remote monitoring of the operation data of stations in various cities and regions, for instance, the State Administration of Radio and Television, has tested the building of remote centralised operation and maintenance centres in several areas. Universities and businesses are also working together to create low-power, high-redundancy launch system components, which would help to stabilise equipment operation and maintenance cycle (Li et al., 2022). Though there are still information islands, monitoring blind zones, premature responses and other shortcomings, overall, the current system has not yet realised higher-level functions including multi-site intelligent collaboration, equipment self-awareness and remote fault closed-loop processing.

Some affluent nations have already entered the scene internationally in automated management of radio and television broadcast infrastructures. Operating a broadcasting transmission network, Media Broadcast Company of Germany, for instance, extensively uses multi-station centralised control technology to combine environmental awareness with digital amplifier control to realise all-weather tracking and management of transmitter power, frequency drift, signal stability and other indicators. Conversely, the NHK Institute of Broadcasting Technology of Japan studies the dynamic adjustment mechanism of transmit power, which is utilised to enhance the uniformity of signal coverage and the efficiency of power use (Sugito et al., 2022). Its concentration is on large-scale urban broadcasting networks. Based on satellite links, PBS and other broadcasting organisations in the western mountainous parts of the USA have installed a remote diagnostic system that can perform system self-tests, log analyses and defect reports without depending on hand inspections. Of considerable relevance to China, these technical solutions have essentially resolved the long-term issues of staffing restrictions and difficult transportation at hilly stations.

All things considered, radio and TV transmitter stations have important characteristics like high continuity and stringent environmental adaptability in system construction and operation and maintenance mode, together with great expertise. Although hardware upgrading, platform building and specification development in China have made some strides recently, there is still clearly a gap in realising effective operation and control of the transmitter station system. Future building should investigate a technical path with replicability and popularity in view of the actual features of China's great geography and unequal regional development, so improving the general O&M system and service quality of the broadcasting and television system.

2.2 Overview of AI key technologies

The conventional operation and maintenance method depending on human experience has issues like slow response speed, many blind spots in monitoring, and difficulty in depositing knowledge as the broadcasting system gets more distributed and automated. The fast evolution of artificial intelligence technology has presented a fresh chance for smart running and maintenance of broadcasting stations. By means of in-depth analysis and mining of massive data produced by equipment operation, artificial intelligence can help to achieve accurate identification of system operation status, fault location, operation trend prediction, and scientific decision support, so promoting O&M system from passive response to active early warning and predictive maintenance, greatly improving the stability of the system and management efficiency.

From the technical system standpoint, the application of artificial intelligence in broadcasting and TV operation and maintenance mostly covers three main categories. Firstly, machine learning (ML) methods, depending on equipment operation logs, sensor data and multimodal information such image and voice, using supervised or unsupervised learning algorithms to build equipment state identification and classification models, which are widely used in fault detection, signal quality assessment and operation mode mining (Attar, 2023). Deep learning (DL) technology follows as a development of ML with strong automatic feature extraction capacity and ability to manage complicated structured data on high dimensions. Excellent performance in time series prediction, image analysis, and anomaly detection makes common network models (CNN), recurrent neural network (RNN) and long short-term memory (LSTM), appealing. Lastly, knowledge-driven expert systems and knowledge mapping technologies, which, via formal expression of O&M experience, equipment logic and fault processes, achieve rule-based reasoning and logical judgement, are fit for broadcasting and TV transmission systems with complex processes and high equipment correlation and offer auxiliary decision making and fault diagnosis support.

At the level of specific AI features, traditional ML methods such as support vector machine (SVM) perform stably in the fault classification task with small samples and high-dimensional features, and are often used to detect the abnormal state of transmitter amplifiers and feeder systems; decision tree (DT) and random forest (RF) are widely used in the comprehensive fault diagnosis of multi-sensor data due to their strong interpretability in terms of the significance of the features (Chen et al., 2023); and integrated learning model such as XGBoost and LightGBM are widely used in recent years due to their high efficiency in the field of fault classification. Recent years have seen LightGBM incorporated into the health monitoring of broadcasting and TV equipment because of their great accuracy and efficiency, which are especially appropriate for challenging multi-label classification issues (Alsafery et al., 2023). Currently, DL uses CNN models extensively for image anomaly detection in thermal imaging and surveillance video of transmitting equipment. While RNN and its LSTM variant excel in processing time series data, which are fit for trend prediction of parameters including transmitting power and voltage. For processing multivariate device status data, more complicated transformer designs are starting to be investigated so that complex interactions between time frames and many devices may be modelled.

Furthermore, showing interesting uses are unsupervised learning and reinforcement learning (RL). Under unlabelled situations, unsupervised techniques including autoencoder, isolation forest and principal component analysis (PCA) are applied for operational state modelling and anomaly detection to help discover rare problems and possible hazards (Yan et al., 2024). By using clustering techniques including K-means and DBSCAN, one can mine normal patterns of equipment functioning, so obtaining state clustering and risk categorisation. Intelligent solutions for O&M scheduling, resource allocation and maintenance route optimisation come from reinforcement learning. Intelligent bodies can independently learn the optimal maintenance techniques by mimicking the state-action-reward mechanism in the surroundings. For instance, deep reinforcement learning (DRL) models have been used to dynamically distribute maintenance resources and optimise inspection paths, hence enhancing O&M system stability and efficiency.

Furthermore, the method of connecting knowledge graph with expert systems offers a fresh insight into intelligent reasoning for TV and radio broadcast systems. The system can automatically identify multi-causal relationships in complex fault scenarios, help to locate the root cause of the problem, and increase diagnostic accuracy and response speed by building a graphical model of equipment hierarchical structure, fault correlation chain and maintenance process and combining it with graph neural network (GNN) for inference and causal analysis. This kind of method is a necessary path for developing highly dependable O&M intelligence since it compensates for the flaws of pure data-driven models in logical reasoning and experience migration.

Time series data analysis technology has evolved into a significant part of intelligent operation and maintenance in broadcasting and television at the level of technological application. Using time series modelling techniques including ARIMA, Prophet and LSTM helps the prediction of operating trends, the identification of anomalous fluctuations, and the estimate of the remaining life of equipment (RUL), since the operational state of transmitter equipment is rather cyclical and trending (Kleban and Stasiuk, 2022). O&M's proactive early warning capacity is much improved by constant monitoring and prediction of important environmental and power consumption indicators including temperature, voltage, and current. Furthermore, increasing multimodal data fusion technologies are more and more important. It can fully grasp the state of the equipment and the environmental impact from several angles by combining text logs, sensor values, image monitoring, and voice information to build a unified intelligent analysis model, so strengthening the accuracy and robustness of anomaly detection.

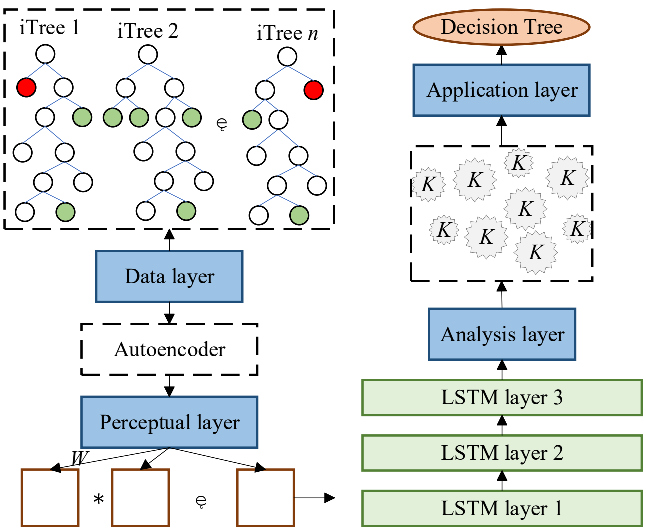
All things considered, AI technology supports intelligent operation and maintenance of radio and television transmitters technically thanks to covering a range of algorithms and models. Various approaches have different benefits spanning several aspects like fault detection, state prediction, maintenance optimisation and logical reasoning. Further deepening the integration of algorithms and scenarios, enhancing the data governance and model deployment mechanism, realising the transformation of AI from an auxiliary tool to the core of intelligent decision making, and supporting the broadcasting TV system to travel towards a new era of more efficient, reliable and intelligent operation and maintenance will help to shape the future.

3 Intelligent O&M system architecture design

3.1 Design of overall system architecture

To develop an end-to-end AI-driven closed-loop O&M system, the total architecture of the system is split into four parts: data layer, perception layer, analysis layer and application layer, to attain an intelligent O&M system for radio and TV transmitters see Figure 1.

Figure 1 Architecture of intelligent O&M system (see online version for colours)



Multi-source heterogeneous data gathering and pre-processing are mostly dependent on the data layer. To guarantee the data quality, the system rejects the anomalies in time and uses the isolation forest method to identify real-time abnormalities in the time-series data acquired by the sensors. Furthermore, employed to compress and denoise the sensed data to increase data transmission efficiency and storage performance is autoencoder housed in edge computing nodes.

Features extraction and initial anomaly identification of multimodal data are tasks of the sensor layer. CNN allows real-time image analysis of infrared thermal imaging and video surveillance data to automatically find equipment surface irregularities and failure indicators. LSTM is incorporated in sensor signal sequences to detect timing irregularities in important indicators such voltage and current, so enhancing the capacity of the perception layer to evaluate the state of equipment.

Adopting artificial intelligence algorithms for equipment state assessment and operation trend prediction, the analysis layer is fundamental for intelligent operation and maintenance. The system generates an LSTM-based timing prediction model to precisely forecast important environmental parameters and future trend of transmit power. Combining O&M experience with structured knowledge of the equipment helps intelligent fault diagnosis and causal analysis by means of knowledge graph reasoning technology, so attaining multi-device, multi-dimensional fault correlation analysis and improving diagnosis accuracy and interpretability.

Intelligent O&M decision making and creation of execution instructions fall to the application layer. Combining the risk assessment output of the analysis layer, the O&M system creates an intelligent O&M rule engine based on DT algorithms and automatically creates maintenance work priorities and inspection scheduling schemes (Cui et al., 2023). Through the graphical interface, this layer supports the operation and maintenance personnel to achieve decision feedback and manual intervention, so promoting the closed loop of human-machine cooperation in operation and maintenance and realising the dynamic optimisation of the operation and maintenance process.

All told, this system works through data cleaning, perception recognition, deep analysis and intelligent decision making, using multi-level AI algorithms as technical support, creating a closed-loop system for the full chain of intelligent O&M of broadcasting and TV transmitters.

3.2 *Core functional modules and algorithm implementation*

Designed around four basic functional modules, data acquisition, state perception, intelligent analysis and decision execution, each of which contains focused AI algorithms to attain effective and accurate O&M management.

3.2.1 *Data acquisition*

The fundamental link of the intelligent O&M system, data collecting, takes care of real-time multi-source heterogeneous data collecting from radio and TV transmitter equipment. These records comprise environmental monitoring indications, sensor-collecting timing signals, equipment operating logs, and remote video monitoring images. The complex and dynamic working environment of the transmitter will surely influence the data collecting process by equipment aging, signal interference, network latency, and other elements, so producing some data anomalies or noise (He et al., 2018). Should this aberrant data remain unnoticed and unprocessed over time, the intelligent O&M system's diagnosis accuracy and forecast effect would suffer directly, and misjudging and misbehaviour may even follow.

The system uses the isolation forest technique to identify real-time anomalies in the time-series data acquired by sensors therefore ensuring data integrity and accuracy. Using several random isolation trees and the length of the routes separating the data points as the anomaly indicator, isolation forest rapidly detects the unusual samples. Calculation of its anomaly score follows:

$$s(x, n) = 2^{-\frac{E(h(x))}{c(n)}} \tag{1}$$

where $s(x, n)$ is the sample x anomaly score; $E(h(x))$ is the average path length of the sample; $c(n)$ is the path length function used for normalisation, defined as:

$$c(n) = 2H(n-1) - \frac{2(n-1)}{n} \tag{2}$$

$$H(i) \approx \ln(i) + 0.5772 \tag{3}$$

where $H(i)$ is the i^{th} summation number which relates to the Euler-Marshaloney constant. This method helps the system to effectively find the abnormalities in the data and pre-filter and tag the sensor data, thereby enhancing the data quality and system robustness. This set of equations adheres to the publicly defined isolation forest algorithm, with all symbol meanings explained in detail within the main text.

Furthermore, the system uses autoencoder technology for dimensionality reduction and denoising of the acquired data, which comprises an encoder that maps the high-dimensional input data into a low-dimensional potential space and a decoder that reconstructs the original data, so addressing the problem of sensor data with high dimensionality and containing noise. With this equation, the training aim is to minimise the mean square error between the reconstructed data and the input data.

$$L(\theta,\phi)=\frac{1}{N}\sum_{i=1}^{N}\left\|x_i-g_\phi\left(f_\theta\left(x_i\right)\right)\right\|^2 \tag{4}$$

where x_i is the i^{th} input sample; f_θ and g_ϕ respectively are the encoder and decoder functions; θ and ϕ are the related network parameters. Iteratively optimising this loss function allows the autoencoder to learn a low-dimensional effective representation of the data, filter out noise components, and raise the computational efficiency and input quality of the next model.

By means of integration isolation forest anomaly detection and autoencoder noise reduction technology, the data collection module delivers high-quality acquisition and preprocessing of multimodal data from radio and TV transmitters. Under the challenging operating environment, this module guarantees the dependability and stability of the system by giving a strong data basis for the later status sensing, fault detection and predictive analysis of the intelligent O&M system.

3.2.2 State perception

State perception performs anomaly detection and real-time monitoring of the running state of TV and radio transmitters. To guarantee dynamic control of equipment health status, the module fully uses multimodal data and combines with DL algorithms to achieve thorough perception of equipment surface faults and sensor timing variations.

CNN is used in image data to automatically learn spatial features and patterns in the image by cascading convolutional and pooling layers, therefore enabling effective identification of equipment surface anomalies (Mao et al., 2021). One can characterise the convolutional layer computational process as follows:

$$y_j^l=\sigma\left(\sum_i x_i^{l-1}*k_{ij}^l+b_j^l\right) \tag{5}$$

where y_j^l is the j^{th} feature map of the l^{th} layer; x_i^{l-1} is the input of the previous layer; k_{ij}^l is the weight of the convolution kernel; b_j^l is the bias term; σ is the activation function; $*$ represents convolution operation. This allows the CNN to automatically record the local details and texture characteristics of the device surface, hence enhancing the accuracy and sensitivity of anomaly detection.

LSTM is used by the system for dynamic feature modelling for the time-series signals the sensors record. Through efficient capture of the long and short-term dependencies of the time-series data across the gating mechanism, LSTM eliminates the gradient vanishing issue of conventional neural networks (Qin et al., 2023). Its fundamental computing actions consist in activating the input gate and the forgetting gate:

$$f_t=\sigma\left(W_f\cdot\left[h_{t-1},x_t\right]+b_f\right) \tag{6}$$

$$i_t=\sigma\left(W_i\cdot\left[h_{t-1},x_t\right]+b_i\right) \tag{7}$$

The equation of cell state update is:

$$C_t=f_t\odot C_{t-1}+i_t\odot\tanh\left(W_C\cdot\left[h_{t-1},x_t\right]+b_C\right) \tag{8}$$

where x represents the input at the current moment, h_{t-1} and C_{t-1} are the assumed state and cell state at the past moment, respectively, the weight matrix W and the bias variable b are the parameters derived from the model training, σ is the sigmoid activation function and $\odot$ represents Hadamard product (element wise multiplication). This technique lets the model realise real-time sensing and early warning of unusual fluctuations and precisely record the time-series changes of important indicators (e.g., voltage, current, temperature).

The system uses the feature-level fusion technique, which fuses the image feature variable f_{img} extracted by CNN with the time series feature variable f_{ts} generated by LSTM to form a comprehensive feature representation f_{fusion}, so fully using the complementary information of image and time series data.

$$f_{fusion}=\alpha\cdot f_{img}+(1-\alpha)\cdot f_{ts} \tag{9}$$

where α is the fusion weight coefficient meant to balance the two characteristics' contribution. $\alpha\in[0,1]$ is determined through validation set grid search. When both the image and temporal feature dimensions are 256, they are fused using weighted summation to maintain dimensional consistency. Subsequent fault detection and state discrimination use the fused feature variables as inputs, hence enhancing the identification capacity and resilience to complicated anomalies of the model.

Combining feature-level fusion technology with two main DL models, CNN and LSTM, allows the state perception module to achieve accurate perception and anomaly detection of the operating state of radio and TV transmitter equipment, so providing a reliable state basis for later intelligent analysis and decision-making.

3.2.3 Intelligent analysis

The analysis layer mostly performs jobs of operation trend prediction and equipment state judgement since the foundation of intelligent O&M system for broadcasting stations is intelligence. Combining multi-source monitoring data and structured knowledge information, this module uses sequence modelling and knowledge reasoning to achieve dynamic identification and intelligent judgement of equipment operation status, so providing data support and logical basis for next diagnosis and decision making.

Using the evolving rules in the historical monitoring data, the system generates a time series prediction model based on LSTM in terms of operation trend prediction, so obtaining advance forecast of important parameters like transmit power, ambient temperature, current, voltage, etc. The LSTM model is appropriate for situations in which the operating state of broadcasting and TV equipment is influenced by the dynamics of several elements since it has a great advantage in modelling nonlinear and long-dependent sequences. The model's fundamental prediction mechanism consists as follows:

$$\hat{y}_{t+1} = \text{LSTM}\left(x_t, x_{t-1}, \ldots, x_{t-n+1}\right) \tag{10}$$

where $\hat{y}_{t+1}$ is the expected value for the time point $t + 1$ and the actual values in the past n moments constitute the input sequence. By means of training, the model can efficiently forecast future trends of important indicators including RUL assessment and preventive maintenance decisions as well as the future trends of power and voltage of the equipment (Badihi et al., 2022).

Regarding fault diagnosis and cause analysis, the system creates a knowledge graph for TV equipment and broadcasting that arranges and shows structural links, operational experience and failure modes expressed graphically. Each entity (e.g., transmitting amplifier, cooling unit, high temperature alarm) acts as a node in the graph, and relationships between entities (e.g., influence, connection, generation) are modelled as edges. The system uses the graph inference mechanism to perform fault localisation and cause inference based on the current state observation which expresses the computational process as follows:

$$F^* = \arg\max P(F|S, K) \tag{11}$$

where F is the collection of fault categories; S is the device state characteristics; K is the structure of the knowledge graph; $P(F|S, K)$ is the likelihood that a fault is F under a given state and knowledge graph, and $*$ represents the fault category with the highest probability. Combining data-driven probabilistic inference with knowledge-driven logical rules increases diagnostic accuracy and interpretability of the system. The approach enhances the generalisability and interpretability of the system by combining rule knowledge with perceptual data, preserves strong diagnostic power in the lack of enough samples or when the samples are slanted in distribution, and thus strengthens the system.

The intelligent analysis module opens the dual channels of data-driven and knowledge-driven, realises the prediction of the operation trend of broadcasting and TV transmitting equipments and intelligent judgement of fault logic, and so improves the foresight and intelligence of the O&M system by introducing LSTM sequence prediction model and knowledge graph inference mechanism.

3.2.4 Decision execution

The secret link in the intelligent O&M system of radio and TV transmitters that turns into actions is the layer of decision-making and execution. Its main responsibility is to create clear operation and maintenance instructions and task scheduling plans depending on the equipment status assessment results and operation trend prediction information supplied by the analysis layer, so attaining effective link from intelligent perception to accurate execution. The module stresses effective reaction, risk prioritisation, dynamic adjustment and human-machine cooperation to guarantee that the system can rapidly dispose of and constantly maximise the system in complicated circumstances.

Regarding intelligent decision generation, the system parses the multi-dimensional state information output from the analysis layer by building a rule engine grounded on DT algorithm. Using the health score, alert level, and expected trend of the equipment as inputs, the rule engine generates, via a sequence of decision nodes, the category of operation and maintenance needs, the degree of urgency of treatment, and the triggering criteria of the tasks individually. Based on the maximisation of information gain ideas, the node division process follows this computation formula:

$$\text{IG}(S, A) = \text{Entropy}(S) - \sum_{v \in \text{Values}(A)} \frac{|S_v|}{|S|} \text{Entropy}\left(S_v\right) \tag{12}$$

where $|S_v|$ is the size of the relevant sub-sample set while obtaining the value of v; IG(S, A) indicates the information gain brought by attribute A on the sample set S; S_v represents a subset of samples with attribute A having a value of v, S is the entire sample set in formula (11), and the symbol is defined using the previous formula. The DT model allows one to automatically match the usual fault patterns and response tactics (Goes et al., 2021). To realise the regularity and automation of O&M decision making, the DT model acquired through training can automatically match typical failure modes and response strategies, and output clear treatment plans, such as immediately dispatching inspection orders, power-limited operation or remote reset attempts, etc.

Regarding resource optimisation and scheduling, the system models several elements like fault level, task urgency, geographic location, path cost, staff skills and availability in a consistent manner, geared toward several restrictions. The aim is to guarantee the response efficiency of high-priority activities while sensibly distributing few O&M resources. Regarding resource optimisation and scheduling, the system models several elements like fault level, task urgency, geographic location, path cost, staff skills and availability in a consistent manner, geared toward several restrictions. The aim is to guarantee the response efficiency of high-priority activities while sensibly distributing few O&M resources. This approach of schedule optimisation seeks to reduce the total system cost, mathematically stated as:

$$\text{TotalCost} = \sum_{i=1}^{N} w_i \cdot C(T_i, R_i) \tag{13}$$

where TotalCost shows the overall cost of all the scheduling chores; N is the overall number of tasks; w_i is the risk weight of work T_i; R_i stands for the mix of the resources allocated to the task; $C(T_i, R_i)$ is the whole cost of the task T_i following the assignment of R_i, including time consumption, path distance, labour cost and service delay, etc. Dynamic scheduling techniques in the system change the allocation scheme in real time to raise scheduling efficiency and resource utilisation. By means of the dynamic scheduling algorithm, the system dynamically adjusts the allocation scheme in real time, therefore optimising the scheduling efficiency and resource utilisation and hence minimising repeated orders and ineffective scheduling.

Simultaneously, the system gives particular focus on human-machine cooperation and feedback systems. Based on seeing the outcomes of automatic decision making, the application layer features a graphical visual interface to facilitate hand intervention and correction by operation and maintenance staff (Landwehr et al., 2022). Based on field experience, operators also can change task priorities, assign schedule items, or confirm and augment system recommendations. Every manual intervention record will be automatically kept and supplied back into the model as system learning samples, which will help to optimise later rules and parameters and propel the adaptive evolution of the model.

Furthermore, supporting advanced tactics such task concurrency control, regional load balancing and multi-task fusion is the system to handle multi-device co-management situations. For devices that are geographically close but have various risk levels, for instance, the system can cleverly combine inspection activities to lower the frequency of repeated visits and enhance the general O&M system effectiveness.

Not only does it guarantee controllability, timeliness and optimisation of O&M strategies in a complex dynamic environment, but also it is the key support link for realising the closed-loop intelligent O&M of the whole process. The decision execution module integrates the four mechanisms of rule reasoning, resource scheduling, human-computer interaction and system feedback, so realising the effective transformation of equipment state perception to intelligent behaviour execution.

4 Experimental results and analyses

4.1 Experimental platform and data sources

This work constructs a special experimental data collecting platform to guarantee that the data used really reflects the operational status and fault characteristics of the transmitter equipment in view of the special needs of the intelligent O&M system for broadcasting TV transmitters. The self-built dataset has become a required tool to reach system verification since there is no public dataset especially for radio and TV transmitters and this kind of equipment has high industry specialisation and scene complexity. Covering important equipment including transmitter power modules, cooling systems and environmental monitoring, the experimental platform is housed in a provincial radio and TV transmitter station and uses a range of sensors including current, voltage, temperature, humidity and vibration sensors to realise continuous time-sequential acquisition of equipment running parameters. Apart from the equipment logs and alarm data automatically captured by the system, it creates a rich multi-dimensional data source to assist intelligent analysis and defect identification.

During data collecting, the platform not only covers the usual functioning condition of the equipment but also creates a simulated fault scenario for common defects including over-temperature, power anomalies and short circuits, etc. On-site human control allows for active collecting of fault data, hence improving the capacity of the model to detect aberrant states. Covering multi-dimensional information from fundamental sensor signals to system operation logs and defect alarm records, the multi-source fusion of experimental data provides an organised and high-quality database. Table 1 lists the major data types together with their purposes:

Table 1 Data categories and their usage in the experimental platform

Data category	*Collected content*	*Data format*	*Collection method*
On-site sensor data	Transmitter power, current, voltage, temperature, humidity	Continuous time-series signals	Real-time sensor acquisition
System logs and alerts	Equipment operation logs, fault alarms	Structured text with timestamps	Automatic recording and manual annotation
Simulated fault data	Over-temperature, overload, short-circuit fault states	Time-series sensor signals	On-site simulated generation

The platform uses a combination of outlier filtering and hand calibration to clean the data and features a method for regular sensor calibration and monitoring of data integrity to guarantee data quality. Professional operation and maintenance staff members also participate in the full fault simulation and data labelling process to guarantee the validity of fault samples and label accuracy at the same time. By means of these measures, this study has built a radio and television transmitter equipment operation database covering several dimensions and multiple states, so offering strong data support for the ensuing intelligent operation and maintenance model training and performance validation based on artificial intelligence algorithms.

4.2 Assessment of intelligent diagnostic and predictive capabilities

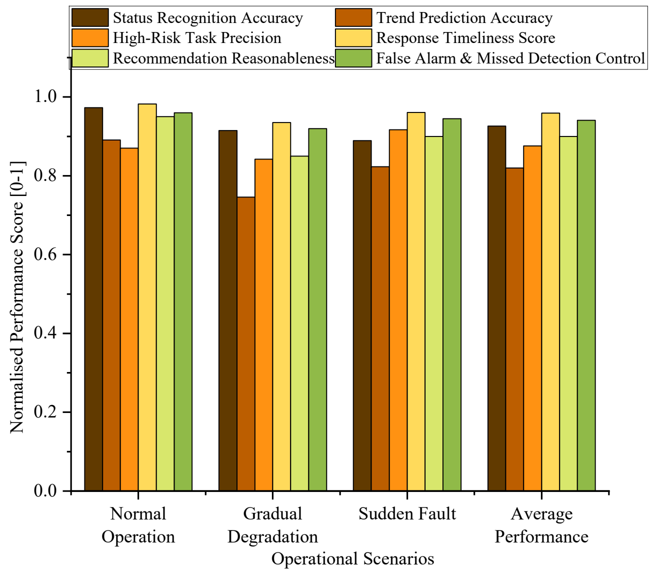
Aiming to evaluate whether the system has the complete intelligence capabilities of cooperative processing, accurate judgement and efficient feedback, this experiment builds an end-to-end closed-loop testing scheme to thoroughly examine the general intelligence level of the system in real scenarios. Unlike the conventional single-model performance test, this experiment stresses the total output effect of the system following the modules run together, so determining if the system can stably achieve the fundamental functions of fault warning, trend judgement and task suggestion. Three typical working conditions, that is, normal operation, gradual degradation, sudden fault and their average performance, are chosen based on the experimental dataset to guarantee that the test covers both common and edge scenarios and to improve the system's flexibility in morphic and complex environments.

Six evaluation criteria are applied in this experiment; all are normalised to the [0, 1] interval to ensure consistent assessment and facilitate direct comparison across different scales. The specific criteria are as follows:

- State recognition accuracy: it is determined by comparing the system's classification output with manually annotated labels. A value closer to 1 indicates higher identification accuracy. This metric assesses the system's ability to correctly identify the current operating condition (normal or abnormal) of the item.
- Trend prediction accuracy: it is based on the relative accuracy value between 0 and 1 derived from the prediction inaccuracy of important indicators (such as transmit power, temperature). In trend modelling, it reflects the system's performance; so, the higher the number indicates the more consistent the trend judgement is (Golan et al., 2020).
- High-risk task hit rate: it tests whether the system can correctly spot high-priority risk events and prevent misjudging low-risk events as high-risk. Originally expressed as a percentage, calculated as the percentage of accuracy of high-risk task prediction was straightly normalised to the 0–1 interval.
- Response timeliness score: it is computed as a score representing the processing speed and utility of the system by showing the ratio between the average processing time of the system from data input to task generating and the theoretical minimum response time.
- Reasonableness score for recommendation development: scored independently by three radio and television system maintenance experts (out of 5) to assess whether the automatically generated task recommendations from the system are logical, actionable and safe (Matson-Koffman et al., 2023). The raw scores are normalised to fit a unified indicator system.
- False alarm/missed alarm control capability: it measures the control effect of the system on false alarms and missed alarms in the alarm output; the closer to 1 denotes that the system has attained a good balance between detection sensitivity and accuracy.

Reflecting the performance of the intelligent algorithms in the key dimensions of whether the identification is accurate, whether the prediction is reliable, whether the response is timely and whether the decision is credible, the above six indicators together constitute the ability of the O&M system in the relevant aspects. Furthermore, reflecting the comprehensive adaptation and landing effect in the actual scenarios is their combined performance. Figure 2 exhibits the experimental results:

Figure 2 Results of intelligent O&M system performance (see online version for colours)



With an accuracy of 0.973 in normal operation, the system maintains a high level in all three types of test scenarios, so fully reflecting the robustness of the classification model in the state-awareness module and indicating that the system can accurately recognise the operating state of the equipment in stable working conditions. Although the recognition accuracy rate lowers somewhat in the progressive aging and sudden failure scenarios, it still maintains a high degree of 0.915 and 0.889, so indicating that the system still has strong generalising capacity and abnormal state recognition ability when confronted with data perturbation or abnormal fluctuation.

Regarding trend prediction accuracy, the three scenarios' scores, 0.891, 0.746 and 0.823, show that the system's modelling capacity is outstanding in normal state and that the prediction accuracy declines during dynamic changes including equipment performance degradation and unexpected events. Particularly in the progressive aging condition, the system suffers from the difficulty of the superposition of long-term trends and short-term perturbations, hence the prediction accuracy falls to 0.746. Generally speaking, the system is quite capable of forecasting operational trends and can offer simple support for risk warning and possible maintenance.

With precision of 0.870, 0.842 and 0.917 in three types of scenarios, averaging 0.876, the system also exhibits good competence in spotting and completing high-risk assignments. Particularly in cases of sudden failure, the great usefulness of the high-risk event detection indicates that the system can rapidly classify risks and respond to signal abnormalities. When handling complex risk events, this performance mostly depends on the cooperative diagnostic structure that combines the classification model with the knowledge graph rule-based reasoning mechanism, which can take into account both data-driven and knowledge-driven, and shows strong stability and judging accuracy.

With a maximum of 0.982 in the normal operation state and 0.961 in the case of unexpected failures, which indicates that the system has efficient real-time processing capabilities in the whole process of data access, computation scheduling, and task generating, the system scores generally high, exceeding 0.93 in all scenarios. This helps to satisfy the high requirements of the broadcasting and TV broadcasting stations for the response speed of operation and maintenance. Especially in unanticipated circumstances, the very high reaction score reflects the improved effect of the streaming processing mechanism and edge computing design in the system architecture, therefore offering a technical basis for later real-time decision making.

Maintaining a high degree of consistency between 0.85 and 0.95 respectively, the reasonableness score of task suggestions and the control ability of false alarms and omissions remain high, indicating that the maintenance tasks output by the system have a high consistency with the manual expert judgement, which is not only executable, but also has a certain degree of interpretability. The combination of knowledge graph and expert rules helps the recommendation module to not only assess whether some thing is wrong but also to provide a proposed path of why something is wrong and how to handle it. The system combines multimodal data cross-valuation and logical rule-based alert filtering in terms of false alarm management to efficiently decrease unproductive activities and missing events, so improving the practical value of usage.

4.3 Comparison of efficiency of O&M systems

This experiment designs a comparison test based on historical data to evaluate the advantages of the intelligent system over the conventional manual O&M mode in terms of response speed, task scheduling efficiency, resource utilisation rate and false alarm control, and other key indicators, so verifying the application effect of the proposed intelligent O&M system in the actual O&M process. Covering a range of typical scenarios, including normal operation, equipment aging and failure emergencies, the experiment chooses the operation and maintenance data of a provincial radio and TV transmitter in the past year, so ensuring that the results of the experiment have a wide range of applicability and real-world reference value.

Whereas the intelligent O&M system real-time monitoring of equipment status and intelligent task generating depends on automated data acquisition, state sensing and intelligent analysis modules, traditional manual O&M depends on experienced engineers for fault monitoring and task scheduling during the experiment. The two operations and maintenance processes are carried out independently for the same batch of data, and the important operation and maintenance indicators are noted to enable side-by-side comparison.

Four main evaluation indicators are chosen in this experiment to compare and analyse the intelligent O&M system with the conventional manual O&M; all the indicators are standardised to enable a fair and complete assessment of the performance variations between the two O&M modes. The indicators have as follows their definitions and interpretations:

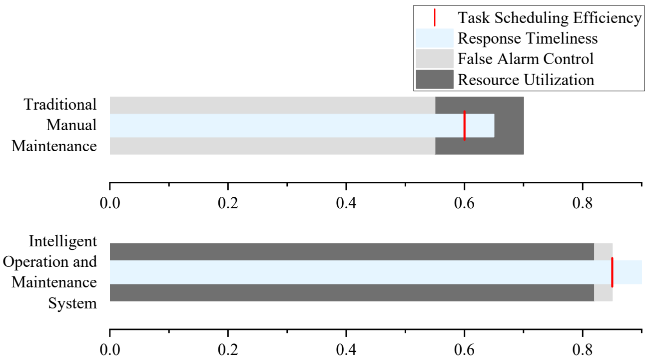
- Response timeliness score: reflecting the system's capacity to react fast to aberrant occurrences, this indicator gauges the average length of time between the onset of a fault and the beginning of an O&M activity. When it comes to radio and TV transmitters, where signal stability is quite important, quick reaction to failures is the secret to guaranteeing company continuity and service quality. Greater reaction timeliness suggests that the system can identify abnormalities faster and initiate swift maintenance responses, therefore lowering the signal interruption risk.
- Efficiency of task scheduling: from planning to execution, this indicator shows the reasonfulness and efficiency of O&M activities. Good scheduling may guarantee that limited personnel and equipment resources are fully used, prevent waste of idle resources and duplicate of work, and improve the general O&M efficiency. In the experiment, the degree of tasks performed in time as intended and the smoothness of inter-task coordination mirror scheduling efficiency. A high index helps the system scheduling method to more precisely arrange maintenance and inspection activities, hence lowering delays and conflicts.
- Resource utilisation: this indicator shows how effectively operation and maintenance resources, such as personnel and inspection tools, managers and equipment are used. In the daily running of radio and TV transmitters, sensible resource allocation not only helps to lower running costs but also enhances work quality. High resource use shows that the system can dynamically change personnel allocation and inspection frequency depending on equipment condition and fault risk, thereby minimising useless inspection and manpower waste and obtaining the best mix between economy and efficiency.

- False alarm control capability: this indicator gauges the system's control effect in the false alarm alert detecting mechanisms. Too many false alarms can cause tiredness and decrease awareness of O&M system staff; even worse, they will overlook the actual flaws, therefore compromising the general system stability. The experiment indicates the system's capacity to filter and recognise false alarms by means of a comparison between the ratio of the number of false alarms and the total number of alarms of the two operation and maintenance modes. Fewer false alarms and more accurate system filtering of the actual aberrant occurrences follow from higher indicator levels.

These four indicators taken together cover the fundamental capabilities of the intelligent O&M system which can more fully reflect the performance of the O&M system in the real-world broadcasting and TV transmitter environment.

Figure 3 displays the experimental results.

Figure 3 Results of the efficiency comparison experiments (see online version for colours)



The intelligent O&M system clearly beats the conventional manual O&M in all respects, confirming its considerable benefit in raising the accuracy and efficiency of O&M.

First, a difference of 38%, the O&M system has a score of 0.90 from the comparison of response timeliness while traditional manual O&M is just 0.65. This variation shows how effectively the O&M system may cut the time from failure to task starting. In particular, the intelligent system detects issues in time and rapidly generates maintenance instructions by means of real-time monitoring and automatic alarm systems, therefore preventing response delays resulting from slow information flow and manual mode of judgement. Consequently, the intelligent system clearly helps to lower equipment downtime and react fast to crises.

Second, with an improvement of 42%, the intelligent O&M system earns a score of 0.85, far better than the 0.60 of conventional manual O&M in terms of job scheduling efficiency. This outcome indicates that, during task allocation and execution, the intelligent O&M system can more effectively use O&M resources, hence preventing scheduling delays and task conflicts resulting from human judgement mistakes or knowledge asymmetry in the manual mode. By means of the data-driven job scheduling algorithm, the O&M system dynamically changes the work priority and inspection frequency based on the present status of the equipment and risk of failure, so enhancing the general O&M efficiency.

Regarding resource use, the intelligent system received 0.82, while traditional manual O&M received 0.70, thereby improving almost 17%. This variation shows the capacity of the O&M system to maximise the use of O&M resources, particularly in terms of personnel and equipment scheduling, therefore preventing repeated work and resource waste. Based on real-time status and equipment defect prediction, the intelligent system can dynamically allocate the use of inspection persons and tools, so optimise the use of resources and lower unnecessary inspections and over-investment.

In terms of the capacity to regulate the false alarm rate, the intelligent system received 0.85 while the conventional manual O&M received 0.55, a 30% difference. This outcome reveals that in defect identification and alarm accuracy the intelligent O&M system is better. By using deep learning and knowledge reasoning, among other technologies, the system can precisely identify possible fault risks, therefore avoiding the phenomena of false alarms resulting from inexperience or trailing information in conventional human O&M. The intelligent O&M system's false alarm rate is much lower than that of manual mode, therefore lowering the interference of false alarm alerts to the O&M staff and increasing their efficiency and attentiveness.

In important respects including reaction time, task scheduling efficiency, resource use, and false alarm management capability, the intelligent O&M system shows notable benefits over conventional manual O&M. These findings confirm the tremendous possibility of an intelligent system in enhancing the O&M efficiency of radio and TV transmitters and offer strong support for its development for useful purposes.

5 Conclusions

This work suggests and designs a form of intelligent O&M system for the intelligent O&M requirements of radio and TV transmitters. Aiming to increase the reaction speed, work scheduling efficiency, resource use, and fault identification accuracy in the O&M process, the O&M system is mostly formed of four modules and incorporates a range of modern artificial intelligence technologies. This work not only shows the inventiveness of the intelligent O&M system in theoretical design but also validates its efficacy in real-world O&M situations by means of comparison between experiment 1 and experiment 2. The O&M system offers a practical option for intelligent O&M in the broadcasting and television sectors since its performance is much enhanced over conventional manual O&M.

There are still certain issues and weaknesses even if this study has produced some findings in the design and implementation of the intelligent O&M system.

On the one hand, in challenging settings the accuracy and resilience of intelligent O&M systems could still need work. The limits of model training data that lack enough samples for some harsh operating circumstances or uncommon faults cause this issue. Conversely, the present system is still in its first stage of application in multimodal data fusion; although it has been able to process sensor data and some image data, the efficiency and accuracy of the system need to be continuously enhanced when handling more varied and high-dimensional data.

Deeply in the following lines, future study can investigate. First, the system may maximise the decision-making process in continuous trials and feedback by including RL algorithms, so improving its adaptation to the constantly changing O&M surroundings. Second, with the popularity of internet of things (IoT) devices, the major direction for the future research of intelligent O&M systems will be large-scale data processing and real-time analysis. The hybrid architecture based on edge computing and cloud computing may be able to provide more effective support for large-scale data processing.

In conclusion, the application of intelligent O&M systems in the field of radio and television transmitters still has lot of room for development; future research can conduct in-depth explorations from improving the prediction accuracy of the system, optimising the multimodal data fusion, introducing RL optimised decision making, etc., to progressively promote the popularity and practice of intelligent O&M.

Declarations

The author declares that he has no conflicts of interest.

References

Alsafery, W., Rana, O. and Perera, C. (2023) 'Sensing within smart buildings: a survey', *ACM Computing Surveys*, Vol. 55, No. 13s, pp.1–35.

Aragón-Zavala, A., Angueira, P., Montalban, J. and Vargas-Rosales, C. (2021) 'Radio propagation in terrestrial broadcasting television systems: a comprehensive survey', *IEEE Access*, Vol. 9, pp.34789–34817.

Attar, H. (2023) 'Joint IoT/ML platforms for smart societies and environments: a review on multimodal information-based learning for safety and security', *ACM Journal of Data and Information Quality*, Vol. 15, No. 3, pp.1–26.

Badihi, H., Zhang, Y., Jiang, B., Pillay, P. and Rakheja, S. (2022) 'A comprehensive review on signal-based and model-based condition monitoring of wind turbines: fault diagnosis and lifetime prognosis', *Proceedings of the IEEE*, Vol. 110, No. 6, pp.754–806.

Chen, S., Yang, R., Zhong, M., Xi, X. and Liu, C. (2023) 'A random forest and model-based hybrid method of fault diagnosis for satellite attitude control systems', *IEEE Transactions on Instrumentation and Measurement*, Vol. 72, pp.1–13.

Cui, Z., Yang, X., Yue, J., Liu, X., Tao, W., Xia, Q. and Wu, C. (2023) 'A review of digital twin technology for electromechanical products: evolution focus throughout key lifecycle phases', *Journal of Manufacturing Systems*, Vol. 70, pp.264–287.

Goes, F., Kempe, M., Van Norel, J. and Lemmink, K. (2021) 'Modelling team performance in soccer using tactical features derived from position tracking data', *IMA Journal of Management Mathematics*, Vol. 32, No. 4, pp.519–533.

Golan, M.S., Jernegan, L.H. and Linkov, I. (2020) 'Trends and applications of resilience analytics in supply chain modeling: systematic literature review in the context of the COVID-19 pandemic', *Environment Systems and Decisions*, Vol. 40, No. 2, pp.222–243.

He, Y., Guo, J. and Zheng, X. (2018) 'From surveillance to digital twin: challenges and recent advances of signal processing for industrial internet of things', *IEEE Signal Processing Magazine*, Vol. 35, No. 5, pp.120–129.

Ikram, M. and Sayagh, Y. (2023) 'The consequences of COVID-19 disruption on sustainable economy in the top 30 high-tech innovative countries', *Global Journal of Flexible Systems Management*, Vol. 24, No. 2, pp.247–269.

Kleban, Y. and Stasiuk, T. (2022) 'Crypto currency price forecast: neural network perspectives', *Visnyk Nacional'noho Banku Ukraïny*, No. 254, pp.29–42.

Landwehr, J.P., Kühl, N., Walk, J. and Gnädig, M. (2022) 'Design knowledge for deep-learning-enabled image-based decision support systems: evidence from power line maintenance decision-making', *Business & Information Systems Engineering*, Vol. 64, No. 6, pp.707–728.

Li, Y., Tao, X., Zhang, X., Wang, M. and Wang, S. (2022) 'Break the data barriers while keeping privacy: a graph differential privacy method', *IEEE Internet of Things Journal*, Vol. 10, No. 5, pp.3840–3850.

Mao, Y., Wang, S., Yu, D. and Zhao, J. (2021) 'Automatic image detection of multi-type surface defects on wind turbine blades based on cascade deep learning network', *Intelligent Data Analysis*, Vol. 25, No. 2, pp.463–482.

Matson-Koffman, D.M., Robinson, S.J., Jakhmola, P., Fochtmann, L.J., Willett, D., Lubin, I.M., Burton, M.M., Tailor, A., Pitts, D.L. and Casey Jr., D.E. (2023) 'An integrated process for co-developing and implementing written and computable clinical practice guidelines', *American Journal of Medical Quality*, Vol. 38, No. 5S, pp.S12–S34.

Qin, C., Chen, L., Cai, Z., Liu, M. and Jin, L. (2023) 'Long short-term memory with activation on gradient', *Neural Networks*, Vol. 164, pp.135–145.

Raptis, T.P., Passarella, A. and Conti, M. (2019) 'Data management in industry 4.0: state of the art and open challenges', *IEEE Access*, Vol. 7, pp.97052–97093.

Shittu, E., Parker, G. and Mock, N. (2018) 'Improving communication resilience for effective disaster relief operations', *Environment Systems and Decisions*, Vol. 38, pp.379–397.

Sugito, Y., Vazquez-Corral, J., Canham, T. and Bertalmío, M. (2022) 'Image quality evaluation in professional HDR/WCG production questions the need for HDR metrics', *IEEE Transactions on Image Processing*, Vol. 31, pp.5163–5177.

Yan, P., Abdulkadir, A., Luley, P-P., Rosenthal, M., Schatte, G.A., Grewe, B.F. and Stadelmann, T. (2024) 'A comprehensive survey of deep transfer learning for anomaly detection in industrial time series: methods, applications, and directions', *IEEE Access*, Vol. 12, pp.3768–3789.

Zhang, C., Dong, L. and Wang, Y. (2023) 'Research on Intelligent operation and maintenance (O&M) method of complex products based on digital twin', *Journal of Computers*, Vol. 34, No. 5, pp.29–43.

Zhang, K. and Chui, T.F.M. (2018) 'A comprehensive review of spatial allocation of LID-BMP-GI practices: strategies and optimization tools', *Science of the Total Environment*, Vol. 621, pp.915–929.

Zhao, X., Jia, Y., Li, A., Jiang, R. and Song, Y. (2020) 'Multi-source knowledge fusion: a survey', *World Wide Web*, Vol. 23, pp.2567–2592.