This article has been accepted for publication in a future proceedings of this conference, but has not been fully edited. Content may change prior to final publication.
Citation information: DOI: 10.1109/ISAP63260.2024.10744407, 2024 22nd International Conference on Intelligent Systems Applications to Power Systems (ISAP)

Deep Learning-based Fire Alarmer for Underground Power Cable Tunnel with Multiple Information Sources

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***Abstract*—Regarding the issue of risk management and control of tunnel cable fires, a cable fire management and control scheme based on Gene Expression Programming (GEP) has been proposed. This scheme comprises three stages: firstly, a cable skin temperature rise model based on load variations has been established; secondly, a cable fire monitoring model based on YOLOv5 has been trained; and finally, a cable fire management and control scheme that integrates GEP has been proposed. Through the fusion analysis of data from the first two stages, the dynamic adjustment of the weight output of different parts is achieved to achieve automatic recognition of optimal states. Through experiments and analysis, the temperature variation patterns of cables under various loads and environmental conditions have been demonstrated, as well as the recognition performance of the fire monitoring model based on YOLOv5, and a dynamic planning scheme for the GEP model has been provided.**

Keywords—cable fire, GEP, temperature model, fire monitoring

I. INTRODUCTION

With the continuous iteration and updating of technology, the evolving landscape of the power system has led to a broader utilization of power cable tunnels, elevating its significance. Typically, power cable tunnels accommodate an array of pipelines, including power and communication lines, with a primary focus on power cable lines supplemented by communication and control cables. Various factors can trigger smoldering or open fires in the cable [1], which, if left unchecked, can disrupt the operation of neighboring cable lines, thereby impeding the regular electricity supply in the vicinity and resulting in substantial economic repercussions. Regardless of the root cause of the cable tunnel fire, it is imperative to recognize the cable's inherent traits of rapid propagation, intense flames, challenging extinguishment, intricate restoration, and severe post-fire consequences [2]. The swift fire spread also induces a sharp rise in the temperature of the conduit, generating copious smoke and toxic fumes that pose a serious threat to individuals near the cable tunnel pathway. Firefighters are required to extinguish the cable tunnel fire, adding complexity to the rescue operation.

The aforementioned factors have spurred advancements in fire warning protocols for power cable systems within the industry. The adoption of sophisticated fire warning systems and strategic positioning have bolstered the industry's capacity to respond to cable tunnel fires, thereby enhancing the safeguarding of the power system's operational integrity [3]. A tunnel fire alarm system must exhibit reliability, sophistication, high sensitivity, and an extremely low false alarm rate, enabling the automatic detection and notification of tunnel space fires seamlessly and without interruption. Sun et al. [4] proposed an auto-enhanced multi-trend BPNN algorithm, which constructs a strong multi-neural network and incorporates one special trend extraction part, to enhance the perception of temperature variation trend during fire initial stage. Bian et al. [5] proposed an approach that utilized a fiber-optic distributed temperature sensing (FO-DTS) system and deep anomaly detection models to monitor the fire exotherm during the early stages of accidents. Li et al. [6] trained a CNN-based neural network model using pictures with fire/smoke and without fire. Experiments showed that the model exhibited a relatively high recognition rate on the self-made dataset. GEP is a powerful intelligent algorithm with mature applications in many scenarios. Huang et al. [7] presented a real-time quality monitoring of the detection and prediction of a defect in fluid dispensing systems. GEP is employed to learn patterns within systems, aiming to express the causal relationships between machine and production state with defect types. Khan et al. [8] utilized GEP to capture the interrelation among Hadoop configuration parameters, thereby automatically adjusting the configurations to enhance Hadoop performance.

Evolutionary on the existing infrastructure construction work of power system brings significant amount of the BIG data being processed [9]. GEP, as an efficient and flexible method for processing big data, has received widespread attention from researchers. Khan et al. [10] presented an Enhanced Parallel Detrended Fluctuation Analysis (EPDFA) algorithm based on enhanced Hadoop platform, to address the big data challenges posed by the rapid deployment of Phasor Measurement Units (PMUs) in power systems globally. GEP is utilized to optimize configuration parameters. The experiment shows that the algorithm optimized by parameters has a significant speed advantage. Kaboli et al. [11] employed optimized GEP to formulate the relationships between historical data and electricity consumption. Sadat et al. [12] utilized GEP to improve the accuracy and robustness of load forecasting in power systems. Malik et al. [13] proposed a new approach for Dissolved gas analysis interpretation using GEP

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for more accurate diagnosis of incipient faults in oil-filled power transformers. Experiments have shown that the method has more advantages than other artificial intelligence methods To enhance the precision of cable fire prediction, this study proposes an adaptive cable fire detection strategy based on GEP. The execution of this strategy unfolds in three key stages: Firstly, meticulous monitoring of the cable's temperature evolution during the initial phase of low temperatures, entails establishing a real-time temperature model to track the cable's temperature and determine the likelihood of a cable fire occurrence during this phase; Secondly, as the cable's temperature approaches a specific threshold below the combustion critical point, the cable transitions into a state of imminent fire, where fire or smoke can be promptly identified through computer vision techniques; Finally, integrating the outcomes of the first two stages using GEP enables dynamic adjustments, culminating in a more comprehensive and precise predictive outcome.

II. CABLE FIRE CONTROL SOLUTION BASED ON GEP

In order to predict the probability of cable fire more accurately, the change of cable state needs to be comprehensively considered. The adaptive solution based on GEP can intelligently provide flexible prediction results according to the change of cable state. The scheme can have automatic learning ability, can automatically learn the data in the target scene, adaptively fit the scene transformation, automatically generate decisions and determine the influence of multiple data distribution. The schematic diagram of the solution is shown in Fig 1.

The implementation steps of the scheme are as follows:

Step 1: The temperature model for the conduction of heat from the conductor to the cable's outer surface is established. By deriving the correlation between the current and the conductor's temperature, the conductor temperature is determined, subsequently calculating the cable's surface temperature through the cable's heat conduction model. A segment of the GEP gene, denoted as G1, is allocated to oversee the real-time monitoring of wire temperature as part of the online operational and maintenance solution.

Step 2: A computer vision monitoring model is developed. As the cable temperature approaches a specific threshold near the critical point for cable burning, the cable is deemed to be in a critical state where a fire may occur. As the temperature continues to rise, the computer vision monitoring model incrementally enhances the significance of fire detection until a fire event is conclusively identified. Upon fire detection, the monitoring model provides real-time updates on the fire's size. This stage incorporates a portion of the gene segment G2 to oversee the real-time monitoring of the computer vision component within the maintenance and operational solution.

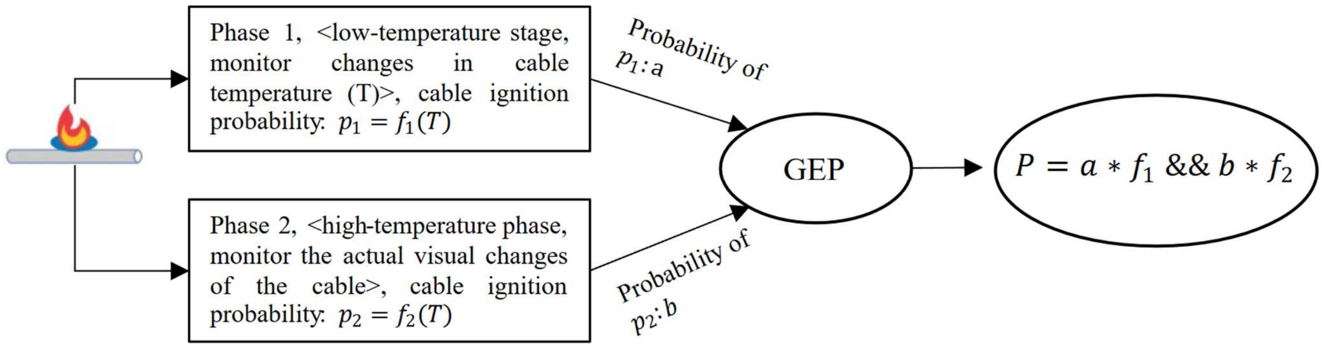

Fig. 1. Solution diagram.

Step 3: A dynamic model for fire determination is constructed utilizing GEP. By conducting a dynamic and comprehensive analysis of the target gene segments G1 and G2, the optimal state of the counterweight is automatically determined. This process enables the accurate distribution of fire judgment across the information sources, facilitating adaptive analysis in various environmental conditions. The integration of GEP allows for the efficient adaptation and optimization of fire determination processes, enhancing the predictive capabilities in diverse scenarios.

A. *Cable Skin Temperature Rise Model Based on Load Variation*

Cables are typically composed of conductors, insulation layers, metal sheathing, and skin. Under normal conditions, the only thing that may cause combustion in cables is the skin, making the temperature state of the cable skin a critical focus. Utilizing the heat transfer properties from the conductor to the cable surface, a one-dimensional heat transfer model is established along the radial direction of the cable cross-section. This model incorporates components such as thermal resistance, heat capacity, heat sources, and other components that represent the material characteristics of each cable layer. The conductor temperature exhibits a positive correlation with the square of the conductor load. Similar to circuit principles, the conductor temperature can be computed once the current load and environmental temperature are determined. Subsequently, the temperatures of each node (i.e., each material layer) can be directly calculated using relevant circuit theory and heat transfer principles. The accuracy of this method hinges on the alignment between the parameter values in the model and the actual cable structure parameters. With highly precise parameter values, this model can effectively calculate the cable skin temperature, ensuring its reliable application across various laying environments.

The model draws upon the guidelines outlined in the IEC-60287 and IEC-60853 international standards, which govern the calculation of the current carrying capacity of power cables. These standards provide the foundation for establishing the relationship between current flow and cable temperature. Specifically, IEC-60287 offers the calculation formula for determining the temperature of a single-core cable under steady-state conditions:

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$$T_c = T_e + (I^2R + 0.5W_d)R_1 + [(1+\lambda_1)I^2R + W_d]R_2 + [(1+\lambda_1+\lambda_2)I^2R + W_d]R_3 + [(1+\lambda_1+\lambda_2)I^2R + W_d]R_4 \quad (1)$$

Where, I is the current flowing through the conductor, (A); T_c is the operating temperature of the conductor, (K); T_e indicates the ambient temperature at which the cable is laid, (K); R is the AC resistance per unit length of the conductor at the highest operating temperature, (Ω/m); W_d is the dielectric loss per unit length of conductor insulation, (W/m); R_1 is the unit length thermal resistance between the conductor and the metal sleeve, (K · m/W); R_2 is the unit length thermal resistance of the lining layer between the metal sleeve and the armor, (K · m/W); R_3 is the thermal resistance per unit length of the cable sheath, (K · m/W); R_4 is the unit length thermal resistance between the cable surface and the surrounding medium, (K · m/W); λ_1 is the ratio of cable metal sheath loss to conductor loss; λ_2 is the ratio of cable armor loss to conductor loss. The specific calculation methods of the above parameters R, W_d, R_1, R_2, R_3, λ_1, λ_2 are shown in the references [14][15].

IEC-60853 gives the formula for calculating the temperature of single core cable under the transient state:

$$\theta_c(t) = W_c[T_a(1-e^{-at}) + T_b(1-e^{-bt})] \quad (2)$$

Where, $\theta_c(t)$ is the temperature rise of the conductor temperature higher than the skin temperature; W_c is the power loss per unit length in the conductor based on the maximum conductor temperature, assuming that the power loss during the transient is a constant. T_a, T_b, a, b are calculated from the thermal resistance T_A and heat capacity Q_A of the inner layer of the conductor and dielectric, and the thermal resistance T_B and heat capacity Q_B of the remaining parts of the conductor and dielectric [16].

By combining the steady state calculation formula and the transient calculation formula of the cable, and considering the relationship between W_c and current, the calculation model of the cable skin temperature is obtained:

$$T_s(I) = T_e + (I^2R + 0.5W_d)R_1 + [(1+\lambda_1)I^2R + W_d]R_2 + [(1+\lambda_1+\lambda_2)I^2R + W_d]R_3 + [(1+\lambda_1+\lambda_2)I^2R + W_d]R_4 - \lim_{t\to\infty} nI^2R[T_a(1-e^{-at}) + T_b(1-e^{-bt})] \quad (3)$$

The meaning of this model is that the temperature of the skin when the current cable reaches the steady state, that is, the maximum temperature that the cable skin can reach under the current load.

B. Cable Fire Monitoring Model based on YOLOv5

For a long time, many researchers have tried to use image processing technology for fire identification. In recent years, thanks to the improvement of computer performance, deep learning has developed rapidly and attracted wide attention. Compared with traditional fire detection schemes, deep learning methods are faster, more accurate, and free from environmental restrictions. Common deep learning network models mainly include You Only Look Once (YOLO) model , Single-Shot multibox Detector (SSD) model, and Faster Region-based Convolutional Neural Network (Faster R-CNN) model. Compared with SSD and R-CNN, the YOLO model has lower complexity and can achieve higher detection accuracy while maintaining high speed, which is very suitable for fire detection, such as target detection scenarios with high real-time requirements. In this paper, YOLOv5 is adopted as the basis of rapid image feature information recognition technology to expand the real-time detection of smoke and open flame in the target area, and the dataset is a self-built cable burning video dataset. The program is implemented as follows.

First of all, data collection is carried out, and the dataset of cable combustion is obtained through video recording of the cable combustion experiment. The settings of the combustion experiment are as follows:

The heating coil is used as a heating source to heat the cable and promote the burning of the cable. The heating coil power is divided into several grades to make the cable produce different combustion effects of small smoke, large smoke, small flame, and large flame. Three monitoring stations are set for the combustion experiment of the cable to monitor the different combustion conditions of the cable from multiple angles and multiple position distances. The images of different camera positions are shown in Fig 2.

Fig. 2. Dataset Example.

The collected videos are labeled frame-by-frame using labelme, which is a data labeling software. The smoke is divided into large and small grades according to the size of the smoke, and then the flame is labeled based on the size of the flame. Once the labeling process is completed, the labeled dataset is obtained. The dataset is then cleaned to remove the files that are not marked, ensuring data accuracy. Subsequently, the cleaned dataset is divided into the training set and the verification set, with a partition ratio of 8:2.

The object detection algorithm based on YOLOv5 deep learning includes four versions: YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, with YOLOv5s being the lightest in terms of weight. Due to considerations of weight file size, recognition accuracy, and detection speed of the model, YOLOv5s, with the fastest detection speed and relatively high recognition accuracy, was selected for the research. The YOLOv5s network comprises four parts, which include input, backbone, feature detection module layer (neck), and prediction. The network structure is depicted in Fig 3.

yolov5s was used to train the data set to obtain the model, and then the multi-channel camera video stream reading mode was used to encapsulate the interface of the yolov5 model with the help of inference files, so that it could provide model inference capability. After configuring the parameter information, the target detection inference effect on the video stream address could be realized by running the code. Then the packaged model is processed in front and back end, and the image inference result of video stream can be obtained. The overall scheme is shown in Fig 4.

C. Cable Fire Control Solution Integrated with GEP

The final cable fire probability is analyzed using GEP, which comprehensively combines the cable skin temperature rise model based on load changes and the cable fire monitoring model based on YOLOv5. This integration allows

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for a more comprehensive and accurate prediction result. The approximate functional relationship is expressed as: $P = a * p_1$ && $b * p_2$ (for weights a and b; weight a should be larger when the temperature is low, and weight b should be larger when the temperature is higher). The specific determination of weight a and weight b allows for dynamic adjustment of the ratio of a and b using GEP to obtain the most accurate prediction method. The '&&' symbol signifies the link equations that GEP utilizes to connect different stages in the target system learning analysis.

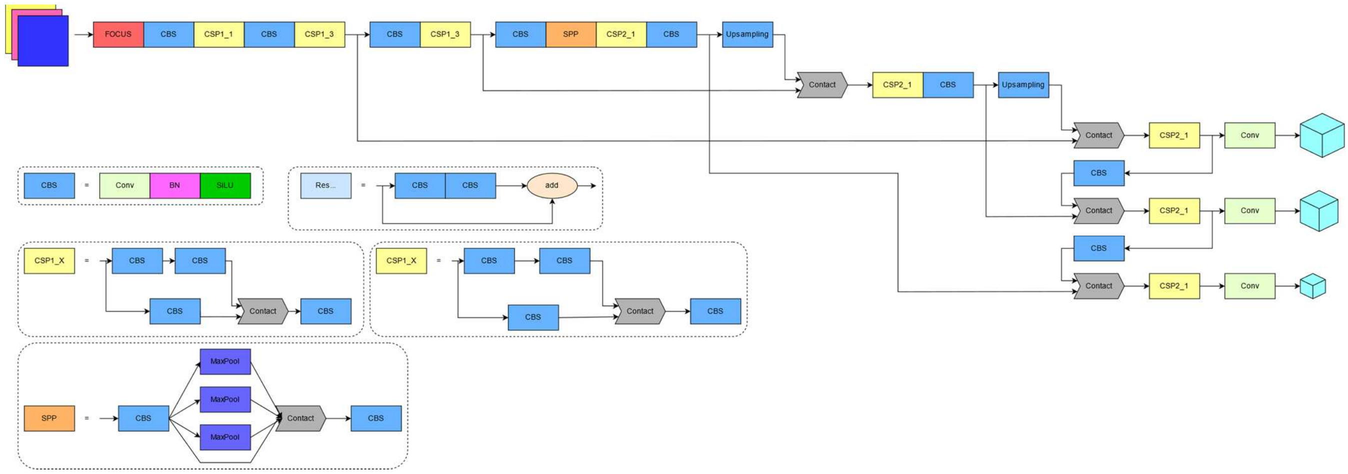

Fig. 3. YOLOv5 Network Architecture Diagram.

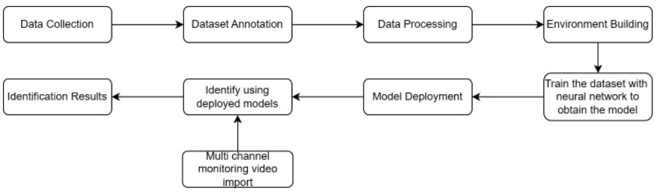

Fig. 4. Monitoring model training scheme.

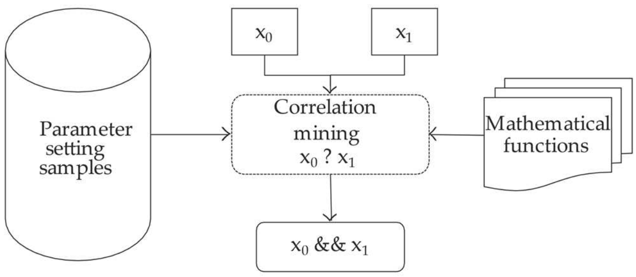

Fig. 5. Introduction to fitting patterns.

Fig 5 illustrates the GEP mining process for establishing the relationship between two crucial parameters, x_0 and x_1, within the target complex system. By delving into the intermediate connections between x_0 and x_1, the '&&' operator is ultimately unearthed to reveal the specific relationship between the two parameters. This methodology is also applied to analyze the counterweight and link relationships of G1 and G2 within this scheme.

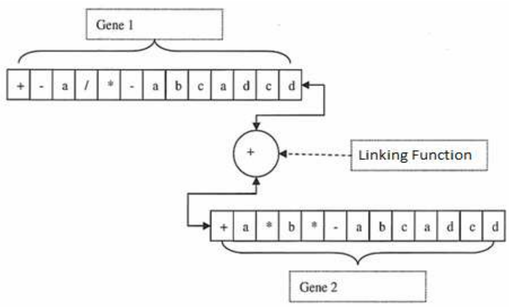

Fig. 6. Introduction to GEP link mode.

Within this solution, in Fig 6, Gene1 in the GEP framework is tasked with the real-time management of the operation and maintenance of the target cable temperature, while Gene2 handles the organization and maintenance of the image detection component of the solution. The Linking Function plays a crucial role in establishing whether the functioning of each small gene collectively determines the low, medium, or high temperature of the target system.

III. Experiments and Analysis

There are significant variations in the melting temperature of cable skin based on different periods of service time. The quality of the cable skin polymer crystal structure directly impacts the melting temperature, with higher perfection leading to a higher melting temperature and vice versa [17]. Typically, a non-service cable with good production quality has a melting temperature of 110°C. As the cable ages, its heat resistance gradually diminishes. In unaged cables, some imperfect crystals begin to melt at approximately 100°C, and at 160°C, the entire cable transitions into a molten state. Given the ability of crosslinked polyethylene to sustain long-term operation at around 90°C, the threshold for the cable's susceptibility to burning is set at 100°C.

The parameter calculation for the load-based cable skin temperature model can be found in reference [14][16], and the specific physical parameters in the calculation formula can be referred to in the IEC 60228 standard. By incorporating all relevant parameters into the calculation formula, the cable skin temperature model with respect to current can be derived. This model allows for the establishment of the relationship between cable skin temperature and current, as illustrated in Fig 7.

In Fig 7, the curves labeled 0°C, 10°C etc. depict the variations in cable temperature with current under different ambient laying temperatures, covering the majority of temperature conditions in underground cable tunnels. By utilizing this model, it is possible to determine the maximum temperature that the cable can attain under a specified load. This information enables proactive monitoring of potential risks associated with elevated temperatures, allowing for early

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identification of issues and facilitating better preparation and decision-making to address or mitigate these risks effectively.

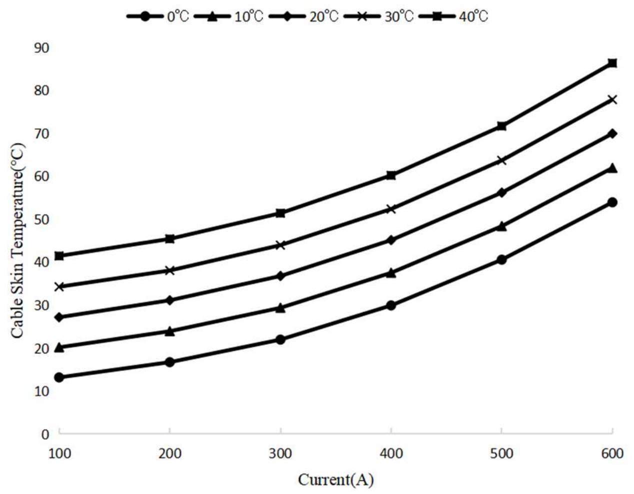

Fig. 7. Temperature vs. current variation graph.

The cable fire monitoring model, based on YOLOv5, has undergone testing and verification. Three camera positions were individually trained to develop corresponding models. Subsequently, each model was employed to assess videos captured from the three camera positions. The average confidence level of each model in detecting flames in the videos from different camera positions was determined and is presented in Table I.

TABLE I. YOLOV5 MODEL RECOGNITION RESULTS

	video1	video2	video3
camera1	0.716	0.768	0.547
camera2	0.662	0.858	0.5375
camera3	0.553	0.573	0.836

From a modeling perspective, it is observed that the recognition performance of the models varies for different camera positions. Model 2 demonstrates the best overall performance, while models 1 and 3 exhibit slightly inferior results. Typically, a model trained on a specific position performs best when recognizing videos from the corresponding position. However, the experimental findings reveal that a model from one position may not always yield the optimal performance when analyzing videos from that same position. For instance, the model trained on position 1 may exhibit better recognition capability for videos from position 2 compared to those from position 1. This outcome could be attributed to factors such as the distance between positions; with position 2 being closer than position 1, and the similarity in the angles of the two positions, which may enhance recognition accuracy. In addition, notably, the recognition performance is highest when applying a model to videos captured from the same camera position.

The experiment shows that variations in monitoring positions, characterized by differing distances and angles, can lead to disparate recognition outcomes. Consequently, assigning greater output weights to the model exhibiting the most favorable recognition performance when recognizing from various monitoring positions can enhance overall recognition accuracy.

In prior research, we have confirmed the exceptional efficacy of GEP in uncovering and exploring pattern relationships between interconnected data components [7][10]. In this study, we will continue to leverage GEP's remarkable data mining prowess to further enhance our understanding of complex data relationships. The cable fire control scheme integrated with GEP combines the cable skin temperature rise model based on load change and the cable fire monitoring model based on YOLOv5. This integration results in a dynamic model for fire judgment that automatically identifies the optimal weight state and enables adaptive analysis in diverse environments. To implement this scheme, the GEP integrates data from the cable skin temperature rise model and the computer vision monitoring system, incorporating information such as wire temperature data and outputs from the monitoring system (e.g., temperature threshold triggering, fire occurrence). The data from the two models are assigned to separate gene segments within the GEP framework. Function nodes within the GEP are defined, and parameters such as gene number, gene length, and link function are set based on the complexity of the problem. The GEP model is then trained through evolutionary iterations to develop dynamic programming capabilities.

After training, the GEP model is evaluated, further optimized, and deployed to the monitoring system. The model processes new data inputs, assesses fire risk, and provides decision support. Additionally, the model continuously adapts and optimizes based on real-time feedback to accommodate environmental changes or new data patterns.

Through this approach, the GEP model comprehensively considers multiple factors, enabling dynamic prediction of cable fire probability and adaptive adjustment of response strategies. This enhances the efficiency and accuracy of fire prevention and response efforts, ultimately improving overall safety in cable fire monitoring and control.

IV. CONCLUSIONS

In this study, a cable fire control solution based on GEP is proposed, which is structured into three key stages. Firstly, the cable skin temperature rise model is established, leveraging load variation data to determine the maximum temperature that the cable skin can reach under the existing load conditions. This model provides crucial insights into how cable temperature fluctuates under different load scenarios and environmental conditions. Secondly, a cable fire monitoring model is developed using computer vision techniques. This model is trained to recognize fire incidents based on visual cues and patterns, enhancing the ability to detect potential fire risks in real-time. Lastly, the cable fire control scheme based on GEP is introduced. By integrating the cable skin temperature rise model and the YOLOv5-based fire monitoring model with GEP, a dynamic programming approach is formulated. This GEP model is designed to dynamically predict cable fire probability and adjust adaptive response strategies based on evolving conditions and data patterns.

Through a series of experiments and analyses, the study demonstrates the temperature variation patterns of cables under different load and environmental conditions, evaluates the effectiveness of the fire monitoring model based on YOLOv5, and presents the dynamic programming scheme of the GEP model. We believe that the integration of the GEP model has the potential to significantly enhance the dynamic prediction of cable fire probability and enable adaptive response strategies, ultimately improving the efficiency and

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accuracy of fire prevention and response efforts in cable fire control scenarios.

In future work, we plan to further optimize the cable skin temperature rise model based on load changes and the fire monitoring model using computer vision to enhance prediction accuracy and identification effectiveness. By integrating more intelligent algorithms and technologies, we aim to elevate the intelligence level of the fire control system, improving its ability to detect and respond to fire incidents efficiently. Additionally, we will consider incorporating additional environmental factors and data sources to develop a more comprehensive fire control scheme capable of addressing fire risks in diverse scenarios. Through continuous research and innovation, we wish to advance cable fire control technology, enhance cable safety and reliability, and provide enhanced protection for individuals' lives and work environments.

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