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Artificial Intelligence for Driverless Travel Cranes for Power Supply Warehouses Technology

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Abstract. *Aiming at the problems of poor sensitivity of obstacle avoidance and weak fault diag-nosis in the operation of unmanned traveling cranes in power material warehouse in the existing technology, a new control scheme for unmanned traveling cranes in power material warehouses is designed, which fully applies the technical characteristics of artificial intelli- gence and con-structs a new artificial intelligence control system, which can realize intelli- gent and automatic monitoring of the operation status of unmanned traveling cranes. The tests show that the method of this study has high location accuracy and strong fault diagnosis capability.*

Keywords: Power material warehouse; driverless traveling crane; traveling crane operating state; traveling wave localisation algorithm model; long and short time memory neural network model.

1. **Introduction.** The power material warehouse plays a vital role in the overall management of re-sources, and with the gradual increase in information on power materials, the man-agement requirements for safety norms and risk avoidance at the warehouse site are beco- ming more and more stringent, which needs to further improve the on-site supervision abi-lity of power material warehouse. In the process of supervising the power material wareho-use, the unmanned traveling crane has a pivotal position. In the management of the power material warehouse, further research is needed on how to accurately capture the dynamic c-haracteristics of the unmanned crane, how to intelligently analyze the information on the m-anagement of electric power materials, how to alarm the fault information in the running p- rocess of the traveling crane, and how to avoid obstacles. Most of the existing technologies use manual monitoring, which is unable to monitor

accurately in a complex weather environ-ment around the clock, track the target trajectory lagging behind, and has poor on-site man-agement capability for power material warehouses.

An optimized radial basis function (RBF) neural network was used to control the running state of the unmanned vehicle. The technology used the RBF neural network to fit the switching control quantity of sliding mode variable structure online, and the improved particle swarm optimization algorithm was used to optimize the calculation of the neural network, which was able to implement the neural network architecture for the transition of the sliding mode surface and improve the control of driverless cars. Although this technology also applies artificial intelligence, it can't locate the fault location. It is difficult to handle and control emergencies [1]. The artificial intelligence method of BP neural network model is used to realize the fault diagnosis of manufacturing system. This technology builds a three-layer fault diagnosis model, including input layer, implicit layer and output layer,which makes full use of the artificial neural network architecture system, carries on the information processing of the different data characteristics collected at the input end in the middle layer, and finally carries on the further processing and calculation through the output layer, which can realize the fast and accurate fault diagnosis and recognition, and also can diagnose the operating state of the unmanned crane [2].

Based on the shortcomings of the above technology, through the artificial intelligence technology of driverless traveling crane control scheme and artificial intelligence technology calculation method technology research, construct the intelligent equipment management system of electric power material warehouse, this system construction better serve the development of the State Grid Power Company and power grid construction. In order to ensure the security of business data and the seamless connection of data trans-mission, the construction of this system is based on the deployment of the local area net-work of electric power warehouse. The application of unmanned traveling crane technol-ogy in the warehouse improves the safety of electric power warehouse operators, en-hances the working efficiency of electric power warehouse materials, and strengthens the accurate research and judgment of the running trajectory and running status of unmanned traveling crane. Through the artificial intelligence of the electric power supplies warehouse driverless traveling crane tech-nology application, breakthroughs in the management mode breakthroughs and in-novations from manual monitoring to automated monitoring of intelligent equipment in electric power warehouses.

2. **Driverless traveling crane control scheme based on artificial intelligence technology.** Based on the shortcomings of the above technology, the innovations of this study are as follows:

(1) An unmanned traveling crane control scheme based on artificial intelligence technology is constructed, which includes an intelligent device layer, a traveling crane information receiving unit, a traveling crane in-formation classification module and a traveling crane control execution module [3], which realizes intelligent and automatic control and monitoring of traveling crane operation.

(2) The application of a large number of artificial intelligence devices and artificial intelligence calculation methods to achieve the acquisition and calculation of data information of unmanned travelling cranes, converting macroscopic data information of the operating status of unmanned travelling cranes into microscopic mathematical thinking, and improving the monitoring of unmanned travelling cranes. Based on the above design ideas, this study designs an unmanned travelling crane control scheme as shown in Figure 1.

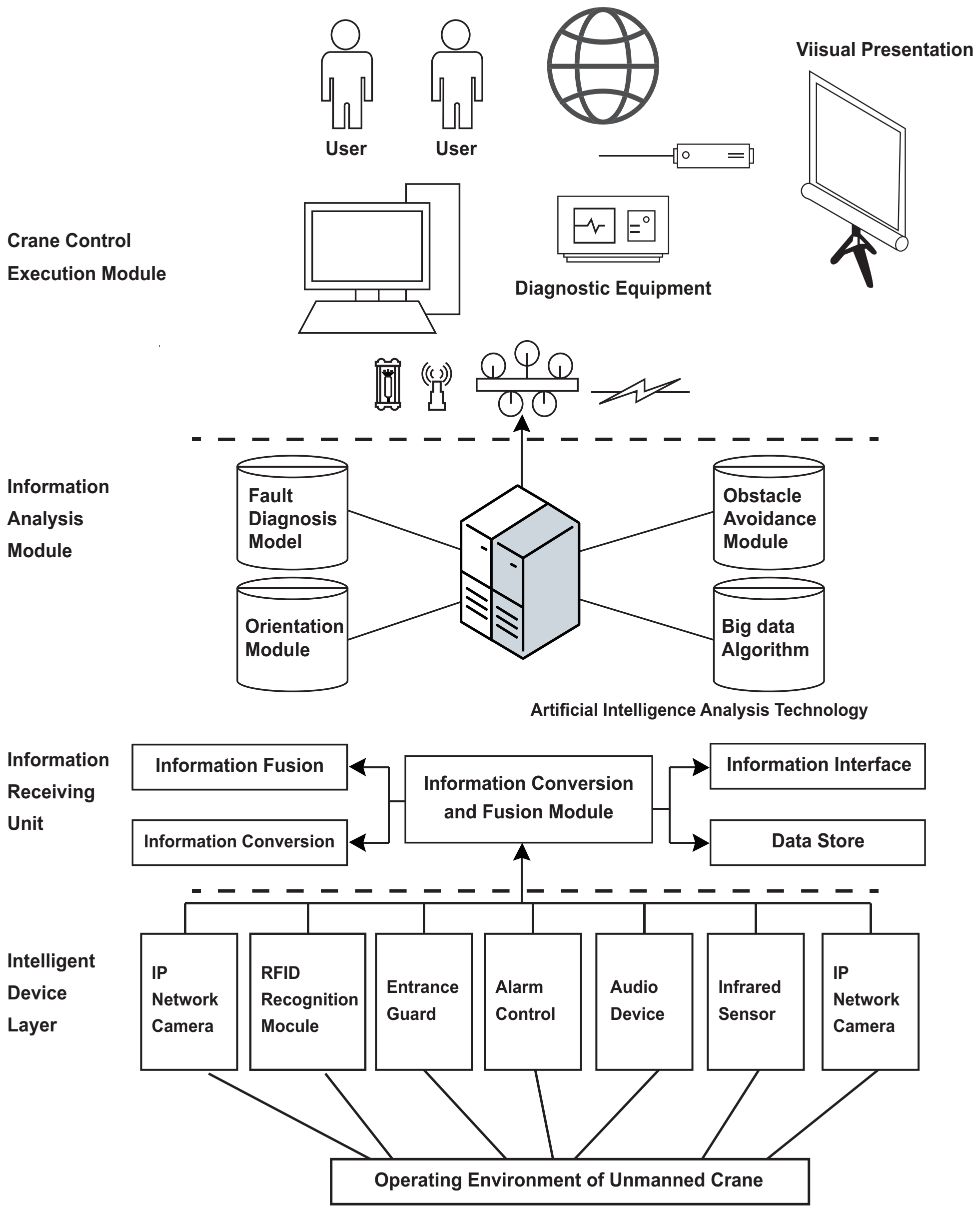

Figure 1. Schematic diagram of the driverless traveling crane control scheme

In the control scheme design of Figure 1, a large number of artificial intelligence devices are set up in the intelligent device layer, such as IP network cameras, RFID identification modules, access control devices, alarm control units, audio devices, infrared sensors [4, 5] and so on. These devices are capable of collecting all kinds of data and in-formation from the operating environment of the unmanned travelling crane. As the traveling crane device usually runs automatically in the three-dimensional direction, it is possible to achieve flexible gripping of different components, and it is also possible to set up PLC + inverter for traveling crane control, which is able to memorize driv-ing,automatic obstacle avoidance, automatic parking, etc. in a specific area [6]. The ac-quired data information is fused with various information on the running status of the traveling crane through the information conversion and fusion module, which converts different macro data information into micro data for analysis [7] and then artificial intel-ligence analysis technology is used to realize the analysis and calculation of different operating states [8]. The intelligent terminal is deployed based on the warehouse local area network, which is guaranteed in the aspects of data transmission stability, timeliness, security, and so on. In the control scheme design in Figure 1, there is a diagnostic equipment module. When the equipment has a fault, the warehouse personnel can find it at the first time, and the possibility that the intelligent terminal cannot obtain data can hardly be considered [9, 10]. This study uses Hadoop (It is a distributed system infrastructure) model to mine the data and constructs a traveling wave localisation method to realize the positioning of the traveling position or fault position of the traveling crane. At the same time, a long and short term memory neural network model is used to achieve fault diagnosis of unmanned travelling cranes, which improves the operation and maintenance research of unmanned travelling cranes [24]. And the images are displayed by means of visualization technology [9, 10]. The user can then control the crane's movements based on the data obtained by the artificial intelli-gence analysis technology, improving the crane's control capability.

For the control scheme design in Figure 1, the intelligent terminal is briefly described, including IP network camera, RFID identification module, access control device, alarm control unit, audio device, infrared sensor, etc. IP network camera: refers to the deployment of cameras based on the local area network of the power warehouse; RFID identification module: refers to the scanning electronic label module based on communication technology; Access control device: refers to the equipment that controls the warehouse exit door; Alarm control unit; It means that as the control center of the automatic fire alarm system, the fire alarm controller has fire alarm function, fire alarm control function, fault alarm function, shielding function, supervision function, self-inspection function, information display and query function, power supply function, etc; Infrared sensor: refers to a technology for collecting data.

For the control scheme design in Figure 1, the information analysis layer, information receiving unit layer and intelligent device layer are briefly described. Intelligent equipment layer: manage intelligent terminals and collect various data information of driverless crane operation; Information receiving unit layer: stores, converts, fuses and processes the data collected by the intelligent terminal; Information analysis layer: analyze the data collected by the terminal, fault analysis, etc; Hanging control module: It is mainly used to process data and intelligently control the operation of the hanging according to the information analysis layer, information receiving unit layer and intelligent equipment layer.

3. **Artificial intelligence technology calculation methods.** The innovation of this study is to use the traveling wave localisation method to locate the traveling position or fault location of the traveling crane, and to use the long and short term memory neural network architecture [11, 12] to implement fault diagnosis of the un-manned traveling crane and to achieve the operating status of the unmanned traveling crane as well as fault diagnosis [13]. The architecture of the algorithm is schematically shown in Figure 2.

3.1. **Traveling wave localisation method.** n order to determine the position of the traveling crane instantly, this study uses the traveling wave localisation method [14], the traveling wave schematic is shown in Figure 3.

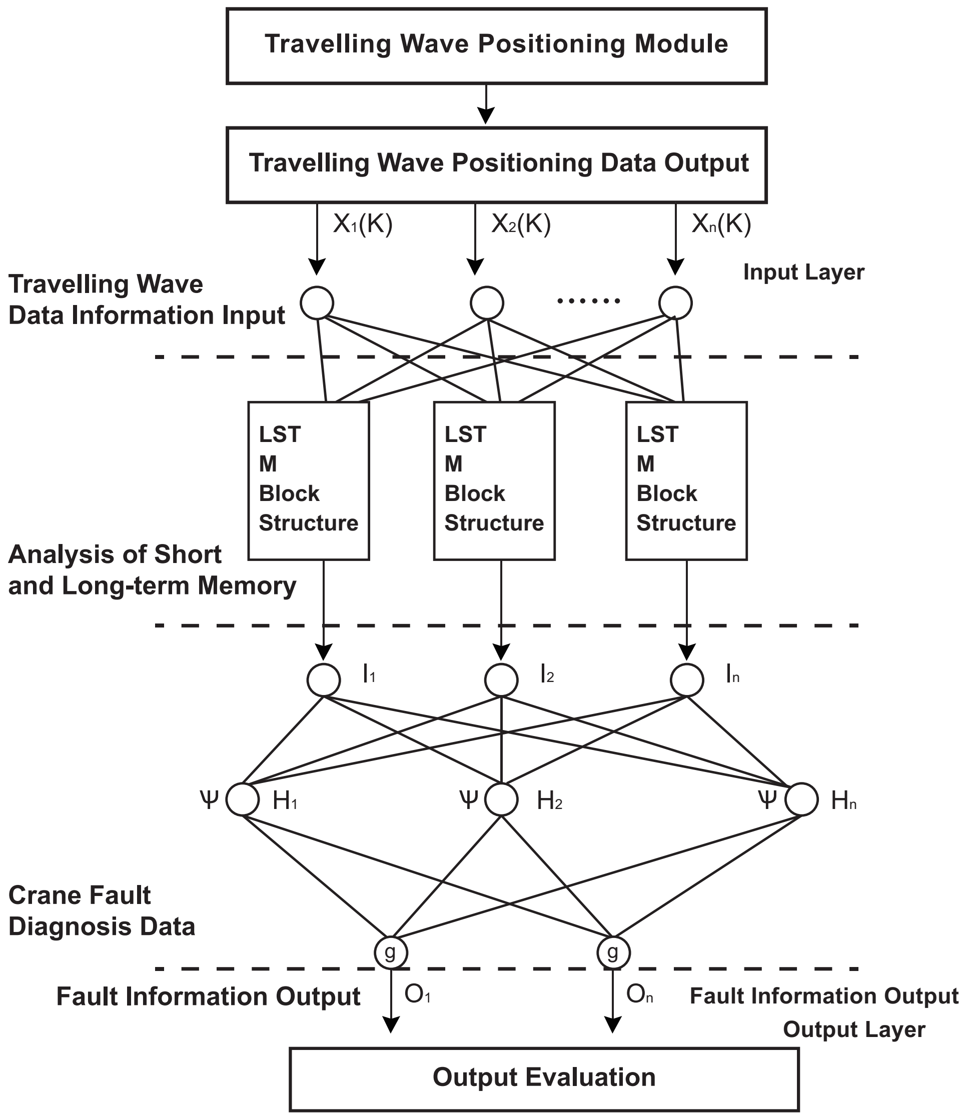

Figure 2. Schematic of the Artificial Intelligence computing architecture

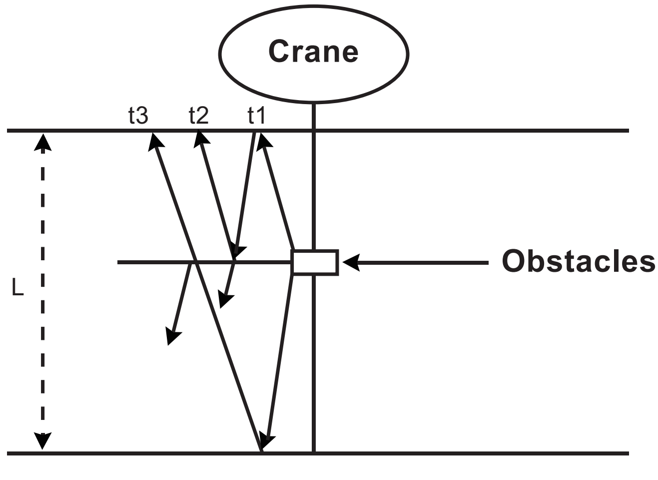

Figure 3. Schematic diagram of the principle of unmanned travelling crane travelling wave location

The obstacle points during the operation of the unmanned travelling crane are constructed by means of the spatial three-dimensional coordinates Where is expressed as the position difference, i.e. the error between the measured and actual value [15, 16], when the travelling wave location device is performing travelling wave ranging. This is expressed through the following Equation:

$$\triangle x = \min(|x' - x_1|, |x' - x_2|) \tag{1}$$

In Equation (1) indicates the length between the obstacle or fault point in the running of the travelling crane and the set standard distance, indicates the length between the obstacle or fault point in the running of the travelling crane and the set other standard distance. Indicates the formal measurement between the travelling wave distance [17] and the set standard distance through the following Equation:

$$\triangle t = |t_1 - t_2| \tag{2}$$

In Equation (2), is the ms-level moment when the travel wave locator reaches the measurement end of the obstacle or fault point during operation, and is the ms-level moment when the travel wave is recorded by the travel wave locator.

The degree of difference indicates the degree of similarity between the waveform released when a traveling wave encounters an obstacle point or a fault point and the data information in the traveling wave history database emitted by the traveling wave locator [18] expressed by the following Equation:

$$\triangle P = \frac{\sum_{n=1}^{i} |x(i) - y(j)|}{n}, \tag{3}$$

In Equation (3), $x(i)$ and $y(j)$ are the discrete data information of the waveform output by the traveling wave locating device when it encounters an obtacle point or a fault point respectively, where represents the historical information of the traveling wave emitted by the traveling wave behavior device. The value is inversely proportional to the similarity value [19].

Through the above introduction, in identifying the obstacle point or fault point, traveling wave ranging of the obstacle point or fault point occurrence area is relatively concentrated, in this study, the origin as the vertex, the cuboid is constructed, non-obstacle points or fault points are scattered within the three-dimensional space system of the obstacle point or fault point [20], the output area of the traveling wave location device can be:

$$H = \{\triangle x \in [0, 7]; \triangle t \in [0, 30]; \triangle P \in [0, 0.1]\} \tag{4}$$

The travelling wave location distance can be expressed by the following Equation:

$$L = \frac{(t_2 - t_1) \times v}{2} \tag{5}$$

In Equation (5), t_1 indicates the point in time when the first detected obstacle or fault point in the running of the traveling crane emits a traveling wave, and t_2 indicates the point in time when the second detected obstacle or fault point in the running of the traveling crane emits a traveling wave, and the distance between the L traveling wave localisation and the obstacle or fault point when the calculation is carried out by the traveling wave method. Using Equation (5), the distance to the traveling wave location is calculated.

3.2. **Long and short term memory neural network model.** After locating the obstacle or fault point through the traveling wave localisation method, this study also adopts the Long and Short Term Memory (LSTM) neural network architecture system to realize the fault detection during the operation of the unmanned traveling crane of the power material warehouse, which needs to incorporate a single LSTM block structure in the neural network architecture model shown in Figure 4.

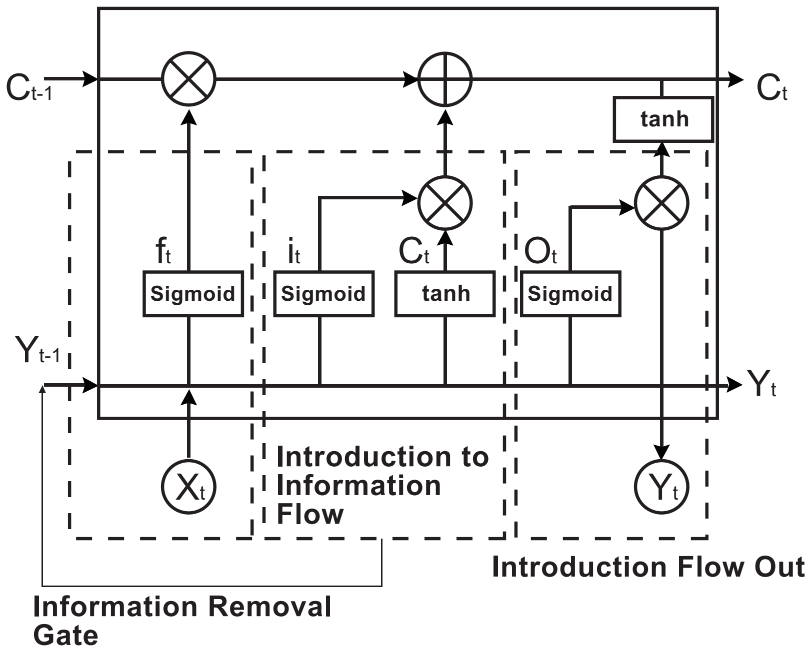

FIGURE 4. Schematic diagram of a single LSTM block architecture

In this research architecture, the LSTM block consists of the storage module C_t ,the in-formation removal gate f_t , the information inflow gate it and the information flow gate Ot, which form a single LSTM block architecture. The storage module C_t enables the input, deletion and reading of information on the operational state of the line crane. The processing is carried out in conjunction with information inflow gates, information removal gates and information flow gates. The information removal gate determines whether the unmanned crane operating status stored in memory module C_t at the previous moment is out of date or can be reapplied, and if the information status history is too old, the information is deleted [21, 22]. The information inflow gate selects data information from the storage module C_t and continuously enables the information to be updated. The infor-mation inflow gate is also able to filter the data information within the storage module C_t so that a single LSTM block structure only considers the relevant information at its output, then improving the information filtering capability.

The Sigmoid function is then called up to calculate the output values of the different gates ft for information removal, it for information inflow and O_t for information flow and C_t for the storage module, expressed by the following Equation:

$$\begin{cases} i_t = \ sigmoid(W_i \times [Y_t - 1, x_t] + b_i), \\ f_t = \ sigmoid(W_f \times [Y_t - 1, x_t]) + b_f), \\ O_t = \ sigmoid(W_O \times [Y_t - 1, x_t] + b_O). \end{cases} \tag{6}$$

In Equation (6), where t denotes the different network node parameter data nodes in the neural network model, $W_{[i,f,C,O]}$ denotes the parameter weight matrix in the neural network model, $b_{[i,f,C,O]}$ denotes the bias vector for the different node weight matrices in the neural network model, X denotes the input unmanned traveling crane operation data information parameters, and Y denotes the unmanned traveling crane operation fault diagnosis data output parameters. The memory module value C_t and the individual LSTM block output Y_t are represented by the following equations:

$$\begin{cases} C_t^* = \tanh(W_C \times [Y_t - 1, x_t] + b_C), \\ C_t = C_t - 1 \odot f_t + \odot C_t \times \odot i_t, \\ Y_t = O_t \odot \tanh(C_t). \end{cases} \tag{7}$$

In Equation (7), where tanh is the hyperbolic tangent function,denotes the multiplication calculated according to the elements in the neural network nodes. In this neural network model,a Softmax classification model is also incorporated, which enables the classification of the position state during the operation of the line crane by means of a regression calculation [23].

Assume that the various state data information during the operation of the un-manned traveling crane is K. Introducing the Softmax classification model, represented by $[X_t, Y_t]$, where the different data information can be represented as $Y_t \in \{1, 2, ..., K\}$, The Softmax classification model is able to evaluate the input unmanned traveling crane operation state data information, assuming that the jth operation state occurs with probability P [24], which can be expressed by the following Equation:

$$P(y^t = j|x^t, \theta) = \frac{\exp(\theta_j x^t)}{\sum_{j=1}^{K} \exp(\theta_j x^t)} \tag{8}$$

In Equation (8), θ is the parameter matrix for the neural network model to calculate the probability, and θ_j is denoted as the column vector of data associated with the $\jmath_{th}$ class in the rowhanging run state, and then the normalized cross-entropy loss function J is activated to find the optimal value of the letter θ [25]. The output expression can then be:

$$J(\theta) = \frac{1}{M} \sum_{t}^{N} \sum_{j}^{K} \log p + \frac{\lambda}{2} \sum_{t}^{N} \sum_{j}^{K} \theta_{tj}^2 \tag{9}$$

In Equation (9), where λ and M are the normalized model parameters of the input function J, the softmax classification model for the unmanned line crane operation data sample x_t is classified in order to achieve the regularization computational requirements by the following Equation:

$$Y_t = \arg\max p \tag{10}$$

By classifying and evaluating the different operating states of the travelling crane, which in turn enables rapid classification, the operation and handling of the crane is improved.

4. **Experiments and analysis.** The following technical solution for this study is verified: the operating system used is Windows 10, 64-bit, and the computer's development tool is Visual Studio 2017, OpenCV 3.0. the computer's hardware environment is CPU: Inter(R) Core(TM) i7; main frequency is 2.59GHz; memory 16G, simulation model Matlab software was used.

4.1. **Validation of the traveling wave localisation method.** The parameter settings for the model using the traveling wave localization algorithm are shown in Table 1.

TABLE 1. Parameters of the traveling wave localisation model Settings

Compound	Formula
Distance measurement output in the form of a line crane	$x' = 14.256km$
The initial traveling wave arrives at the measurement end at the ms level	$t_1 = 526ms$
Output of the traveling wave positioner at ms level	$t_2 = 802ms$
Distance to nearest line crane 1	$x_1 = 14km$
Distance to nearest line crane 2	$x_2 = 15km$
Variance value	$\triangle P = 0.0561$
Variance value	$\triangle P = 0.0436km$
Variance value	$\triangle x = 0km$

Assume that the motion trajectory of the unmanned travelling crane is shown in Figure 5.

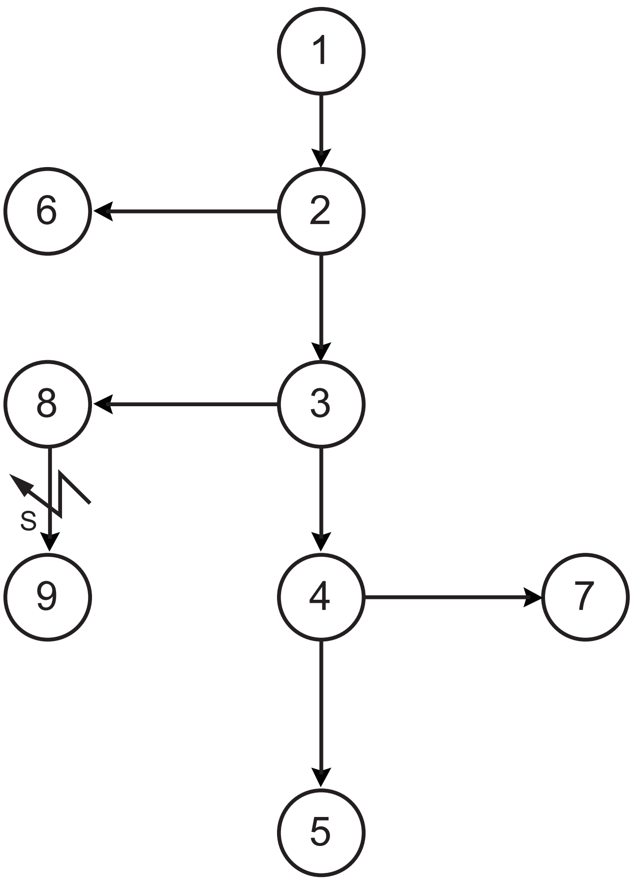

FIGURE 5. Unmanned travelling crane in operation

The route lengths of the unmanned travelling crane trajectory in Figure 5 are shown in Table 2.

Table 2. Route lengths for unmanned travelling crane trajectories

Trajectory of the travelling crane	Line length/ km	Obstacle points	Length of obsta-cle point/ km
1-2	15 km	4-7	3.2km
2-3	12 km	3-8	9.5 km
3-4	9 km	8-9	17.3 km
4-5	5 km	2-6	10 km

With the fault point settings in Table 2, the unmanned travelling crane was operated according to the trajectory in Table 2, where the sampling frequency during operation was 2MHz and the data from 2ms after the fault was taken for subsequent analysis. Based on the characteristic points of the fault to be tested output from Table 1 - Table 2 above, the coordinate point was set to (0, 0.0436, 0.0561). The fault point is then placed in the 3D coordinate system, and the output obstacle or fault point is shown in Figure 6.

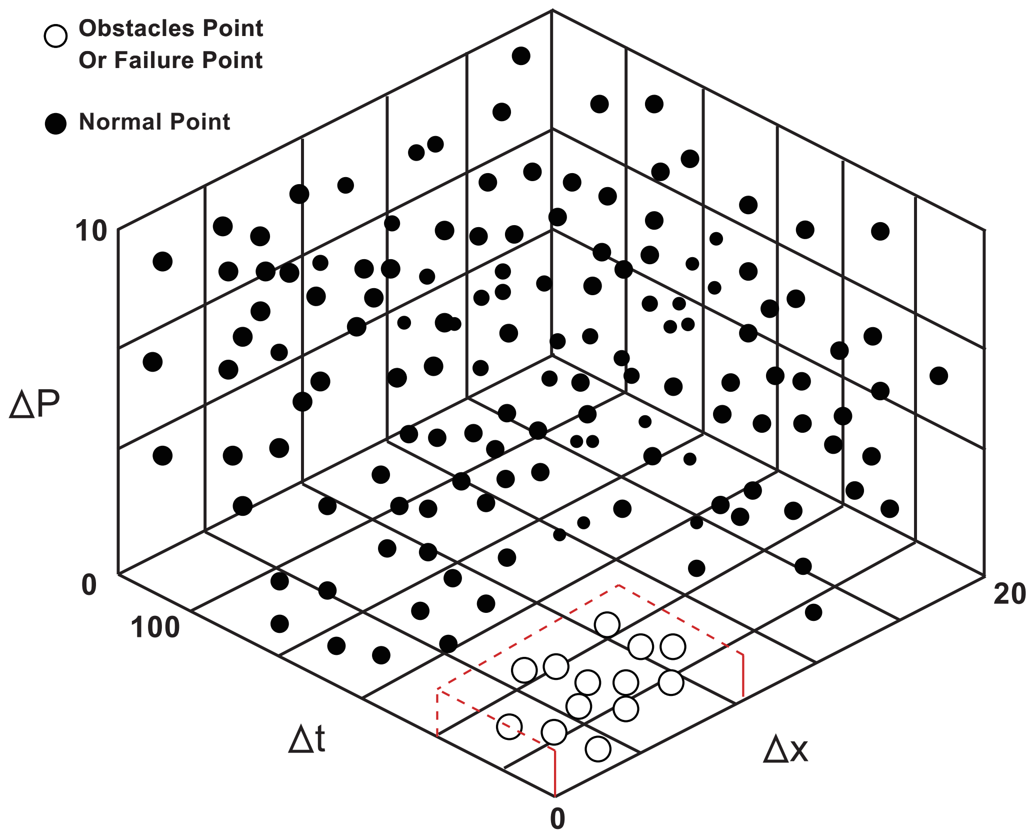

Figure 6. Schematic diagram of the distribution of fault points

As can be seen by the fault point distribution diagram in Figure 6, where the white dots indicate detected obstacle points or fault points and the black dots indicate normal areas where no obstacle points or fault points are detected. Therefore, the method of this study enables the location information of the unmanned travelling crane to be obtained quickly.

Table 3. Schematic table of distance measurement comparisons

Items	Failure point 1	Failure point 2	Failure point 3
Actual value	41.52	32.43	23.12
Methodology of this study	41.01	31.98	22.92
$reference_1$	37.41	27.32	16.73
$reference_2$	35.26	23.30	12.51

As can be seen by the comparative schematic table in Table 3, the method of this study has a high degree of accuracy in localisation.

4.2. **Long and short term memory neural network model validation.** Continuing with the data information tables in Tables 1 and 2, assuming multiple artificially created avoidance or fault points, the information tables are shown in Table 3. Through 3 hours of measurements, 12 test samples were selected and the method of this study was compared and analysed with the method 1 [1] and the method 2 [2] respectively, then the fault measurements are shown in Table 4.

Table 4. Schematic table of distance measurement comparisons

Measurement position	number of man-made faults/pc	reference 1 test/pc	reference 2 test/pc	Methodology of this study/pc
1#	5970	4870	4470	5921
2#	5900	4600	4320	5899
3#	5990	4890	4520	5953
4#	56967	5667	5217	6962
5#	4983	3883	3123	4973
6#	5762	4662	4012	5742
7#	5932	4532	4122	5912
8#	5764	4464	4014	5742

As can be seen through Table 4, among the 12 groups of different data information, only the method of this study detects more fault points when detecting fault test points. The detection error is verified below. That is, the difference between the actual detected location and the actual location. A diagram of the detection error is shown in Figure 7.

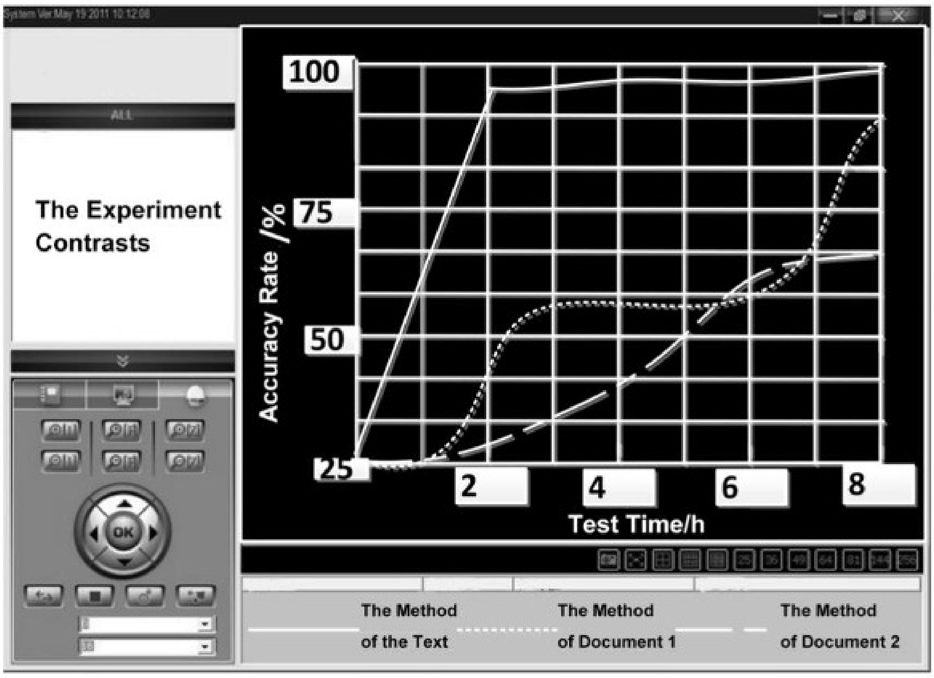

Figure 7. Schematic comparison of detection errors

As can be seen in Figure 7, the method in this study basically achieves test balance after 2 hours of testing, with an average test accuracy of over 95%. Therefore, the method in this study has a low error rate and high testing accuracy.

5. **Discussion.** In view of the problems existing in the electric power material warehouse, this paper, through the application of the control scheme of the driverless crane of the artificial intelligence technology and the calculation method of the artificial intelligence technology, proposes the use of the traveling wave positioning method, the short-term and short-term memory neural network model, and the collection of the crane operation information based on the intelligent finger of the electric power warehouse, to realize the analysis and calculation of the different operation states of the driverless crane of the electric power material warehouse, The operation position and fault diagnosis can solve the problem of driverless lifting in the unmanned power warehouse. Through driverless lifting technology, the personal safety of personnel in the warehouse can be improved and the labor cost of the power warehouse can be reduced.

In recent years, the new generation of information technology represented by mobile internet, cloud computing, big data, the Internet of Things, artificial intelligence, etc. has become increasingly mature and widely used. The requirements of the power industry for the standardization, automation and intelligent construction of warehouses have been continuously improved. The innovation in new ideas and new models has become an important way of innovation for power grid enterprises at present. The driverless lifting technology of material warehouse is to optimize the internal process of electric power material warehouse, reduce warehouse safety accidents, and improve the efficiency of material operation in electric power warehouse. The application of driverless lifting technology of artificial intelligence electric power material warehouse contributes to the construction of electric power intelligent warehouse.

At the 2022 Digital Work Conference held by the State Grid of China, it was proposed that it is imperative to strengthen the digital technology and intelligent support of the new power system of the power grid, transform from the manual management mode to the intelligent management mode, and "create big data support, networked sharing, and intelligent cooperation", The research on driverless crane technology of electric power material warehouse is to promote the integration and application of new technologies and new concepts of power grid as a means to promote the innovative development and iterative upgrading of the construction system of electric power material warehouse.

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