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SECTION 8.
INFORMATICS, COMPUTER ENGINEERING AND AUTOMATION

8.1 Decision systems in the design of electrical machines

Modern decision-making systems are constantly evolving. Today, it is difficult to imagine any branch of industrial production without the use of artificial intelligence systems capable of making decisions. On the one hand, it is cost-effective, and on the other hand, significantly improves the quality of process management. The process of designing electric machines is no exception. The use of a decision-making system to calculate the heat and mass transfer processes of electric motors makes it possible to reduce the complexity of this process.

Recently, researchers from different countries are paying more and more attention to the development and use of active decision-making systems in various branches of industrial production. According to the traditional classification, decision-making systems are divided into static and dynamic. But today in foreign periodicals a class of active decision-making systems is distinguished [178-182]. Active decision-making systems differ from dynamic decision-making systems by the participation of the human factor in the control loop. Thus, if in a dynamic decision-making system the share of the human operator in the decision-making process may be 30 to 50%, then in active decision-making systems this percentage of participation is reduced to a minimum of 5 to 10% [180,181].

Obviously, this approach to the organization of an active decision-making system and its implementation in the management process must take into account a number of factors that contribute to the qualitative improvement of its functioning [181-184]:

- the presence of close information interaction of the management system with the environment with the use of specially organized information communication channels;

- fundamental openness of the system in order to increase its intelligence and improve its behavior;
- availability of mechanisms for forecasting changes in the environment and system behavior;
- construction of a control system based on a multilevel hierarchical structure that satisfies the following rule: as the rank of the hierarchy increases, the intelligence of the system increases and the requirements for its accuracy decrease and vice versa;
- preservation of functioning in case of partial severance of ties or loss of control influences from the higher levels of the hierarchy of the control system.

In other words, an active decision-making system should be easily rebuilt (adapted) to external changes,

for which it requires the presence of the following subordinate levels [182-184]:

- training;
- self-organization (restructuring);
- forecast (forecast) of events (situations);
- work with event databases (databases) (DB) and knowledge (DB);
- decision making;
- planning of operations on realization of the formed decision;
- adaptations;
- performing.

In this case, the first five of these form the strategic level of an active decision-making system, the rest perform its tactical functions. The functional diagram of the active decision-making system is shown in Fig. 59.

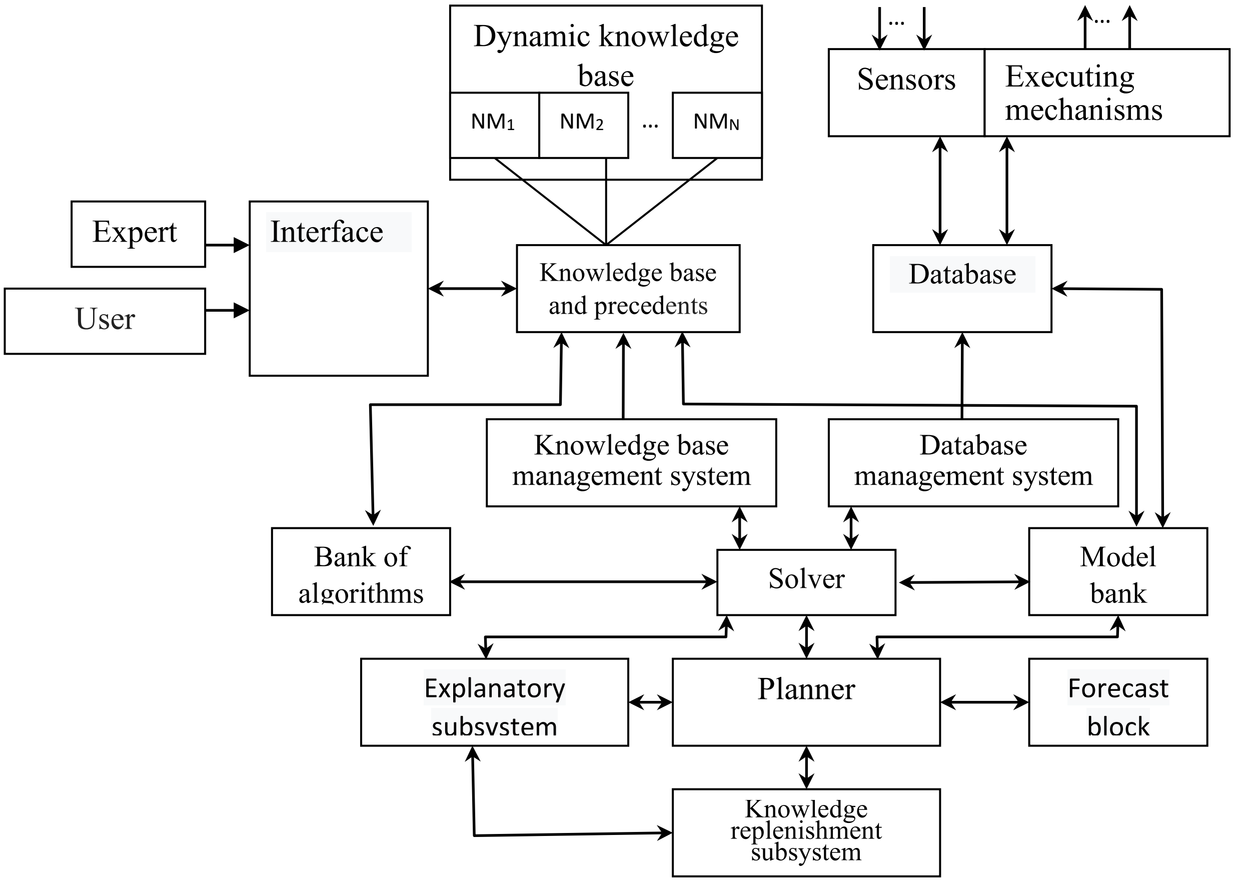

Figure 59. The process of interaction of subsystems of the active decision-making system.

The solver (logical inference machine) of the active decision-making system is complex, because along with the known methods and knowledge (predicate logic, semantic networks, frames, product inference) in the active decision-making system can be used methods based on soft calculations (fuzzy logic (NL), genetic algorithms (GA), neural networks (NM), cognitive networks (CM), probabilistic derivation (IU) (heuristics). horytmiv models and increased mobility computing process solver active decision-making system and, consequently, the quality pryymayemyh decisions. With a powerful solver, an active decision-making system adapts relatively easily to an external dynamic model, allowing you to set and solve direct, inverse, and mixed tasks.

An active decision-making system allows real-time modeling, forecasting and evaluation of the efficiency of the electric motor.

The knowledge bases of the active decision-making system contain declarative and procedural knowledge. Procedural bases include conceptual knowledge bases (BAS): concepts in the form of formulas, dependencies, tables, procedures, etc. Declarative are knowledge bases (BEZ), which are descriptive (qualitative) in nature. In this case, BKZ and BEZ closely interact with each other, constantly checking for inconsistencies (redundancy) of knowledge. In the process of interaction with the object and its own heterogeneous database, an active decision-making system provides training and self-learning. Facts and knowledge are checked in real-time scanning mode. The new situation "sets" a precedent and is stored in the database. Elements of traditional modeling tools in an active decision-making system carry out:

- mathematical modeling;
- preservation of a priori and a posteriori data in the database of the active decision-making system (ascending information and research results).

Additional "flexibility" and mobility of the database in the active decision-making system is achieved by combining models of artificial intelligence and mathematical model (MM) of the studied engine. For this purpose in MM of the engine it is necessary to consider:

- requirements for MM;
- combination of deterministic and stochastic models;
- mechanisms of work with MM;
- training and formalization in an active decision-making system with verification of its adequacy.

The above allows you to increase the accuracy, reliability and correct operation of an active decision-making system.

In the process of monitoring and managing the operation of the engine, an active decision-making system is able to fully control the parameters, analyze (model) the current situation with a forecast of its development (information from sensors).

One of the classic tasks of monitoring engine parameters is a disorder (determining the trend of control data). In the general case, trend analysis allows you to control the time series formed by a sequence of values of controlled indicators, and determine the presence of a trend: changes (disorders) in this series. The value of trend analysis in modern active decision-making systems is very high, as it allows to identify defects at an early stage of their development (even if the values of controlled parameters are within acceptable limits).

Denote by $x(t)$, $t = 1,2, \dots, N,$ sequence of discrete observations

$$x(t) = f(t) + \zeta(t) \tag{1}$$

on the background of obstacles $\zeta(t)$ with zero mean and variance σ^2. We will use a set of polynomials as trend models

$$f_j(t) = \sum_{s=0}^{j-1} c_{sj} t^s, \ (j = 1,2,\dots,n), \tag{2}$$

with unknown coefficients c_{sj}, where j - model type index.

In the current assessment, model (2) is convenient to present in the form

$$f_j(t + \Delta t) = \sum_{s=0}^{j-1} f_j^{(s)}(t) \cdot \frac{\Delta t^s}{s!}, \ (j = 1,2,\dots,n), \tag{3}$$

where Δt - time counted from the current time t; $f_j^{(s)}(t)$ - s-th derivative function $f_j(t)$. We will determine the value of the function $f_j(t)$ on the sliding $x(t - N + 1), x(t - N + 2), \dots, x(t)$ voters of observations of constant volume N, which allows you to track changes in the coefficients c_{sj} models (2). Regular data correspond to the presence of a corresponding pattern.

Violation of this pattern occurs when changing the coefficients c_{sj} in (2). The task is to build a neural boundary detector (dynamic knowledge base of the active decision-making system), which allows as a result of processing observations $x(t)$ to establish the facts of violations of the law and the time of occurrence of these violations (trends).

BZ and precedents of the active decision-making system can store the following information:

- assessment of the randomness of the discrepancy between the given mathematical expectations and the sample mean (parametric methods that require knowledge of a priori information about the object, usually the standard deviation of the parameter under study);

- assessment of the affiliation of two samples of one general population (non-parametric methods that do not require a priori information, classical criteria: Halda-Abbe and its modifications [185]);

- trend analysis of controlled parameters based on recurrent neural networks. Description of the classic criteria for trend detection: Halda-Abbe; Neumann-Pearson; modified r-criterion; integral *S*-criterion can be found, for example, in [8]. A comparative evaluation of the effectiveness of trend analysis of neuro-boundary and classical criteria was performed.

A comparative study of the criteria was conducted on the basis of simulation, which allowed to check a wide range of changes, measurement errors and the intensity of the trend. The value of the controlled parameter is equal to the sum of the deterministic basis and the random normally distributed obstacle with variance ζ. The deterministic component became on the interval $[0,t_0]$, and then changes linearly with the pace $a = tg(\alpha)$ (1/s), (where a - trend intensity). During the simulation, the value a of a varied in the range $[0{,}01;1]$; and value ζ in the range $[0{,}001;1]$. In the simulation, a selective variance calculated on the stationary interval $[0,t_0]$ was used to adjust the MM.

Starting from the moment t_0, the values of the criteria were calculated and the presence of the trend was checked. The effectiveness of the criteria was assessed by the time of operation of the criteria from the beginning of the trend τ_0 by the time that corresponds to the detection of the trend $\tau_{ЗАП}$.

To solve this problem, it is necessary to implement on the basis of recurrent NM two series-connected filters - low frequency (LF) and high frequency (HF).

The woofer filter "passes" a constant component $f_j(t)$ and "cuts off" the obstacle $\zeta(t)$, and the RF filter "passes" $f_j^{(s)}(t)$ and "cuts" $f_j(t)$ and obstacle $\zeta(t)$. The implementation of woofer and RF filters based on recurrent NM is shown in Fig. 60

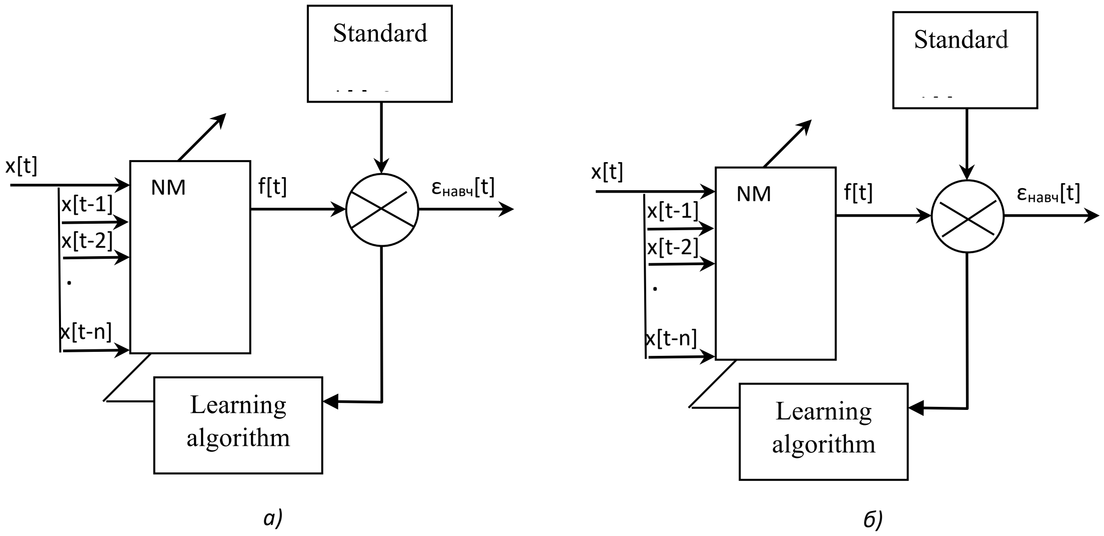

Figure 60. LF (a) and HF (b) - filters based on recurrent NM.

It is known from NM theory [186-188] that static NM architectures are able to approximate multidimensional, nonlinear static functions. Identification of dynamic systems, on the other hand, requires models with appropriate memory elements. Therefore, static full-size NMs must expand with dynamic structures. One of the possibilities of dynamic expansion is the addition of external filters that implement a dynamic model offline. Such NM with external dynamics include [186-188]:

- nonlinear models with feedback from the output;

- nonlinear models with finite impulse response; - nonlinear orthogonal models of basis functions. These options differ in that they are implemented by appropriate external filters. The structure of the external filter is shown in Figure 61.

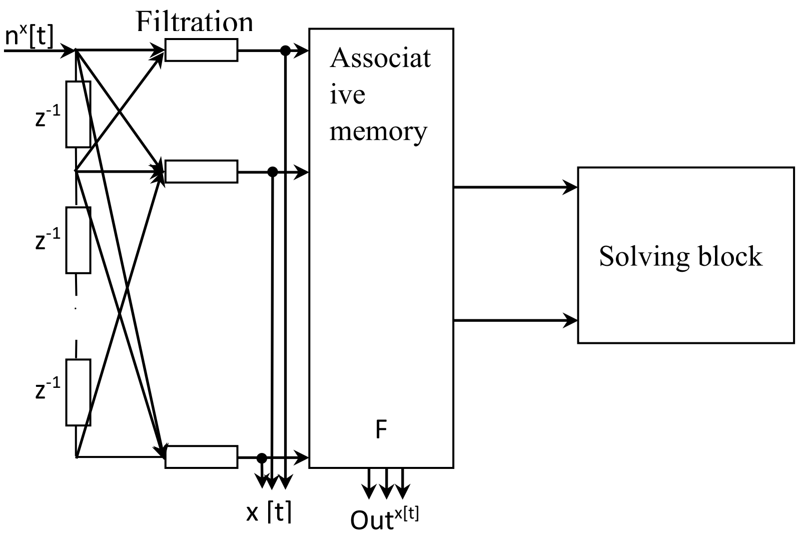

Figure 61. Scheme of the external filter.

During pre-processing it is considered to function $f(t)$ and $\zeta(t)$ not correlated. Required to be vector $Out^x(t)$ output values of the filter $Out_l^x(t)$, $l=1,N$, representing a reaction to an external action, approaching the desired function from the useful signal:

$$Out^x(t) \approx Ff(t), \tag{4}$$

where $F=(F_l)$ - some vector operator describing the mapping of many useful signals into the output signals of the filter [189].

As a measure of approximation $Out^x(t)$ to $Ff(t)$ the general case, you can choose the functionality:

$$J = J\{\varphi[Ff(t) - Out^x(t)]\}, \tag{5}$$

where $\varphi[\bullet]$ - some measure of vector function.

In the simplest case [189] (Fig. 3) the input signal is fed to a set of series-connected functional elements having a delay z^{-1} (in synapses). Their input values are represented as signals $In^x(t-kz^{-1})$, k=1,N with scales w_{jk}, forming a vector of estimates of useful signals $(x_j(t))$, on the basis of which by means of a network realizing a matrix of operators (F_{lj}), the vector of output signals is formed $(Out_l^x(t))$:

$$Out_l^x(t) = F_{lj}\left[\sum_k W_{jk} In^x\left(t - kz^{-1}\right)\right] \tag{6}$$

where l=1,N.

The task of filtering is to reproduce the useful signal against the background of noise and perform the desired conversion.

To solve this problem, it is necessary to minimize the standard deviation of the estimate of the useful signal $x_j(t)$ than expected j - useful signal $f_j(t)$, characterizing the corresponding useful result of the NM filter, to find:

$$\min_{W_{jk}} M\left\{\sum_j \left[f_j(t) - \sum_k W_{jk} In^x\left(t - kz^{-1}\right)\right]^2\right\}, \tag{7}$$

where M - mathematical expectation.

According to this criterion, classical algorithms of filter adaptation can be implemented using a priori information about the useful signal and noise [186-191].

Based on the above, to solve this problem as a static NM that implements the woofer filter, a perceptron was chosen; for the HF filter - NM RBF (radial-basis function).

A signal having N samples $x = [x_1, ..., x_N]$, can be approximated by NM with G neurons in the hidden layer by the following equations:

for the perceptron

$$f(t) = \sum_{i=0}^{G} W_i^{(0)} q\left(\overline{W}_i^{(h)^T} \bar{t}\right), \tag{8}$$

for RBF

$$f(t) = \sum_{i=0}^{G} W_i^{(0)} R_i q\left(\bar{t}, \overline{W}_i^{(h)}\right), \tag{9}$$

where $q[\bullet]$ - different types of basis functions of a multilayer perceptron with a scalar argument (the original N-dimensional approximation problem by weight superposition decomposes into simple scalar basis functions; compression of the N-dimensional input space to a 1-dimensional input $f(\bullet)$ carried out by a scalar product $\overline{W}_i^{(h)^T} \bar{t}$); $R(\bullet)$ - weighted basic functions of RBF (each basic function is realized by a separate neuron).

The decisive rule for the NM ensemble, which implements LF and HF filters, is as follows:

$$\alpha = \frac{\sum_{j=1}^{N} \left[f_{j+1}(t) - f_j(t) \right]^2}{t} \geq C, \tag{10}$$

where the numerator of the expression (10) means adding the sum of the deviations of the parameters (C - the threshold of operation (sensitivity) of the controlled NM; when (normal operation), when (trend)).

In the process of mathematical modeling on the ensemble NM (perceptron - RBF), which implements recurrent filters (dynamic knowledge base of the active decision-making system), in comparison with the classical criteria for detecting the trend of engine parameters, the following results were obtained (Fig. 62) $\frac{3\sigma}{a}$ for 5% significance level, which corresponds to the probability of making the right decision P=0.95.

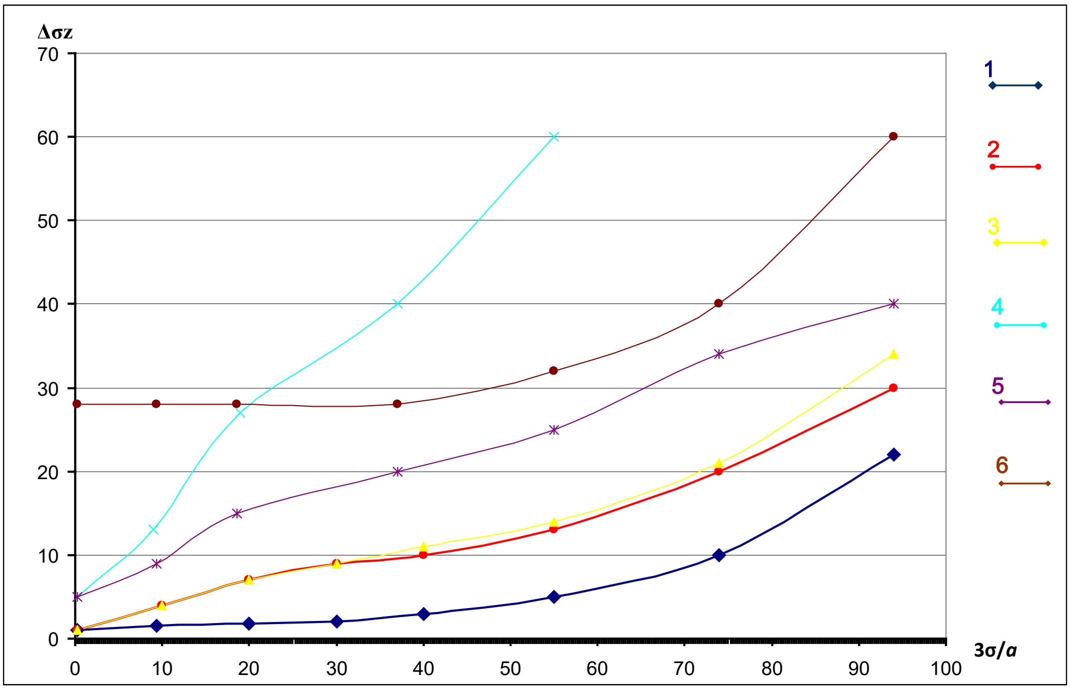

Figure 62 - Characteristics of trend criteria for 5% significance level in dimensionless coordinates.

In Figure 62, the numbers indicate: 1 - neural network criterion; 2 - s-criterion; 3 - S'-criterion; 4 - r'-Halda-Abbe test; 5 - modified r'-criterion; 6 - u-criterion.

Changing in the sample for training (50 data): σ_y - standard deviation of measurement error; α - trend angle; τ_0 - the moment of the trend; it was found that neural network criteria are more effective than classical (have better sensitivity) recognition (appearance) of the moment of disorder (trend) of the controlled parameters of the electric motor, even in conditions of strong interference (table 20).

Table 20.

Comparative assessment of trend definition

Criteria	Measured sample	Trend time (measurement)	Recognition quality (%)	The quality of trend recognition when changing		
				σ_y (%)	α (%)	τ_0 (sensitivity)
Classic	50	7-8	95	70-95	60-95	10-25 (measurements)
Neural networks	50	4-5	100	95-100	95-100	3-5 (measurements)

At present, when solving complex complex tasks of information monitoring and operation of engines, complex ensemble NM can be successfully used, which, in comparison with conventional fully-connected NM, can provide additional advantages in practice: decomposition of a complex dynamic object (its systems) into a number simple objects (subsystems); On easier to adapt to changing external conditions (in the class of adaptive, self-tuning systems); NA structure can be optimized for a specific task; the speed and accuracy of the NA are significantly higher than the classic fully-connected NM;

HA provide a better approximation of piecewise continuous functions.

The above advantages of NA over conventional fully-connected NM give the possibility of their further application in solving problems of information monitoring, operation management and design of electric motors.

8.2 Applying of hexagonal raster in image formation

Introduction

Today researchers pay attention to the advantages of the hexagonal raster by formation and representation of an image more often [192-193]. These benefits allow to increase the realism of graphical images forming in many cases [193]. Advantages stem from hexagon`s ability to cover screen surface without gaps and overlays and