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Article

# A framework for hydro-power vibration dynamic measurement and decision-making based on natural language processing

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**Abstract:** The safety management construction of the hydro-power units is necessary to improve the level of engineering quality and economic benefits. However, the traditional hydro-power units lack a unified safety management decision-making platform, making knowledge retrieval and recommendation difficult. To improve the safety management level of the hydro-power units, the present article provides a framework of intelligent query and auxiliary decision-making in the traditional hydro-power operations. Based on the natural language processing technologies, the auxiliary decision-making platform is composed of three parts, namely, deep semantic similarity model, bidirectional long short-term memory network model and neural collaborative filtering algorithm. Lastly, a case study is conducted, and the auxiliary decision-making platform can provide the user the relevant knowledge guidance to the problem, including defect causes, handling methods, dangerous point analysis and operation preparation, which is helpful to improve the safety management level of the hydro-power units.

**Keywords:** hydro-power operations; vibration dynamic measurement; natural language processing; intelligent query; auxiliary decision-making

## 1. Introduction

To improve the hydro-power energy production efficiency, China is accelerating the safety management construction of the hydro-power units. The safety management construction of the hydro-power units has become a long-term mechanism to consolidate the quality foundation and prevent the quality failures. Mean- while, the safety management construction of the hydro-power units is necessary to improve the level of engineering quality and economic benefits. In recent years, a large amount of textual materials related to the hydro-power operations have been accumulated. How to extract valuable information from such a large amount of textual materials related to the hydro-power operations to effectively support the safety management decisions has become a hot topic. With the rapid development of the natural language processing technologies, the effective means to support the safety management decisions of the hydro-power operations have been provided [1–10]. For example, Kaur et al. have developed a novel and improved intelligent search engine using natural language processing [1]. Using the search engine, the user can query the database system in the natural language. The intelligent search engine will convert the natural language query into the DBMS language query to retrieve the data from the database. Bais and Machkour focused on applying a new approach to automate the operation of the natural language interfaces for databases [2]. In the approach, a supervised learning technique was applied to induce rules that transform natural language queries into unambiguous expressions. Sangeetha and Hariprasad give a general framework for a smart database interface which could be linked to any database [5]. One of the most striking features of the interface is domain- independence. The smart interface employs speech recognition techniques to convert spoken language input into text. Then, a semantic matching technique is employed in converting natural language query to SQL words, complemented by using dictionary and a set of production rules. Owei proposed the conceptual query language-with-natural language (CQL/NL), which used information extraction methods to filter NL query statements for search predicates that were derived from constructs on conceptual schemas [6].

Firstly, the description of textual materials related to the hydro-power operations is to record the problems encountered, corresponding solutions and specific information of the abnormal handling operation standard guidance document. Then, it is to guess the cause of the problem and find the reason through detection methods. Finally, there is the execution of linked tasks, standard assignments and task distribution. For the hydro-power units, there are a large number of named entities with diverse forms of expression, such as equipment names, equipment parts and defects, which are difficult to include them in the dictionary. Moreover, the problematic text tends to be colloquial and does not fully follow the grammatical structure, resulting in the inability to find the central word through syntactic analysis methods and perform structural division. Thus, the key technologies in traditional sentence information extraction, such as named entity recognition and syntactic analysis, are difficult to achieve satisfying results in abnormal handling case texts [11–16]. Currently, there are the following problems for the hydro-power operations: (1) low efficiency of knowledge retrieval; (2) lack of efficient decision support mechanisms; (3) difficulty in inheriting work experience without knowledge management mechanisms. In practical applications, textual materials related to the hydro-power operations can only be found through title retrieval in existing systems, making it impossible to conduct full-text content retrieval and lack efficient management mechanisms. It requires the introduction of semantic recognition technology, which mainly refers to natural language question answering that enables search engines to intelligently display entities, attributes and the relationships between entities [17–26].

Understanding textual materials related to the hydro-power operations by the natural language processing technologies, a standardized set of knowledge for the hydro-power units is established, which is composed of two parts: (1) unifying various internal archives and documents of the hydro-power units to achieve intelligent retrieval technology for the hydro-power operations; (2) building a decision model using natural language processing to calculate text similarity and intelligent search technology, including current situation introduction, cause analysis, handling methods, hazard point analysis, operation preparation, protective measures, operation procedures and quality standards. The traditional hydro-power units lack a unified safety management decision-making platform, and the management of textual materials related to the hydro-power operations is complex, making knowledge retrieval and recommendation difficult. The present article aims to provide a framework of intelligent query and auxiliary decision-making in the traditional hydro-power operations, improving the safety management level of the hydro-power units.

## 2. Framework of hydro-power safety management decision-making based on NLP

To satisfy the safety management requirements of the hydro-power units, the auxiliary decision-making platform introduces a service-oriented framework, as designed in **Figure 1**. The application layer, application infrastructure layer, service layer, data layer and environment layer adopt loosely coupled protocols, different layers use a customized port to achieve communication. The auxiliary decision-making platform can achieve system management, information management, intelligent query and management functions. Each functional module appears in a unique distributed service component form, obtaining the required functionality from the dashboard management platform.

(1) The application layer implements the calling of various functions of the basic layer through the dash- board management platform.

(2) The application infrastructure layer provides various basic modules of the platform, including data acquisition, data processing, data management, permission management and deep semantic similarity models.

(3) The service layer mainly provides real time library service, history library service, file service, message service, event service, log service and permission service.

(4) The data layer mainly provides data storage, including real time database, history database, file and unstructured data storage.

(5) The environment layer includes server configuration and deployment configuration of the hydro-power operations knowledge auxiliary platform.

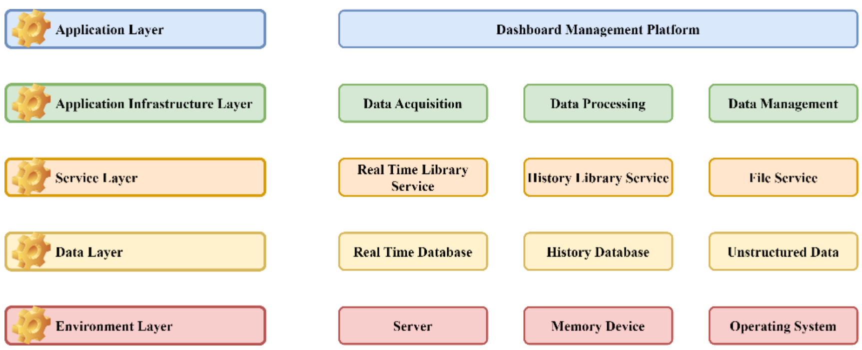



**Figure 1.** Framework of hydro-power safety management decision-making based on NLP.

## 3. Key technologies of intelligent hydro-power safety management decision-making

### 3.1. Deep semantic similarity model

A deep semantic similarity model (DSSM) is adopted to achieve intelligent retrieval of textual materials related to the hydro-power operations. The core idea of DSSM is to map the text information of the problem to be retrieved (Query) and the textual materials related to the hydro-power operations (Doc) onto the same semantic space, and calculate the implicit semantic score by maximizing the cosine similarity between Query and Doc to achieve the goal of searching for hydro-power problems.

**Figure 2** shows the model structure of DSSM. The model utilizes the hash characteristics of multi-layer constitutive nonlinear projection words, such as water turbine guide vane sleeve leakage, maps the high-dimensional sparse text characteristics in semantics to low dimensional dense characteristics by deep neural network (DNN), and the last layer of DNN forms the features in the semantic space.

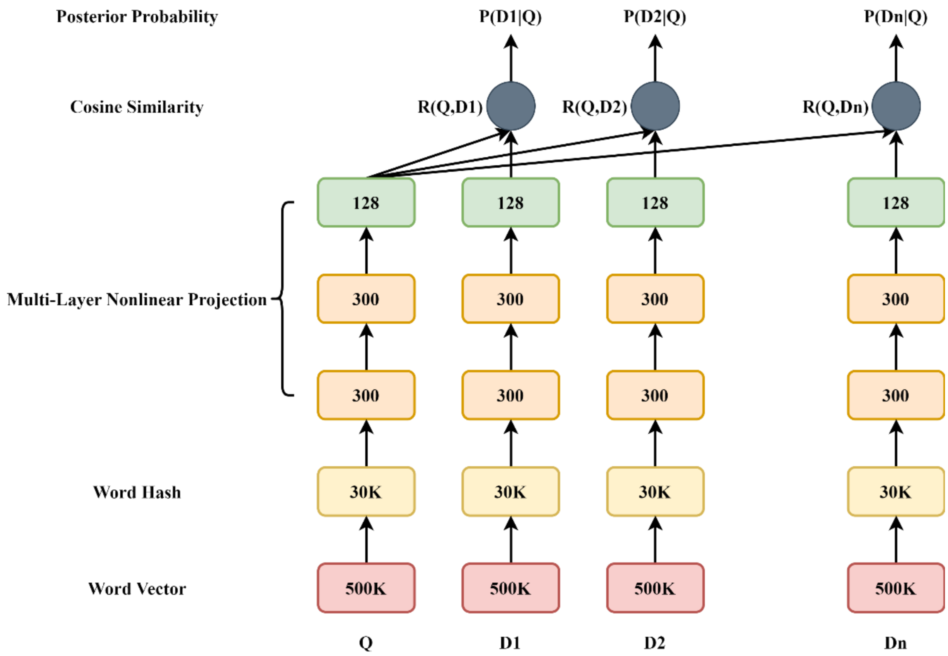



**Figure 2.** Model structure of DSSM.

Specifically, the input of DNN, such as water turbine guide vane sleeve leakage, is a high-dimensional vector, to query the word vectors in the document, firstly map the word vectors to the corresponding semantic vectors, the equation is

$$l1 = W1x$$

where $l1$ is the hidden layer representation vector, $W1$ is the learning weight matrix, and x is the original text feature input vector. To reduce dimensions in the semantic space of word vectors, the multi-layer nonlinear mapping is adopted, namely,

$$li = f(Wili - 1 + bi), i = 2,\cdot\cdot\cdot, N - 1$$

where the activation function is

$$f(x) = \frac{1 - \exp(-2x)}{1 + \exp(-2x)}$$

To calculate the correlation score between a document and a query question, the cosine similarity is adopted, namely,

$$R(Q, D) = \cos(y_Q, y_D) = \frac{y_Q^T y_D}{\|y_Q\|\|y_D\|}$$

where $y_Q$ is the output vector of the problem query vector after multi-layer nonlinear mapping, $y_D$ is the output vector of the document vector after multi-layer nonlinear mapping, $y_Q^T$ is the transposition of $y_Q$. The DSSM model learns the weight matrix and bias vector parameters in the neural network through supervised training methods, that is, calculating the maximum click document Doc conditional likelihood under the given problem Query. The posterior probability of a given problem Query is calculated by

$$P(D|Q) = \frac{\exp(\gamma R(Q,D))}{\sum_{d \in D} \exp(\gamma R(Q,D))}$$

where $\gamma$ is the candidate file sets to be arranged, namely, softmax smoothing factor, $\exp(x)$ is the soft- max normalization function, $R(Q, D)$ is the similarity score between the corresponding problem vector and document vector. The loss function is

$$L = -\sum_{(Q,D^+)} \log(P(D^+|Q))$$

where $-\sum_{(Q,D^+)} \log(x)$ is the negative logarithmic function of the corresponding problem vector and document vector, $P(D^+|Q)$ is the maximum likelihood function of the problem vector in the positive document vector, which maximizes the probability of finding the document given the query problem.

### 3.2. Bidirectional long short-term memory network model

The long short-term memory network model (LSTM) is adopted to capture sentence representations of a large amount of textual materials related to the hydro-power operations. The structure of LSTM is similar to that of recurrent neural network (RNN), and the most important improvement is the addition of three gate control architectures in the hidden layer h, namely, forget gate, input gate and output gate, as well as the addition of a hidden state. **Figure 3** shows the principle of the hidden layer structure of LSTM.

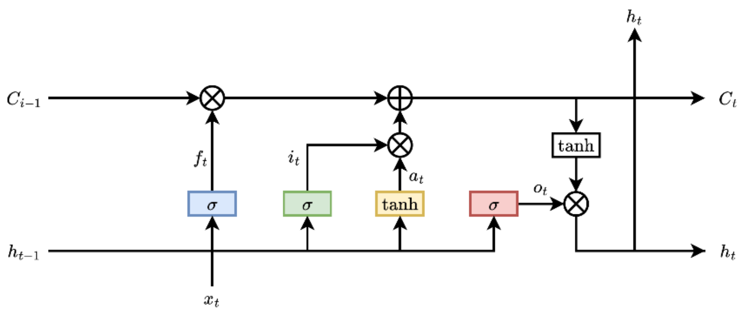



**Figure 3.** Principle of the hidden layer structure of LSTM.

The calculation process of LSTM is

$$a(t) = tanh(Waht - 1 + Uaxt + ba)$$

$$f(t) = \sigma(Wfht - 1 + Ufxt + bf)$$

$$i(t) = \sigma(Wiht - 1 + Uixt + bi)$$

$$o(t) = \sigma(Woht - 1 + Uoxt + bo)$$

where $tanh(x) = (1 - exp(-2x))/(1 + exp(-2x))$, $\sigma(x) = 1/(1 + exp(-x))$, $f(t)$ is the forget gate value at time $t$, $i(t)$ is the input gate value at time $t$, $o(t)$ is the output gate value at time $t$, $a(t)$ is to extract the feature of ht-1 and $x(t)$ at time $t$, $x(t)$ is the input at time $t$, ht-1 is the representation of the hidden layer at time $t-1$, $Wf$, $Wi$, $Wa$ and $Wo$ are the weight coefficients to extract the feature of ht-1, $Uf$, $Ui$, $Ua$ and $Uo$ are the weight coefficients to extract the feature of $x(t)$, $bf$, $bi$, $ba$ and $bo$ are the offset values to extract the feature, $tanh(x)$ and $\sigma(x)$ are the activation functions of the neural network.

For example, there are no cracks on the guide vane shaft, a bidirectional long short-term memory network model (BiLSTM) is adopted to capture bidirectional semantic dependencies in the sentence. **Figure 4** shows the structure of BiLSTM. The BiLSTM model is composed of two LSTM models, namely, forward processing sequence and backward processing sequence. After 6 time steps, the forward processing sequence outputs a forward result vector, and the backward processing sequence outputs a backward result vector, by combing these two result vectors, the output of BiLSTM is obtained.

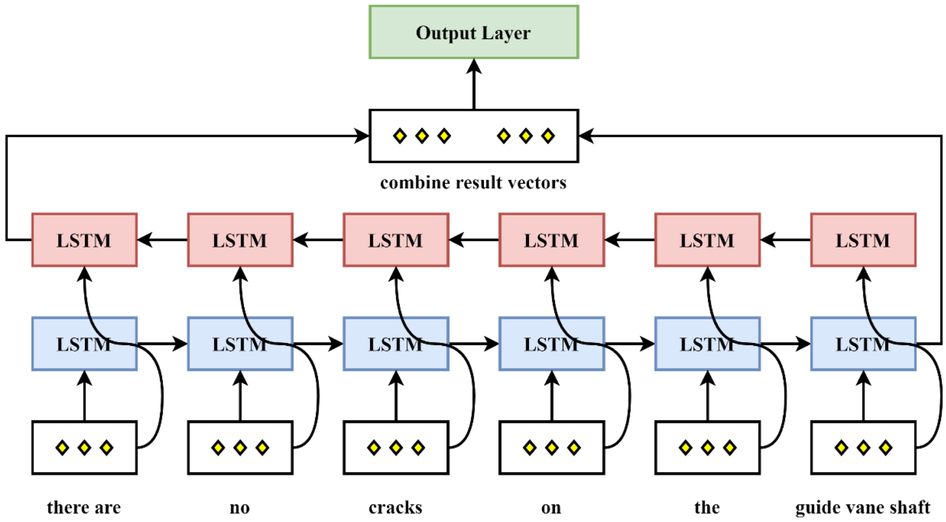



**Figure 4.** Structure of BiLSTM.

### 3.3. Neural collaborative filtering algorithm for intelligent recommendation

The auxiliary decision-making platform adopts a neural collaborative filtering algorithm (NCF) to achieve the intelligent recommendation of the hydro-power operations. Firstly, the model learns low dimensional vector representations of the hydro-power operations and text data through embedding layers, then, uses multi-layer neural networks for feature extraction of sentence representations. Due to the lack of inner product calculation in traditional matrix factorization, the feature cross fusion ability is greatly improved. The NCF model combines the matrix factorization model of nonlinear activation functions with the MLP multi-layer perceptron collaborative filtering mode to enhance the feature extraction capability of the model.

As shown in **Figure 5**, the GMF layer and MLP layer in NCF share the embedding layer, and the combined representation interaction is output as a function.

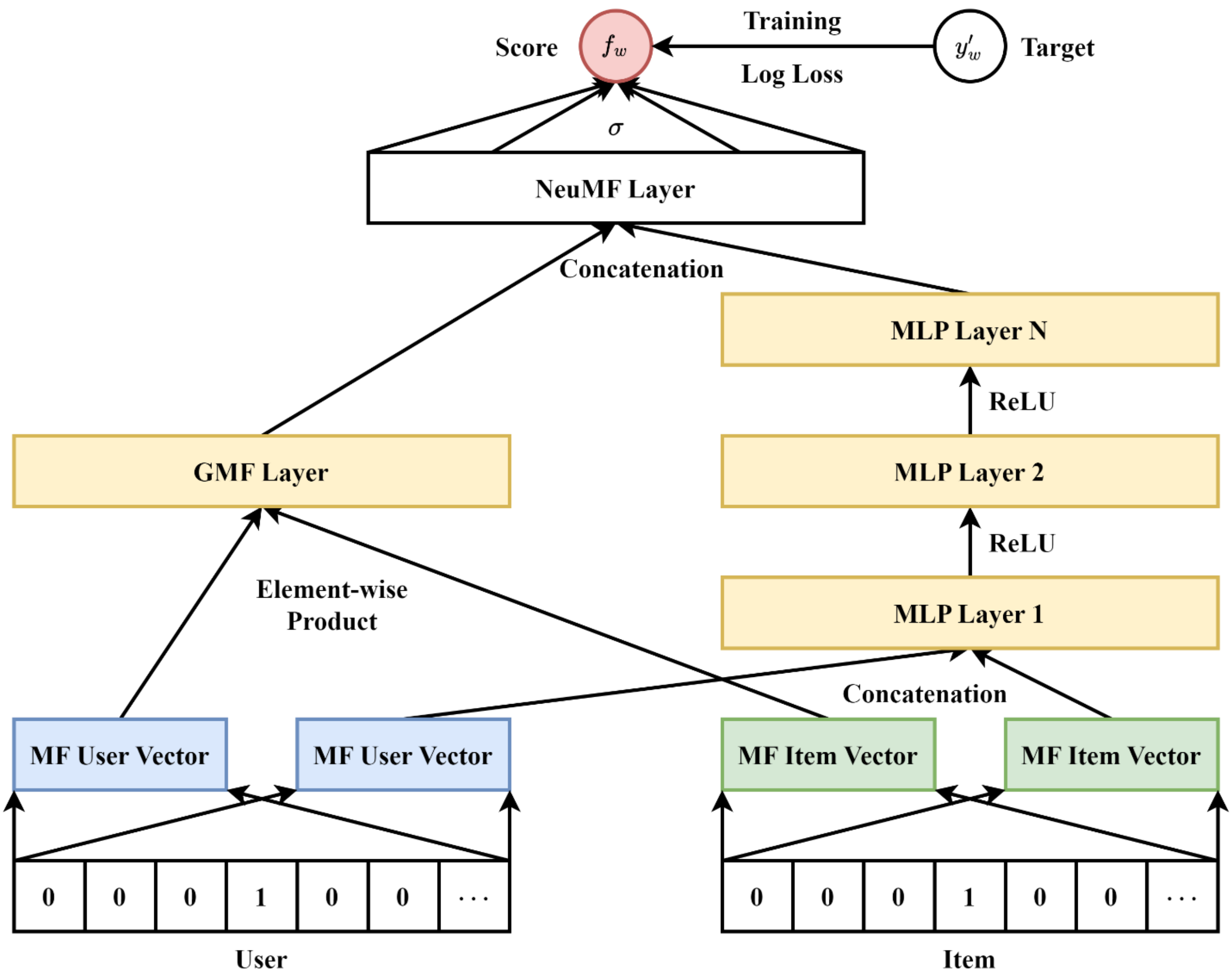



**Figure 5.** Adopting neural collaborative filtering algorithm (NCF) to achieve intelligent recommendation.

The model to combine GMP and MLP is

$$yui = \sigma(h^T a(p_u \odot q_i) + W(p_u, q_i)^T + b)$$

where $\sigma$ is the sigmoid activation function, $p_u$ is the query problem characteristic vector, $q_i$ is the corresponding document characteristic vector, $\odot$ is the vector combining operation, $W$ is the model learning parameter matrix, $b$ is the linear offset. To improve the representation ability of NCF, we combine GMF and MLP, namely,

$$\varphi^{GMP} = p_u^G \odot q_i^G$$

$$\emptyset^{MLP} = a_L(W_L^T\left(a_{L-1}\left(\cdots a_2\left(W_2^T\left(p_u^M, q_i^M\right)^T + b_2\right)\cdots\right)\right) + b_L)$$

$$y_{ui} = \sigma(h^T(\emptyset^{GMP}, \emptyset^{MLP})^T)$$

where $p_u^G$ is the user insertion of GMP, $p_u^M$ is the user insertion of MLP, $q_i^G$ and $q_i^M$ are the insertions of the query problem text and the corresponding document, respectively, $a_L(\cdot)$ is the output of the L-layer perception machine. The ReLU function is adopted to be the activation function of the model, NCF combines the linear MF and the non-linear DNNs to model the representation between the user and the recommendation. The standard back-propagation algorithm is suitable to the parameters of the model.

## 4. Case study of intelligent query and auxiliary decision-making

During the hydro-power operations, different problems may occur. For example, as shown in **Figure 6**, taking water turbine guide vane sleeve leakage as an example, intelligent query and recommendation are carried out through the auxiliary decision-making platform, which automatically provides feedback on defect causes, handling methods, dangerous point analysis, operation preparation and other knowledge guidance.

Firstly, water turbine guide vane sleeve leakage is sent to the DSSM and BiLSTM models, the auxiliary decision-making platform will retrieve the relevant records from the database (from the experts and opera-tions cases), such as leakage of the 14th guide vane sleeve under the 5F top cover of the 5th hydroelectric generator unit. Meanwhile, the NCF model is adopted to achieve the intelligent recommendation of the similar cases, after the corresponding case is selected, the auxiliary decision-making platform will provide the user the relevant knowledge guidance to the problem, including defect causes, handling methods, dan-gerous point analysis and operation preparation, which is helpful to improve the safety management level of the hydro-power units. Furthermore, to validate the performance of the intelligent recommendation system, **Figure 7** shows the normalized confusion matrix, and **Figure 8** shows the F1-confidence, precision-confidence, precision-recall and recall-confidence curves. When two similar query words are input into the intelligent recommendation system, the system is able to distinguish these two query words, the normalized confusion matrix is clear. Meanwhile, with the increase of the confidence, the precision of the model improves, and the recall rate is relatively low at the relatively high precision, namely, the stability and precision of the model is able to satisfy the engineering demand.

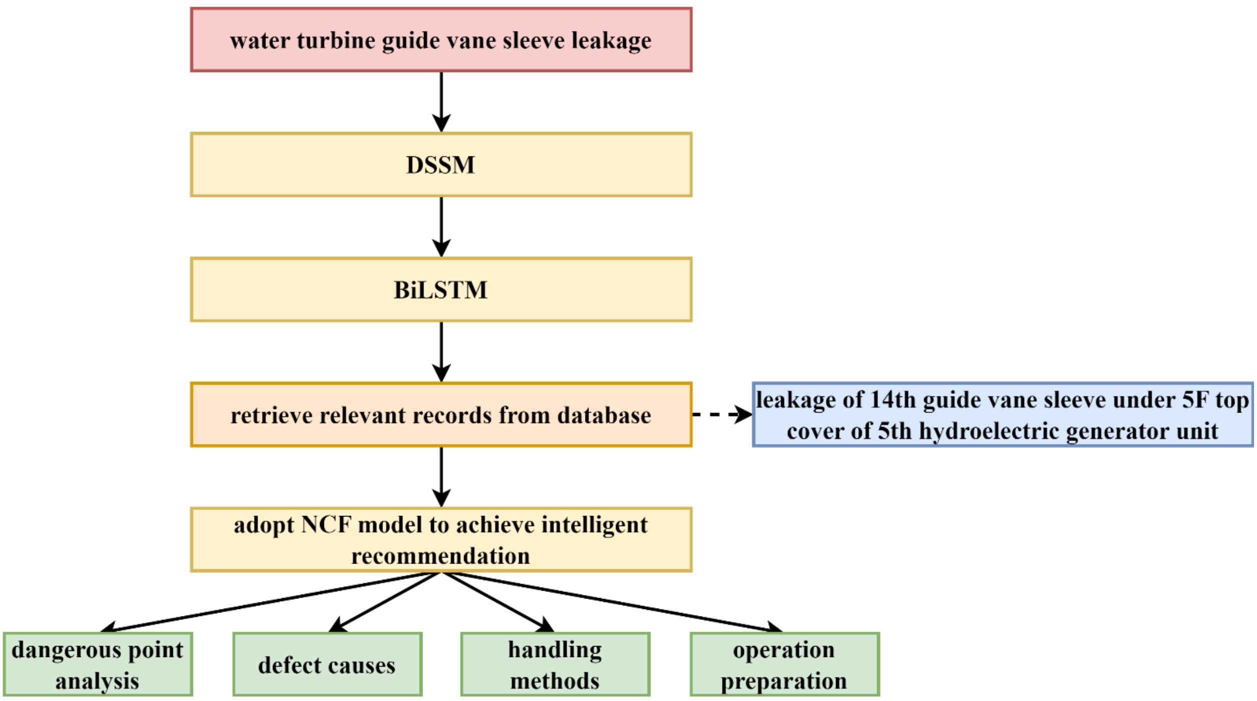



**Figure 6.** The auxiliary decision-making platform carried out intelligent query and recommendation.

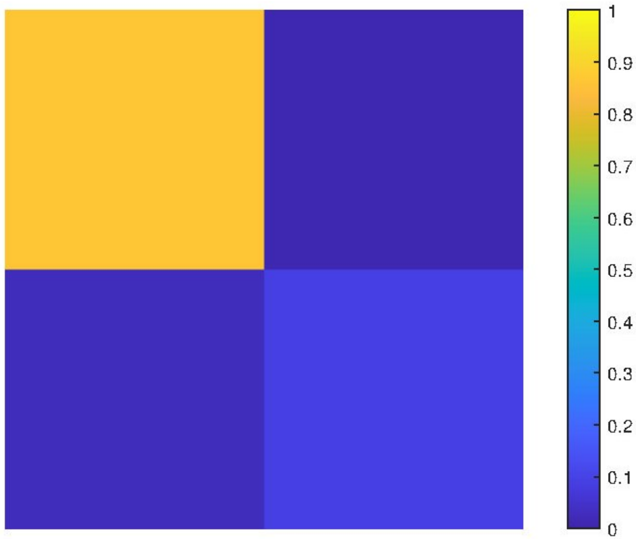
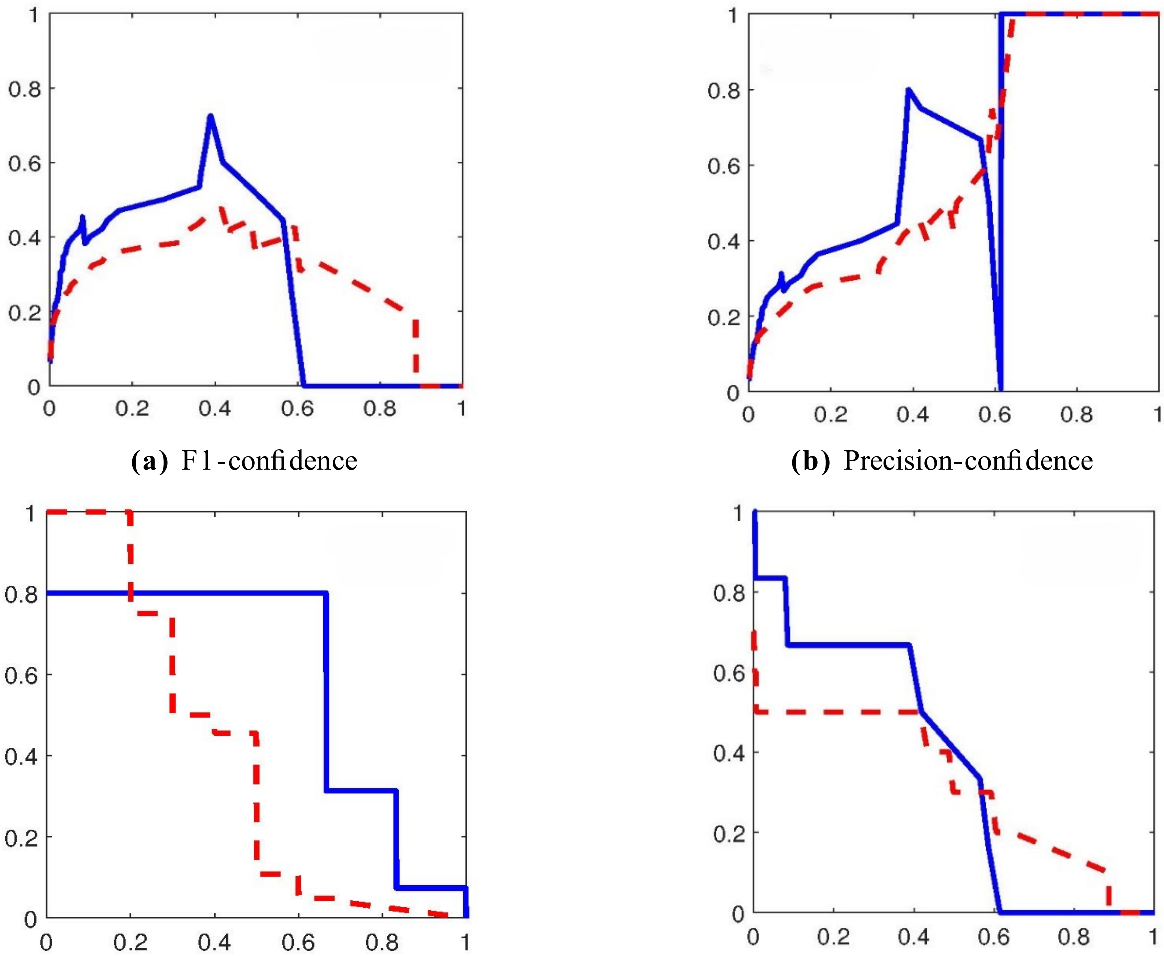



**Figure 7.** Normalized confusion matrix.




**(a)** F1-confidence

**(b)** Precision-confidence

**(c)** Precision-recall

**(d)** Recall-confidence

**Figure 8.** F1-confidence, precision-confidence, precision-recall and recall-confidence curves.

## 5. Conclusions

To improve the safety management level of the hydro-power units, the present article provides a frame- work of intelligent query and auxiliary decision-making in the traditional hydro-power operations, making knowledge retrieval and recommendation convenient. The auxiliary decision-making platform is based on the natural language processing technologies, which is composed of three parts, namely, deep semantic similarity model, bidirectional long short-term memory network model and neural collaborative filtering algorithm. The deep semantic similarity model is to achieve intelligent retrieval of textual materials related to the hydro-power operations, the long short-term memory network model is to capture sentence representations of a large amount of textual materials related to the hydro-power operations, and the neural collaborative filtering algorithm is to achieve the intelligent recommendation of the hydro-power operations. To effectively support the safety management decisions, extracting valuable information from a large amount of textual materials related to the hydro-power operations is important. To validate the framework, a case study is con- ducted, and the auxiliary decision-making platform can provide the user the relevant knowledge guidance to the problem, including defect causes, handling methods, dangerous point analysis and operation preparation.

To improve the level of engineering quality and economic benefits, the auxiliary decision-making platform construction is necessary. Firstly, various internal archives and documents are unified, achieving intelligent retrieval technology for the hydro-power operations. Moreover, via the auxiliary decision-making platform, the current situation introduction, cause analysis, handling methods and operation preparation are timely and correctly provided, making the troubleshooting and disposal more efficient, as well as avoiding the human mis-operation. However, some limitations of the auxiliary decision-making platform should be pointed out. To make the auxiliary decision-making platform perform well, a large amount of textual materials related to the hydro-power operations are necessary. At the same time, the dictionary should include a large number of named entities with diverse forms of expression, such as equipment names, equipment parts and defects, which is time-consuming. Moreover, the problematic text tends to be colloquial and does not fully follow the grammatical structure, resulting in the inability to find the central word through syntactic analysis methods and perform structural division. Thus, some expert experience should be introduced to correct the problematic text.

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**Availability of data and materials:** The experimental data used to support the finding of the present study is available from the corresponding author upon request.

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