The artificial intelligence methods testing in case of engineering diagnostics system creation of the synchronous machines

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Abstract. Due to the lack of the exact mathematical processes description for internal faults diagnosis of synchronous machine rotor winding. To solve the problem of concurrent processing of the indirect diagnostic signs complex connected with the concrete type of multiple disabilities. It is the author's opinion that such problem is necessary to solve by artificial intelligence systems accepted in the theory and practice. The architecture of intelligent diagnostic system and the technical condition forecast of the synchronous machine rotor winding on the basis of the fuzzy logic mathematical tool are offered. Diagnosing reliability of and selectivity support determination of synchronous machine rotor winding defect category is reached by complex conjugation of separation of diagnostic information sensitive methods on the basis of intellectual digital signal processing methods. It is proved experimentally that the fuzzy logic using provided diagnosing reliability of synchronous machine rotor winding turn-to-turn short-circuit at the 1,5% level of rotor pole winding Visualization of all making decision stages about the existence and defect type was made in Fuzzy Logic Toolbox software package.

1. Introduction
The high performance system synchronous machines engineering diagnostics creation considering features of their construction and meeting the modern demand for technical and economic performances. It effectively works autonomous and as a part of automatic process control systems. It represents an urgent scientific and technical problem. The purpose of this paper consists of the allocation intellectual method development of selective diagnostic information about the turn-to-turn short-circuits on the basis of the fuzzy logic mathematical tool.

Using sensitive data to turn-to-turn short-circuit methods and the fuzzy logic mathematical tool to adjust the fuzzy inference algorithm for the flaw detection of the rotor winding turn-to-turn short-circuits. For this purpose the informative indirect indicators of turn-to-turn short-circuit in the alternator rotor, according to authors it is necessary to use regulating performance deflection and rotational frequency vibration level.

2. The research methods and techniques
Fuzzy logic using in the performance of a problem of selective flaw detection is based on interrelation between the defect and diagnostic signs allocated from the set of observable parameters. At the same time it is necessary to consider that each component is comprised of the element of fuzziness and also owing to features of obtaining primary information (a hindrance, a measurement error, etc.) and the
conclusion could not be absolute ("accurate") [1]. Various parameters deviations and defects arising in of diagnostics object can influence the allocated diagnostic sign at the same time. At the same time defect influence on each of diagnostic signs can vary from any strong influence to total absence. For definition of extent of this influence in diagnostic system, the linguistic values of the validity presented to the table 1 are used.

Table 1. The linguistic values

| The symbolic notation | Interpretation |
|-----------------------|---------------|
| NB (Negative Big)     | Existence of steady diagnostic signs of considerable defect development |
| NM (Negative Middle)  | Steady diagnostic defect signs existence |
| NS (Negative Small)   | Existence of diagnostic signs of accident in a primitive state of development |
| PS (Positive Small)   | The deviation of diagnostic signs at the admissible level |
| PB (Positive Big)     | All parameters at the standard level |

Figure 1. Turn-to-turn short-circuit diagnostic expert system of synchronous machine rotor winding on the basis of fuzzy logic.

It is necessary to set linguistic variables to use linguistic truth values. The linguistic variable is the variable which accepts values in the form of words and phrases of the natural language just like the algebraic variable accepts numerical values. The linguistic variable separate value is named as linguistic term. Term is a membership function of some set defined in the specified interval [2]. Each term of the linguistic variable can be considered as some fuzzy subset determined by the basic variable. For example, for the description of vibration existence we use Xf "Vibration", for the description of regulating performance deflection level of alternator we use Xp "Regulating performance deflection", for the description of turn-to-turn short-circuit existence we use "Turn-to-turn short-circuit". Let's say that these variables can accept values according to table 1:
Intelligent diagnostic system work of technical condition of alternator rotor on the basis of fuzzy logic is composed of two stages Pic. 1 [2]:

1) Fazzifikation is a transformation of input absolute values in linguistic value;
2) The logical conclusion with previously made knowledge base using.

Input terms are formed by the expert on the basis of the knowledge and sensitivity to defect of diagnostic signs.

The allocation method sensitivity of a diagnostic sign of turn-to-turn short-circuit in the alternator rotor winding based on the analysis of regulating performance deflection in 2,75 … 3% of winding [3,6,9,11] has experimentally been proved. From there the following key values for the term "Regulating performance deflection" have been defined:

![Figure 2. Input terms: "Regulating performance deflection"](image_url)

When determining the term "Vibration" we recognize that this sign is confirming and has no accurate limit values. For vibration there is a standard value. The upward bias or downward bias needs to be perceived as emergence of changes in the machine, which can be a rotor winding defect. On that basis terms for "Vibration" have been defined:

![Figure 3. Input terms "Vibration"](image_url)

For output variables it is also necessary to create terms. Terms for the output variable "Turn-to-turn short-circuit" proceeding from five linguistic values of a defect status, the table 1, we set the following terms:
The interrelation between the diagnostic signs and defects is formed in reliance on rule base. Receiving the fuzzy inference is made on a specific algorithm. Basis for making operation of the fuzzy logical inference is the rule base containing fuzzy statements like "IF" - "THAT" and membership function to linguistic terms.

For the flaw detection "Turn-to-turn short-circuit" the rule base has been created, the table 2. [4,5].

Besides the rule base can be presented in the form of the structured text:

RULE_1: IF "Regulating performance deflection = PB" And "Vibration = PB" THAT "Turn-to-turn short-circuit = PB" (F1);

RULE_2: IF "Regulating performance deflection = PS" And "Vibration = PB" THAT "Turn-to-turn short-circuit = PS" (F2);

RULE_15: IF "Regulating performance deflection = PB" And "Vibration = NB" THAT "Turn-to-turn short-circuit = PS" (F15).

\[
\begin{align*}
R.1 & \text{ IF } X_p \text{ is PB And } X_f \text{ is PB THAT } Y \text{ is PB (F1)}; \\
R.2 & \text{ IF } X_p \text{ is PS And } X_f \text{ is PB THAT } Y \text{ is PS (F2)}; \\
R.3 & \text{ IF } X_p \text{ is PB And } X_f \text{ is NB THAT } Y \text{ is PS (F15)}. \\
\end{align*}
\]

where \( F_i \) - reliability expert assessment of the existing rule. This coefficient defines the importance of the rule or confidence in truth degree of the decision received from fuzzy rules. [10]

**Table 2. The rule base**

| №  | Rejection of the regulating performance | Vibration | Turn-to-turn short-circuit |
|----|----------------------------------------|-----------|---------------------------|
| 1  | PB                                     | PB        | PB                        |
| 2  | PS                                     | PB        | PS                        |
| 3  | NS                                     | PB        | PS                        |
| 4  | NM                                     | PB        | PS                        |
| 5  | NB                                     | PB        | PS                        |
| 6  | PB                                     | NS        | PB                        |
| 7  | PS                                     | NS        | PS                        |
| 8  | NS                                     | NS        | NS                        |
| 9  | NM                                     | NS        | NM                        |
| 10 | NB                                     | NS        | NB                        |
| 11 | PS                                     | NB        | PS                        |
| 12 | NS                                     | NB        | NS                        |
| 13 | NM                                     | NB        | NM                        |
| 14 | NB                                     | NB        | NB                        |
| 15 | PB                                     | NB        | PS                        |
Rules from 1 to 15 have the compound conclusion. As the logic connective is presented by operator "And", that membership function of the statement in the conclusion is  
\[ \mu' = \min\{\mu(x_1), \mu(x_2)\} \]

Then all indistinct sets assigned for each term of each output linguistic variable integrate together and the single indistinct set, value for each removed linguistic variable [7 - 11] is created.

3. Experimental corroboration
In a generator charge coil the GAB-4-T/230 the tee off 4% of winding loops has been created. At their short circuit the diagnostic system has given result in the form of the fuzzy conclusion NS (Negative small, the existence of accident diagnostic signs in a primitive state of development, table 1) which is to say that steady sign of turn-to-turn short-circuit exists. Increase in vibration at 50% eccentricity was observed, but the system hasn't issued the conclusion about the existence of turn-to-turn short-circuit that means that the system works logically [12 – 21].

4. Conclusion
The diagnostic system of rotor equipment technical condition in this paper was developed, on the basis of a fuzzy logic which is capable to separate selectively diagnostic signs of the eccentricity and synchronous generator rotor winding turn-to-turn short-circuits.

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