The task of assessing the risk in the operation of a complex free formal system

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Abstract. The article discusses the use of a vaguely defined knowledge base and neural networks for risk assessment when using complex poorly formalized systems. An example of the risk assessment task is the operation of a storage facility for the transport or storage of industrial products. Consideration of a fire with different parameters is required as an anomalous external influence. The storage response, measured by the assessment of the safety of the content and its non-penetration into the external environment, can vary depending on the current state of the system, for example, the degree of possible damage in emergency conditions.

1. Introduction

Complex, loosely formalized systems with external factors can exhibit a variety of non-linear behavior. The task of information modeling when assessing the risk to an object in external immersion is to predict its behavior in normal and abnormal conditions.

Consider a relatively simple and practical model based on storage measurements under various fire conditions. In fact, the model built was based on numerical modeling rather than real data. This does not, however, reduce the value of the review, as numerical calculations manage to account for a wide range of fires for the same store [1, 2].

Uncertainty in the coefficients describing the thermal properties of the materials, as well as numerical effects, make a noise in the data used, bringing the modeling conditions closer to the real ones. In the current practice of neural network modeling data of this kind are called realistic (as opposed to artificial and real data).

The database of collected data contains 8 parameters describing storage and fire conditions.

Fire parameters include two coordinates of the flame area, the diameter of the area, the temperature of the fire and its duration.
The two output variables are the maximum value of the temperature inside the storage during the entire fire, as well as the length of time during which the temperature inside the storage exceeded a certain threshold value corresponding to the critical level of possible damage to the contents of the storage [3,4].

The information model of the storage response was based on a network of counter-distribution and a multi-layered network with training on the method of reverse spreading the error. Direct, reverse and combined tasks were considered.

2. Results and discussion

To solve this problem, let’s look at the class of adaptive networks functionally equivalent to fuzzy reasoning systems.

Below are the architecture and rules of operation of each layer of the neuro-fuzzy network.

The neuro-fuzzy network implements Sugeno’s fuzzy output system in the form of a five-layer neural network of direct signal transmission.

The first layer is the thermals of input variables;

The second layer is antecedents (messages) of fuzzy rules;

The third layer is the normalization of the degrees of compliance;

The fourth layer is the conclusion of the rules;

The fifth layer is the aggregation of results obtained by different rules [5,6].

The knowledge base of such a system contains two fuzzy if-then rules of the Takagi-Sugeno type:

Layer 1: Each node of this layer is an adaptive node with the following node function:

$$O_i^1 = \mu_{A_i}(x),$$

where $x$ - node input, $A_i$ - linguistic variable associated with this node function. In other words, $O_i^1$ - variable membership function $A_i$, determining the degree to which this $x$ satisfies $A_i$. Normally, as a $\mu_{A_i}(x)$ the bell-shaped function is chosen:

$$\mu_{A_i}(x) = \frac{1}{1 + \left(\frac{x-c_i}{a_i b_i}\right)^{2b_i}},$$

where $\{a_i, b_i, c_i\}$ - set of parameters for this layer. The parameters of this layer refer to the so-called premise parameters.

Layer 2: Each node of this layer is a fixed node that multiplies input signals, and the output value of the node is the weight of some rule:

$$\omega_i = \mu_{A_i}(x) \times \mu_{B_i}(x), \quad i = \overline{1,n}.$$ 

Layer 3: Each $i$ - node of this layer determines the ratio of weight $i$-rule to the sum of the weights of all rules:

$$\overline{\omega_i} = \frac{\omega_i}{\sum_{j=1}^{n} \omega_j}, \quad i = \overline{1,n}.$$ 

The 3rd layer output signals are called normalized weights.

Layer 4: The nodes of this layer are defined by linear (for the Sugeno-type model) functions of output variables:

$$O_i^4 = \overline{\omega_i} f_i, \quad i = \overline{1,n}.$$
where $\bar{\omega}_i$ - third layer output signal of this layer (so-called output parameters).

Layer 5: The only node in this layer is a fixed node, which calculates the full output value of the adaptive network as the sum of all inputs:

$$O^5 = \sum_i \bar{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i}.$$

Typical training procedures for neural networks can be used to configure a neural fuzzy network, since it uses only differentiable functions. Typically, a combination of backpropagation and least squares gradient descent is used. The backpropagation algorithm adjusts the parameters of the rule antecedents, i.e. membership functions. The coefficients of rule conclusions are estimated by the least square’s method, since they are linearly related to the network output. Each iteration of the tuning procedure is performed in two stages [7].

At the first stage, a training sample is fed to the inputs, and the optimal parameters of the nodes of the fourth layer are found by the discrepancy between the desired and actual network behavior by the iterative least square’s method. At the second stage, the residual is transmitted from the network output to the inputs, and the parameters of the nodes of the first layer are modified by the error back propagation method. In this case, the coefficients of rule conclusions found at the first stage do not change. The iterative tuning procedure continues as long as the residual exceeds a predetermined value.

The neural network for the direct problem contains 6 inputs and 2 estimated outputs. The direct task for this application will answer the following questions:

- What will be the maximum temperature inside the storage with the known parameters of the fire?
- Does the internal temperature exceed the set critical value or not? If so, how long will the system be in critical conditions?
- Which corresponds to the greater risk of damage to the contents of the storage facility: a short but high temperature fire, or a prolonged moderate heat load?

The inverse problem corresponds to the estimation of the parameters of external influence from the measurements of the system response [8,9]. The thermal regime inside the storage is controlled by temperature sensors. Reverse model queries are diagnostic in nature:

- What is the duration and temperature of the flame?
- How far from the store did the fire occur and what was the size of the flame?
- What is the actual extent of damage to the storage facility?

The most interesting combined problem considers some of the parameters as known, and the rest as unknown. When training a neural network for a combined task, the set of variables used as input and output can partially or completely overlap.

The combined task answers all requests of the direct and inverse tasks, but has additional capabilities:

- Assessment of the state of the storage by external and internal dimensions.
- What are the most severe fire conditions under which the storehouse still retains its contents?

The reverse and combined tasks should be considered as ill-posed.

The range of possible values of the physical parameters was limited by the maximum fire temperatures (achieved when burning the enriched fuel), the distances and dimensions of the flame at which the heat transfer to the storage leads to a typical threshold for fire alarm sensors. The duration of the fire was limited to 1 hour [10-11].

At the first stage, the proposed technology investigated the correctness of the problem over the entire range of parameter values. For this purpose, seven parameters were selected sequentially out of eight
included in the model. These parameters were considered known, and the remaining eighth parameter was considered unknown. Thus, each of the parameters was tested in turn as unknown. During modeling, the learning error of a multilayer reverse propagation network was determined [12]. All calculations were carried out for large neural networks, so the resulting error is associated only with the incorrectness of the problem.

Numerical modeling showed that both direct problems, when the output variables of the problem were considered unknown - the maximum temperature inside the storage facility and the duration of the period when the specified temperature level was exceeded, are correctly posed. The value of the learning error did not exceed 1% [13-15]. In contrast, all six inverse / combined problems turned out to be incorrect with a learning error of 25-35%. This result is fundamental for planning subsequent experiments with the information model: attempts to evaluate the solution of inverse problems over the entire range of values (without differential analysis of correctness) will be unsuccessful [16].

To select an effective neural network model for a (correctly posed) direct problem, the dependence of the learning and generalization error on the volume of data used in training and the number of free weight parameters in the neural network was studied.

Applications require a compact and fast neural network model that is easy to train and has a low generalization error. These requirements are somewhat contradictory; therefore, the experience of a large number of computer experiments was summarized. The following features were found:

- The degree of generalization improves only by 50-80% with an increase in the volume of the training database (and, accordingly, training costs) 3-4 times. Hence, large amounts of data can be avoided.
- The use of neural networks with the number of free parameters close to the number of records in the database leads to a generalization error 10 times greater than the training error. In this case, the predictive capabilities of the system are not great.
- A suitable neural network for a direct task is characterized by 10-15 neurons on a hidden layer with up to 100 synaptic connections, trained on a database of 300-500 records, it shows a training error of 2-3% with a generalization error of up to 5%.

Based on the selected neural network model, the neural network was trained and a number of information requests to it were investigated.

3. Conclusion

The first series of queries was performed to determine the temperature range and fire durations at which the storage contents do not overheat. Fires occurring in the immediate vicinity of the storage facility and having a diameter of up to 15 m were considered. These results, when applied to specific storage samples, can form the basis of technical requirements for fire services. The second problem is related to the study of the dependence of the thermal conditions inside the system on the distance to the epicenter of the fire.

It is interesting to note that there is some intermediate value of the distance to the fire, at which the heat transfer to the storage is maximum. On the basis of this model, many other practical issues can be investigated. Since the neural network only works in the mode of direct unloaded operation when analyzing queries, the query execution time is minimal.

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