Intellectual technologies in the problems of thermal power engineering control: formalization of fuzzy information processing results using the artificial intelligence methodology

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Abstract. Exploitation conditions of power stations in variable modes and related changes of their technical state actualized problems of creating models for decision-making and state recognition basing on diagnostics using the fuzzy logic for identification their state and managing recovering processes. There is no unified methodological approach for obtaining the relevant information is a case of fuzziness and inhomogeneity of the raw information about the equipment state. The existing methods for extracting knowledge are usually unable to provide the correspondence between of the aggregates model parameters and the actual object state. The switchover of the power engineering from the preventive repair to the one, which is implemented according to the actual technical state, increased the responsibility of those who estimate the volume and the duration of the work. It may lead to inadequacy of the diagnostics and the decision-making models if corresponding methodological preparations do not take fuzziness into account, because the nature of the state information is of this kind. In this paper, we introduce a new model which formalizes the equipment state using not only exact information, but fuzzy as well. This model is more adequate to the actual state, than traditional analogs, and may be used in order to increase the efficiency and the service period of the power installations.

1. Introduction
After a long recession caused by the USSR disintegration, thermal power engineering in Russia is now recovering and can be characterized by a gradual increase of exploited resources and production capacities. At the same time, the most of the installed equipment is rather old and its planned service period has been expired. As a result, the equipment is often functioning in non-stable or emergency states and needs to be either carefully controlled or repaired. In order to be effective, these activities should be preceded by accurate diagnostics. However, traditional diagnostic models are based on the conservative forms of technical maintenance which suppose that all repairs are planned and precautionary. Such repairs provide satisfactory results when the equipment is exploited within its normal service period and have little effect when it is old. The reason is that traditional diagnostic models adequately describe only stable equipment states becoming rigid when it is exhausted. Because of these reasons, the thermal power engineering switched from the preventive equipment repair (or decreasing its loading) towards those, which
is implemented according to the actual technical state. It drastically increased the responsibility of those who estimate the volume and the duration of the work.

In order to be more adequate, the diagnostic models should take into account all peculiarities, natural for aging aggregates. The main problem is caused by the fact that it is very hard to obtain the relevant information about the equipment when it is in non-stable or nearly emergent state. The long exploitation period leads to accumulation the uncertainty which is not assumed in the basic diagnostic models. The processes in the power stations may be very quick and information about them is vague. Indicators are noisy or floating because of many impact factors different in their nature.

Instead of considering such noisiness as an obstacle we can use it as an additional source of information about the equipment and supplement the model with this information and create a new more adequate one. A very efficient instrument for measuring such noisy information is fuzzy logic and adjacent methods. Inaccurate and noisy values are considered as elements of some parametric spaces of fuzzy numbers drawn from heuristic, linguistic, expert and stochastic data. This knowledge about the state's uncertainty obtained after the functional diagnostics of various power stations, increases model's completeness allowing to recognize and eliminate the developing defects quickly and improve the aggregates efficiency.

The main investigated object in this paper is the state diagnostic processes of the functioning thermal power stations. The main goal of this work consists in developing the intelligent diagnostic systems which employ fuzzy information in order to deal with complex equipment in thermal power engineering. In this paper, we develop a new concept of maintenance and exploitation of thermal power installations according to their actual technical state instead of planned and precautionary service. Our results support the idea of employing the integral approaches and methods which exploit various information and computation instruments as a main mean when making decision. We widely use fuzzy information and employ artificial intelligence methodology in order to formalize it. As the result, we are able to improve the quality of the models of identification, forecasting, decision-making and optimization during the diagnostics.

Our results contribute into creating a new integral expert environment and to represent the controlled object via the model, adequate to its actual state, which is embedded into management contour (taking a thermal power station turbine as an example). Evaluation and identification of various parameters and characteristics of actual processes following by their comparison with normal indications allow to notice any significant deviations and quickly make necessary decisions in order to preserve or improve the thermal power station efficiency.

Despite the presence of various contemporary diagnostic technologies, it is impossible to obtain a comprehensive picture about the equipment state without using the extensive experience and practical knowledge of the personnel and their intellectual abilities. For being useful during the decision-making process, such experience and knowledge should be easily accessible, what may be achieved if they are formalized and stored with the help of computers. Thus, it is very important to upgrade traditional diagnostic methods as well as creating new intellectual means and techniques. Accumulating and generalization of classical as well as fuzzy knowledge and experience and their formalization about such complex systems and power stations (especially in the case of aging equipment and incompleteness of information about the recourse) require intellectual information systems, which are able to implement search procedures, managing and control intelligently.

The fuzzy technologies of information systems, which are used in this paper, are based on Zadeh’s fuzzy sets theory [1], classical Kantor’s theory [2], fuzzy measure thesis due to Barona [3] and trusting function features due to Shafer [4]. The mechanism of making the correspondence between the recognized objects (see Atkinson [5]) is done analogously to the human central cerebral system due to Anokhin [6]. For the knowledge representation we use operations research
theory thesis about the closest neighbour as employing the axioms of the affinity of topological space in the observations set. At that, the modelled object is moving through the stationary trajectory with non-stationary perturbations and nature states in the real-time scale. The objects formalizations are considered as per Morris [7] as semantic and pragmatic.

2. Methodology of representing the plant as a complex mechanism

In this paper, we develop a new progressive approach to powerplant installations diagnostics. We do not consider the installation as an aggregate of the elements vulnerable to different breakage [8, 9]. Instead, the power plant installation is considered as a whole, and the process is modelled at the intersection of four state fields: fluctuations, temperature, modes and time, which define its diagnostic state. The complete description is done by the following parameters.

$$\Sigma = (X, Y, \Omega, A, B, I, J_p, Z, D, t, M_{PC}, Q, W_\Sigma, G_\Sigma, \eta_\Phi, \phi_\Phi),$$

where $X$ — the inputs, $Y$ — the outputs, $\Omega$ — the external environment (power consumers, the whole power system, environment etc.), $A$ and $B$ — the internal object structure, $I$ — information about the object state, $Z$ — the features of the state, $J_p$ — attributes of the working capacity, $D$ — attributes of the accident, $Q$ — values of the states forming operators, $W_\Sigma$ — source data processing operator, $G_\Sigma$ — data transformation operator, $\eta_\Phi$ — functional relation of output from time moments at the input and output, $\phi_\Phi$ — functional relation of attributes from time moments at the input and output.

Let $\tilde{F}_i$ be the set of classes which is obtained after the preliminary analysis and describe the technical state of the object which is controlled by the hybrid system, $F = \{\tilde{F}_i\}$, $i = 1, r$. This set is mapped as a fuzzy set with the corresponding membership functions $\mu(F_i)$, such as

$$\tilde{F}_i = \frac{\sum_{i=1}^{r} \mu(F_i)}{F_i}.$$

The relational equation for the power installation considered as the complex mechanism for the static case is as follows:

$$Y_j = \phi_j(\alpha_1, \alpha_2, \ldots, \alpha_m, x_1, x_2, \ldots, x_n), \quad j = \overline{1, J}.$$

For the dynamic case this equation looks like

$$Y_{j,t} = \phi_j(\alpha_1, \alpha_2, \ldots, \alpha_m, x_{1,t}, x_{2,t}, \ldots, x_{n,t}), \quad j = \overline{1, J}.$$

Then the controlled object state may be represented as a subset of the logical Descartes product of the two spaces $C \subset X \times Y$, where $C$ is the state, $X = \{x_i\}$ is the set of input parameters values, $Y = \{y_i\}$ is the set of output parameters values (see fig. 1).

Due to uncertainty of the knowledge about the object, we use the fuzzy model of its description according to the given structure. Further, the structure of this fuzzy model we represent as an aggregate of term-sets composed of the linguistic input and output variables with the corresponding membership functions and an implication variant. All these parameters are united under the control rule of how does the system work.

If there exist uncertain knowledge about the object, its model is depicted via a fuzzy equation $B = A \circ R$, where $\text{card}(A) + \text{card}(B) = \aleph$ (aleph-zero) is the system dimension; $\tilde{A} \subset A \subset X$, $\tilde{B} \subset B \subset Y$; $A = \sum \mu(\alpha)/\alpha$ is the fuzzy input set; $\tilde{B} = \sum \mu(\beta)/\beta$ is the fuzzy output set; $\alpha, \beta$ — elements of the linguistic variables term-sets; $\mu(\alpha), \mu(\beta)$ — their corresponding membership
Figure 1. Control zones of efficient mechanism (considered as a hybrid system) performance; here $[X_1]$ — vector of the boundary parameters of the mechanism performance state; $[X_2]$ — vector of the observed state parameters.

functions; $\circ$ — Zadeh maximin composition [1, 10, 11, 12]; $R$ — the fuzzy relation $X \times Y$ in the form of the control rule

"A : IF ... THEN ...," which is expressed as the matrix of the fuzzy relation with the following elements:

$$
\mu(\alpha, \beta) = \max_{\alpha} \min_{\beta} \{\mu(\alpha), \mu(\alpha, \beta)\},
$$

where "$\int$" — the operation of combination the one-element fuzzy sets $\mu_A(x)|x$ and $\mu_B(y)|y$; "$\rightarrow$" — the variant of implication; $\land$ — the logical minimum.

Using the membership functions, the model equation (1) can be written as follows:

$$
\mu(\alpha, \beta) = \max_{\alpha} \min_{\beta} \{\mu(\alpha), \mu(\alpha, \beta)\}.
$$

The technical state of the mechanism is evaluated according to the set of diagnostic features $Z = \{Z_j\}, \ j = 1, n$, represented in the form of fuzzy-relation matrixes $R_i^e, \ i = 1, m$, which consists of model parameters (in general case, it may be $m \neq n$ because the relation between $Z$ and $R$ is not mutually unequivocal).

The set of technical states classes $F$ and the set of diagnostic features $Z$ are related according to some rule $R^* : F \rightarrow Z$, what means that every technical state is mirrored in the corresponding diagnostic features implementations. Further, this relation is formalized in the form of the corresponding relational matrix. Assuming that the obtained relation is fuzzy, we represent it via the fuzzy-relational matrix $R^*$ with elements, which are identified by experts knowledge. In this case, the set of diagnostic features $Z$ will be also fuzzy:

$$
\tilde{Z} = \sum \mu_j^Z/Z_j, \ \tilde{Z} = F \circ R^*.
$$

(2)
Figure 2. Ultimate power installation diagnosis in the graphical form (an \( i j \)-th confidence interval).

Here \( \mu^Z_j \) — operators for forming the fuzzy set \( \tilde{Z} \), which are defined by calculating the membership functions as follows:

\[
\mu^Z_j = (|z_j - z^*|),
\]

where \( | \cdot | \) — the distance between the a priori defined values of the diagnostic features \( z_j \) and their assessments. We estimate solutions efficiency with the help of the following function:

\[
M^F_{I} = \{ \mu^F_{I}, \mu^{F*}_{I} \},
\]

where \( M^F_{I} \) — a generalized membership function for the \( I \)-th technical state of the class \( F \) by the parameter \( M \) (this parameter defines the power of the installation, net-efficiency, specific heat expenditure by kw/h etc.): \( \mu^F_{I} \) — a priori membership function; \( \mu^{F*}_{I} \) — a posteriori membership function, which is obtained according to the measurement results by solving inverse to the (2) equation. The maximal efficiency is determined according to the function

\[
M^F_{I} \rightarrow \max \{ \min \{ F^* \} \} \quad \text{eq. (3)}
\]

So, the introduced formalization is intended for determining the input data in order to solve the extreme problem of evaluating the technical state. The solution of the state evaluating problem is obtained according to the goal function (3) in the following form:

\[
F^* = \text{opt}\{ \max M^F_{I}, \min M^{F*}_{I} \}
\]

Further, we construct controlling rules, which reflect the admissible range of the input and output parameters changes. As the result, we obtain 400 product rules for the knowledge database; their general view is as follows:

\[
IF u IS u_{\min}, \quad THEN v IS v_{\max}, \quad OR \quad IF u IS u_{\max}, \quad THEN v IS v_{\min}.
\]
This condition poses certain requirements on the parameters measurement procedure (during the state diagnostics). These parameters should be measured in the definition area of the boundary terms of the linguistic variables as close to the edges of the regulation range as possible (on the edges of the power characteristic intervals).

The information gathered during the diagnostic experiments while the process of power installations control and assessment, is presented in the graphical form (see fig. 2). Here $[X_i]$ — the vector of the observed parameters and the experts assessments; $[X_j]$ — the boundary parameters values; 1 — the boundaries of the isolated areas; 2 — the stable states; 3 — zones of the unstable installation states; 4 — points in the states space; 5 — observation points, 6 — the regression hypercurve, 7,8 — the edges of the boundary installation states; 9 — the area of information uncertainty; 10 — fuzzy areas of the expert information; $[\text{min} \div \text{max}]$ — parameters of the experimental confidence interval at the observation interval. The criteria of the working capacity consists in the fact that the diagnostic parameter hits the admission area, i.e. the confidence interval.

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