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Application of Artificial Intelligence Techniques in Assessing the Safety of Lifting Equipment

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Abstract

The focus of the article is addressing the use of artificial neural networks in evaluating the probability of potential accidents occurring while operating lifting crane machinery. The information is obtained from telemetric readings collected by microcontroller load limiters, and also from the results of routine technical and daily equipment condition inspections, which may involve stochastic data.

Keywords: Artificial Intelligence, Assessing ,the Safety of Lifting Equipment

1- Introduction

The telemetric data received from lifting crane equipment and similar devices, along with the facility's local security system indicators, is analyzed to develop and implement technology for evaluating current and predicting near-future emergency risks. Utilizing fuzzy sets for input information and considering the dynamic discrete nature of safety equipment data flow, the application of machine learning techniques, neural networks, big data processing, and clustering combined with fuzzy data analysis methods is the best approach based on industry best practices to achieve optimal performance for decision making. The methods described in [1-3] were developed previously.

The main outcomes of the proposed approach include:

- Examining the use of neural network data analysis with fuzzy input information to classify accident severity and probability of hazardous events.

- Exploring mechanisms for collecting statistical data and processing telemetry data for various parameters, including recognizing and classifying historically accumulated data based on telemetry parameter types and changes.

The development and analysis of the general problem to evaluate the risk of emergencies at dangerous facilities involve the use of a multi-layer neural network with forward propagation. This neural network takes the solutions of two previous problems as inputs.

It's important to note that the solution to the first research problem is based on fuzzy inference, which includes fuzzification, application of fuzzy production rules, and defuzzification, such as the Takagi-Sugeno method. The predominant approaches in this area involve the use of the 5-layer Takagi-Sugeno-Kanga (TSK) neural network and the three-layer Wang-Mendel network [4, 5]. The network can be trained using supervised or unsupervised learning based on input data clustering.

To resolve the second one problem, the maximum relevant to the issues of category and clustering the classical multilayer neural networks and recurrent neural network may be used. The second one option is most advantageous for studying time series and indicators [6].

In standard, the technology of neural networks is the most extensively used within the delivery systems chance assessment problems [7-8], construction [9-10], evaluation of material homes [11], information technologies [12] and others.

2- Data and methods

Stages for implementing the study of artificial neural networks for predicting the risk of emergencies with lifting crane devices include the following [13]:

- Structuring and analysis of the input information;
- Assessment of mechanisms for transforming the input information into target indicators for solving the problem of predicting the risk of emergencies;

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- Determining the type and structure of the artificial neural network (ANN) elements; Learning neural network on the reference data set; Neural network performance check.

The input information of neural network is divided into the following types:

a) Information from questionnaires Features of the information flow:

- Lack of historically accumulated data;
- Fuzzy nature of information in the form of linguistic variable values ;
- Availability of an expert mechanism for assessing the influence of input information on the output parameters of the network, including a system of production rules of fuzzy type and coefficient-type additive models for obtaining the final result;

b) Information of a monitoring nature, accumulated during the entire operation of the crane safety device, containing sections of general information, such as "Statistics of operating cycles", "Operating time", "Quality of control", etc., as well as operational information recorded frames with an interval of 1 s, some of which are used in the neural network model:

- time indication;
- boom length indication;
- indication of the lifted load;
- indicator of rated lifting capacity for the current value of boom length and reach;
- indication of the platform rotation angle;
- sign of the presence of power lines;
- information about the coordinate protection parameters set;
- warning signals indicating that the load exceeds the level of 90% of the nominal allowable value;
- entry of the load level into the range from 100 to 110%
- warning signals indicating the approach to the permissible boundaries of coordinate

protection;

- signal of device operation for complete stop of mechanisms. Features of the information flow:
- Dynamic structure of information;
- The presence of a random nature due to external influences (wind load, random vibrations of the lifting mechanisms), possible accidental influences on the crane operator's control;
- Availability of historical data, most of which is related to accident-free operating modes of the crane and almost missing data in the case of an emergency;
- Ability to supplement the monitoring data for the selected characteristic time interval in order to retrain the neural network.

Thus, from the analysis of the input information, it was decided to use ANN for the analysis of information flows of both types and obtaining results with an assessment of the risk of an emergency when using a crane. However, the structural elements of such network should be different for various information flows.

3- Results and discussions

A 4-layer neural network has been developed to address the issue of ensuring lifting crane compliance with industrial safety standards at varying levels (red for non-compliance, yellow for partial compliance along with risk reduction measures, and green for full compliance). This neural network is designed to handle the task of classifying multiple parameters using input data obtained from surveys. The implementation involves using Python as the programming language, with an interpreter version 3.6. For machine learning, Tensorflow version 1.8.0, which includes Keras version 2.1.6, a deep learning library, is utilized alongside additional mathematical and infrastructure packages.

The network inputs included different categories of answers, such as:

- What is the life cycle of the equipment?
- When was the industrial safety expertise of the crane conducted?
- Is insurance available?
- When was the last maintenance performed and what were the results?
- How does the level of flange wear compare to its original thickness?
- Are there any cracks of any size on drums and hooks, welds, and base metal?
- What is the level of wear of a drum?

The values of the corresponding linguistic variables are the answers. There are a total of 100 inputs. The value of the linguistic variable checked off on the list is indicated by a one, while the others are indicated by zeros.

Figure 1 illustrates the overall architecture of the neural network, organized into layers. The network consists of 4 fully connected layers. A Dropout layer with a dropout rate of 0.1 is included to mitigate overfitting. The inner layers use a hyperbolic tangent activation function, while the output layer uses a threshold function. There are 6 outputs, each corresponding to the binary encoding of 3 levels of accident severity and 3 levels of event probability. Model performance is evaluated using the mean squared error (MSE) function, measuring the root-mean-square error between the output and reference neuron values. The stochastic gradient descent method is employed as an optimizer.

The structure that is shown is the best it can be due to numerous studies on ANN parameters, including:

- the activation functions used in layers;
- the initializers of scales;
- the loss functions utilized;
- the optimizers applied;
- and the number of neurons on hidden layers.

The error backpropagation method was used to train the network. It's important to note that training the system with a complete set of input reference values is quite challenging. During training, we focused on elements near the hyperplanes section that corresponded to the severity levels of accident consequences and the probability of hazardous events. The remaining input information was checked during neural network trained validation, confirming the effectiveness of the proposed approach.

For the analysis of statistical data gathered throughout the entire usage of the crane safety system, two methods are being taken into account. The initial method involves the utilization of a recurrent neural network (RNN).

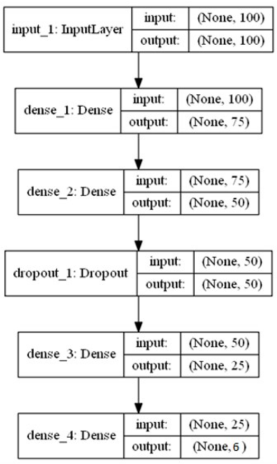

Fig. 1. General diagram of a neural network.

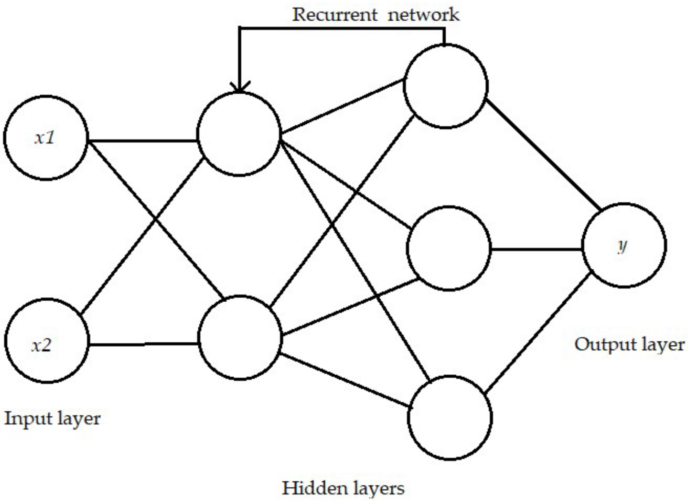

Fig. 2. Scheme of a recurrent neural network.

The values of the registered parameters by the safety device, as shown in Figure 2, serve as the network inputs and are taken from the specified time window width ΔT. The optimal number of points on the time base of the signal within the chosen window ranged from 20 to 30. The number of neurons in the output layer was chosen between 6 to 10, aligning with the crane mechanism's degrees of freedom (lifting, carriage movement, turning, rail movement) and the cargo movement process constraints (carrying capacity, coordinate protection, presence of power lines).

Classifying signals using unsupervised learning is the primary objective, with the aim of uncovering their internal structure. The quantity of neurons in the two concealed layers was systematically diminished to form a trapezoidal network structure. The categorization of documented signals enabled the differentiation of classes based on the crane mechanisms' motion types, along with concurrent alterations in the recorded traits.

I propose a plan to classify each recorded signal in more detail by constructing separate classifier networks. These networks are fed with the time base of the selected signal (20 to 30 samples) to determine subclasses: uniform parameter change, change with acceleration, and random change.

The final outputs of the RNN indicate whether there is a change in the telemetry parameters, including single parameters or combinations, and the nature of these parameter changes. These outputs are integrated with the outputs of the ANN, which assess the risk of an accident based on check-lists, and serve as inputs to a multilayer network for making swift assessments of the crane's condition in real time and predicting crane operations based on varied input data streams.

The analysis of telemetry data can also involve an initial processing of the time series within a chosen window using a specific telemetry parameter.

$p(t_k), k = 1,2,..,20 (\Delta T = 20)$

For this, on the basis of the least squares method, an approximation dependence of the quantity $p(t)$ in the form of a square polynomial is calculated

$$p(t) \approx f(t) = a + b \cdot t + c \cdot t^2 \quad (1)$$

In this case, the value $r_1 = a + 10b + 400c/3$ determines the average value of the recorded parameter over the interval, is the average value of the speed on the interval,

$r_2 = b + 20c$ is the average value of the speed on the interval,

$r_3 = 2c$ average acceleration value,

$r_4 = \sum_{k=1}^{20} (p(t_k) - f(t_k))^2$ the root-mean-square error of approximation, proportional

to the influence on the recorded parameter of random processes of a natural nature or control mechanisms.

In this scenario, the inputs for the RNN do not consist of the temporal parameter values within the specified window but rather the values, which decreases the number of neurons in the input layer, cutting down on the network's learning time and operational errors. The overall process for assessing risk in order to ensure the safe operation of the facility is depicted in Figure 3.

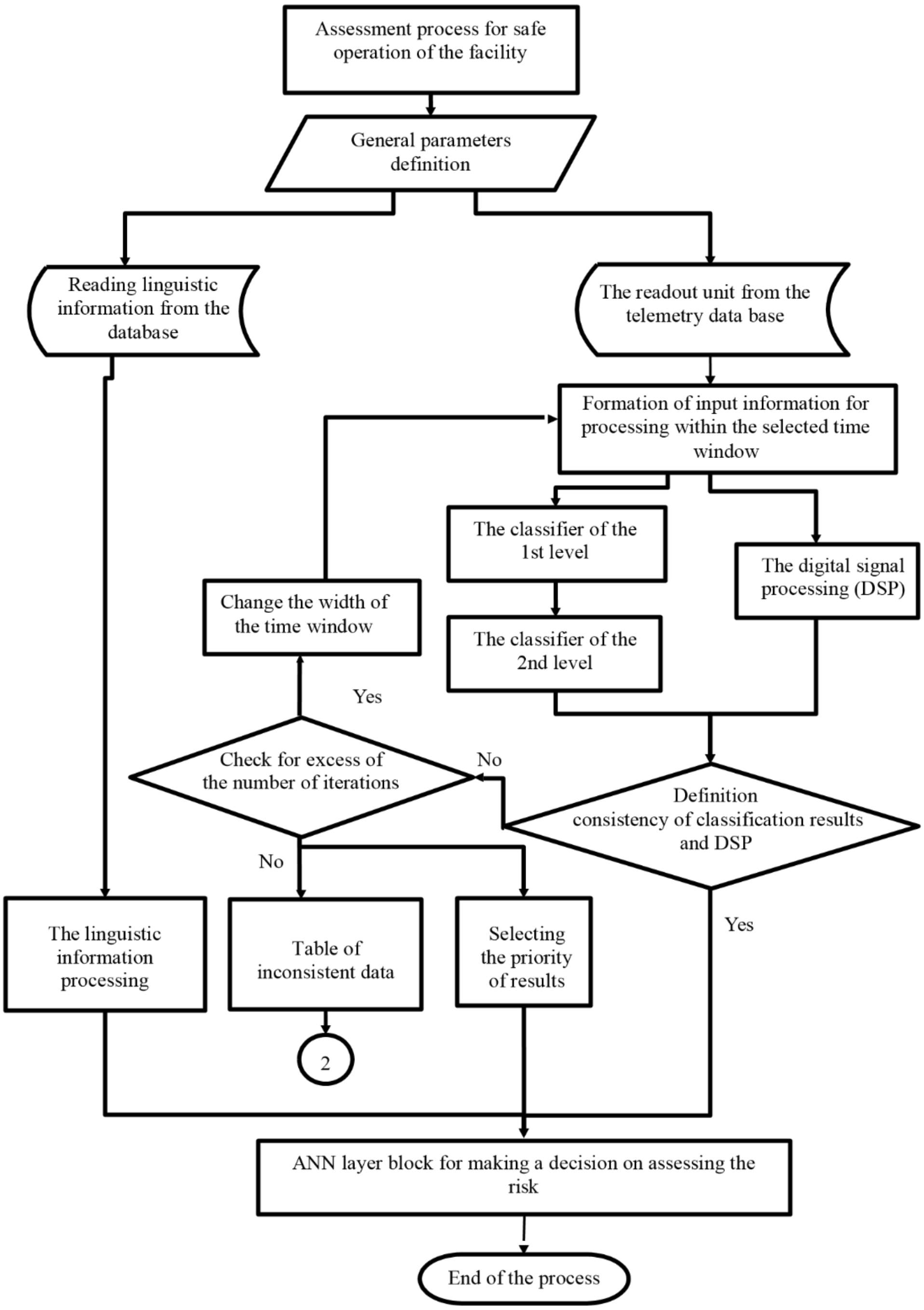

Fig. 3. General scheme of the risk assessment process for safe operation of the facility.

The description of the purpose of the circuit blocks is as follows:

1. Definition of general parameters sets the starting point and duration of the telemetry time series sample for the chosen crane.
2. The telemetry database's readout unit retrieves data from the table and converts it into Python data arrays.
3. Preparation of input data for processing within the specified time frame involves creating information for input to neural network classifiers at the 1st and 2nd levels.
4. The 1st level classifier categorizes the time series based on the types of physical processes occurring on the crane, such as load lifting, carriage movement, rail movement, rotation, entry into coordinate protection zones, and approach to carrying capacity limit zones.

5. The classifier of the 2nd level classifies information for time series by the nature of the change into the following classes: no change, uniform change, accelerated change, random change.

6. The digital signal processing block calculates the numerical characteristics $r_i, i = 1,2,3,4$ for their comparison in the block Determination of the consistency of the classification and DSP results with the recognized signal membership classes

7. The Check for excess of the number of iterations and Change the width of the time window blocks regulate the matching process by decreasing the length of the time series with a limit on the number of iterations of changing the given length.

8. In case of unsatisfactory work of the classifiers, telemetry data is included in the table of inconsistent data for network retraining (mark 2)

9. The block for reading linguistic information from the database on checklists implements reading information from the table and fuzzifies the corresponding values of linguistic variables.

10. The linguistic information processing unit prepares information as inputs to ANN.

The ANN layer block for making a decision on assessing the risk of safe operation of an object at this stage of the project implementation, together with block 10, is a single fourlayer ANN, the study of which is described above

4- Conclusions

Consequently, after examining the tasks involved in processing operational and statistical input, it can be inferred that utilizing neural network methods offers advantages over algorithmic methods in detecting hazardous conditions during crane operations based on the following characteristics:

- Telemetry data concerning the performance of lifting crane equipment within the operational information system is institutionalized, accumulates over time, and diminishes the level of uncertainty when addressing risk-related issues. Additionally, neural networks possess the capability to learn and undergo retraining, enabling their successful utilization in situations involving the accumulation of statistical data.

Artificial neural networks are capable of recognizing undiscovered patterns present in large data structures. This ability is crucial for effectively analyzing significant information streams, not only for accurately describing the operational reliability of a crane but also for predicting the object's behavior during situations with inadequate telemetric data. The neural network approach provides the means to assess diverse information fed into the system from a singular standpoint, encompassing fuzzy nature and telemetric time data.

- After training the neural network, the computing mechanism operates at its fastest, which is crucial for ensuring stability and scalability in real-time systems.

- Neural networks can effectively handle weak signals and noise, which is essential for ensuring the reliability of information processing in telemetry data analysis.

- The project utilizes neural networks alongside digital signal processing algorithms and statistical methods, rather than completely replacing algorithmic methods, thus enhancing the reliability of the system under development.

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