Intelligent control systems using algorithms of the entropic potential method

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Abstract. As part of neural network systems, an artificial neural network can perform various functions like diagnostics of technological equipment, control of moving objects and technological processes, forecasting situations, as well as assessing the state and monitoring of technological processes.

1. Introduction
At the junction of the classical theory of adaptive control and the theory of neural networks, a new section of the theory of intelligent control, neuroregulation, is being developed.

As part of neural network systems, an artificial neural network can perform various functions like diagnostics of technological equipment, control of moving objects and technological processes, forecasting situations, as well as assessing the state and monitoring of technological processes. The ability to form control actions of almost any form makes artificial neural networks (ANNs) a means adequate to the level of complexity of a nonlinear problem. Since neural network systems are teaching, their adaptability in the process of functioning, with uncontrolled changes, the current measuring information about the system and its external environment allows us to adjust the real-time control function of the dynamic and static characteristics of the object. In turn, the ability to parallel signal processing allows them to be used to control multidimensional or multichannel objects.

2. Method
To solve engineering problems of production, intelligent control must have the following properties:

- learning ability and adaptability;
- a relatively simple control algorithm and a man-machine interface convenient for free communication with the controlled object;
- the ability to promptly incorporate new components and technical adjustments that provide better solutions under the constraints imposed by technical means.

The practical application of the technology of expert systems made it possible to develop an intelligent controller with high adaptive properties and great functional flexibility, as well as for the blocks of the knowledge base of the identifier block, the technology of neural network structures is
used, which provides a high level of performance and reliability of the ACS due to parallel processing of signals, the homogeneity of structural elements and their redundancy.

Intelligent control systems (IntCS), which include a dynamic expert subsystem, belong to the class of a new generation of control systems that have the property of great dynamism of intelligent solutions for predicting the state of an object, controlling real dynamic external and output influences, as well as for implementing the principles of integration, openness, hierarchy, vitality.

The structure of the search intelligent control system (in figure 1) is based on the works on search adaptive control, considered in detail in the works of G Ziebolz, N M Paynter, N M Alexandrovsky, S V Egorov, I I Perelman and I M Borzenko. The optimal control actions given in the structure are implemented using the neuroexpert model of the control object (NMCO), with the use of which it is possible to predict its output parameters in an accelerated time scale, with various possible options for management decisions [1].

In figure 1, where the following designations are accepted: $W_K^D(t)$, $W_H^D(t)$, $U^D(t)$, $Y^D(t)$, $S^D(t)$ are the real (D) values of the vector functions of controlled (K) and uncontrolled (H) external influences, control and output actions, states of the technological object of control at the moment of time, measured (H) the values of the vectors of external, control and output actions, as well as the states of the control object (CO); $Y(t) = \{W_K(t), U(t), Y(t), S(t)\}$ is the vector of estimates of the corresponding variables of the control object; NI - non-instrumental information; IB is an interface block.

In general, the structure of the IntCS consists of the following subsystems:

- a dynamic expert subsystem (DES), represented by a knowledge base (KB), a logical inference subsystem in which the main tasks of making management decisions are carried out, an explanation subsystem, an intelligent solver, a planner, where the optimal sequence of actions necessary to determine the controls $U(t)$ and interface blocks.
- a modeling subsystem designed for conditional and unconditional forecasting (predictor), retrospective analysis of the trajectories of an object (regnator), recognition of typical situations (recognizer) [2].

Figure 1. The functional structure of the search IntCS of controlled external influences of the program component of the output action $W_K^D(t)$, accumulated and modified in the knowledge base.

And also the following designations have been introduced into the structures:
• TB - training block;
• SAB - settings adjusting block [3];
• \( H(t), H_2(t), H_3(t) \) - vectors of network settings;
• TSB - time scaling block,
• \( \delta Y(t) \) - indirect estimates of the effects of uncontrollable external influences;
• \( \delta Y(t|t + T_n), W_K(t|t + T_n) \) - predicted in real time estimates \( \delta Y(t) \) and \( W_K^D(t) \) on the \( t|t + T_n \) and \( \delta Y(\theta|t + T_n/x) \) intervals;
• \( W_K(\theta|\theta + T_n/x) \) - values \( \delta Y(t|t + T_n) \) and \( W_K(t|t + T_n) \) in accelerated time;
• \( \{Y(\theta|\theta + T_n/x)\} \) - predictive estimates of the output actions of the control object, obtained in accelerated time for various options of possible control actions \( \{U(\theta|\theta + T_n/x)\} \);
• \( \{\tilde{W}_M(\theta|\theta + T_n/x)\} \) - the reaction of the control object model to \( W_K(\theta|\theta + T_n/x) \) and \( \{U(\theta|\theta + T_n/x)\} \);
• \( T_p \) is the predicting interval;
• \( \theta = t/x \) - accelerated time;
• \( x = 1 \) - coefficient of acceleration of time.

The structure of the NMCO (copy № 1) built within the framework of the concept of program-disturbed motion, has the following form

\[
\hat{Y}_{M1}(t) = \Phi_1 \left( Y_p(t), W_K^D(t) \right) + \Phi_2 \left( \delta(\tilde{U}(t - T_P^{CO}), \delta W_K(t - T_P^{CO})) \right) \tag{1}
\]

where:

• \( \Phi_1(*) \) is the production model of the correspondence of program control actions and base levels;
• \( \Phi_2(*) \) - neural network model of the influence of deviations from the program and basic levels of input actions on the change in the output action;
• \( \delta U(t) \) - assessment of the implemented regulatory actions;
• \( W_K(t) = W_K^D(t) + \delta W_K(t) \) - estimates of controlled external influences;
• \( \delta W_K(t) \) - deviations from \( W_K^D(t) \);
• \( T^{CO} \) - memory interval.

The structure of the predictive NMCO (copy № 2) is as follows

\[
\{\hat{Y}_{M2}(\theta|\theta + T_n/x)\} = \Phi_1 \left( U_p(\theta|\theta + T_n/x), W_K^D(\theta|\theta + T_n/x) \right) + \Phi_2 \left( \delta(\tilde{U}(\theta|\theta + T_n/x), \delta W_K(\theta|\theta + T_n/x)) \right) \\
\tilde{U}(\theta|\theta + T_n/x) = Y_p(\theta|\theta + T_n/x) + \{\delta W_K(\theta|\theta + T_n/x)\} \\
W_K(\theta|\theta + T_n/x) = W_K^D(\theta|\theta + T_n/x) + \delta W_K(\theta|\theta + T_n/x) \tag{2}
\]

where:

• \( \delta(\tilde{U}(\theta|\theta + T_n/x) \) - options for possible regulatory impacts;
• \( U_p(\theta|\theta + T_n/x), W_K(\theta|\theta + T_n/x) \) - program controls and basic levels of controlled external influences read from the knowledge base on the forecasting interval;
• \( \delta W_K(\theta|\theta + T_n/x) \) - forecast of deviations from the basic levels of controlled external influences in an accelerated mode of time.

In the search IntCS the following is carried out:
- optimization of control on a sliding $\left( t_0, t_0 + T_0 \right)$, where $T_0$ is the optimization interval, $n$ is the cycle number of the system operation, while the forecasting interval, in the general case, is greater than or equal to the optimization interval;
- extrapolation of controlled disturbances and indirect estimates of the effects of uncontrolled disturbances, reduced to the output of the object;
- real-time assessment of the effects of uncontrolled disturbances $\delta Y(t)$ using the NMCO, as well as the search for optimal control in an accelerated mode of time on the predictive NMCO.

The search engine optimization algorithm is used to repeatedly experiment with different variants of control actions in accelerated time. The calculation of the vector $U(t)$ during the $n^{th}$ cycle of the system operation is carried out by implementing various options for the future control action on the object model. The received signal $U(t)$ is realized at the facility and remains unchanged during the $(n + 1)^{th}$ cycle of the system operation. After that, a new cycle of work of the system begins [4].

![Figure 2](image-url)

**Figure 2.** Functional structure of a non-search IntCS.

In a non-searching IntCS (in figure 2), the following is carried out:

- estimation of $\delta Y(t)$ the help of NMCO according to the expression (1);
- obtaining unconditional predictive estimates of controlled external influences $W_K(t + T_n)$ using the unconditional prediction block (UPB) No. 1 (extrapolator) and the effects of uncontrolled external influences $\delta Y(t + T_n)$ using the UPB No. 2;
- determination of the conditional forecast of the output impact of $T^{CO}$ using NMCO

$$\hat{Y}_{M2}(t + T_n) = \Phi_1(U_P(t + T_n), W_K(t + T_n)) + \Phi_2(\delta W_K(t - T_P + T_n)) (t + T_P)$$  \hspace{1cm} (3)

where $U_P(t + T_n), W_K(t + T_n)$ are the impacts on the interval $(t + T_n)$ from the knowledge base and $\Phi_2$ - production (heuristic) and neural network models;
- determination of the conditional forecast of the output impact of the control object
\( \hat{Y}(t|t+T_n) = \hat{Y}_{M2}(t|t+T_n) + \delta Y(t|t+T_n); \) (4)

- reading the task \( Y^*(t|t+T_n) \) from the knowledge base on the interval \( (t|t+T_n) \);
- calculation of regulatory influences

\[ \delta U(t) = f_1(Y^*(t|t+T_P) - \hat{Y}(t|t+T_P)) \] (5)

where \( f(*) \) - neural network operator of the inverse model;
- calculation of control actions

\[ U(t) = U_p(t) + \delta U(t) \] (6)

where \( U_n(t) \) - program control actions read from the knowledge base;
- implementation of the obtained control \( U(t) \) for a new cycle of the system operation.

The relevance of the choice and implementation of approaches and algorithms for organizing monitoring and control in conditions of uncertainty has an increasing tendency due to the increased requirements for the quality and efficiency of monitoring and control processes, as well as the intellectualization of these processes [5].

For the synthesis of research algorithms and decision-making, it is expedient and important that the measure of the states of uncertainty be numerically definable. There is no definite solution to this problem. There are alternative approaches and directions with their own capabilities and characteristics.

### 3. Result and discussion

The approach based on the use of methods and technologies of the theory of entropy potentials (TEP) is largely adapted to the specifics of the nature of the occurrence of states of uncertainty, industries. The basis for the creation of the TEP was, as one of the target tasks, the possibility of organizing monitoring and control in conditions of a priori uncertainty.

The description of the states of uncertainty of any parameter \( X \) can be carried out on the basis of the values of the concepts of entropy potential (EP) \( \Delta_e \) and complex entropy potential (CEP) - \( L_\Delta \) the relationship between which is described by the expression

\[ L_\Delta = \frac{\Delta_e}{|X_n|} = \frac{K_e \sigma}{|X_n|} \] (7)

In expression (7), the following characteristics of the parameter are additionally involved:

- \( \sigma \) - the value of the standard deviation (SD);
- \( K_e \) - the value of the entropy coefficient;
- \( X_n \) - the value of the base value, against which its state of uncertainty is analyzed.

The SD value represents the average deviation of the parameter from its mathematical expectation \( m \). The quantity characterizes the variable properties of the distribution law of the parameter, the predictability of the appearance of its various values. For real distribution laws, the values of the entropy coefficient are within the limits

\[ 1 \leq K_e \leq 2.07 \] (8)

In the "classical" presentation, the value of EP is defined as half of the range of variation of the distribution with the law of uniform density, which has the same entropy \( H_X \). Based on this, the relationship between these values was described on the basis of the concept of the magnitude of the entropy coefficient in the form

\[ \Delta_e = \frac{1}{2} e^{H_X} = K_e \sigma \] (9)
where \( H_x = -\int_{-\infty}^{\infty} p(x) \ln p(x) dx \) is the entropy of the analyzed parameter \( x \), and \( p(x) \) is its probability distribution density. Currently, methods have been developed for determining the values of the quantities.

\( K_e \) for various situations with initial data, as well as the values of these coefficients for a number of typical distribution laws.

The quality control of the temperature control process can be carried out in various ways, for example, by purposefully changing the value of SD - \( \sigma \).

The quantity \( \Delta z \) has the dimension of the analyzed parameter and actually characterizes the "unified", based on the concept of entropy, the interval of its variation [6].

Let the uncertainty states of the system for some parameter \( x \) at two successive stages be characterized by the values of the entropy potentials \( \Delta x_1 \) and \( \Delta x_2 \). Then the change in this state can be characterized by the ratio of these EP values, which, taking into account (9), will take the form

\[
\frac{\Delta x_1}{\Delta x_2} = \frac{H_{x_1}}{H_{x_2}} = e^{H_{x_1} - H_{x_2}} = e^l
\]

(10)

where \( l = H_{x_1} - H_{x_2} \) is the amount of information "generated" by the change in the state of uncertainty of the parameter during the transition from one stage to another.

From expression (10) it follows

\[
I = \ln \frac{\Delta x_1}{\Delta x_2} = \ln \frac{K_{x_1} \sigma_1}{K_{x_2} \sigma_2} = \ln \frac{K_{x_1}}{K_{x_2}} + \ln \frac{\sigma_1}{\sigma_2} = \ln k_{ke} + \ln \frac{\sigma_1}{\sigma_2} = I_l + I_p
\]

(11)

where \( k_{ke} = \frac{K_{x_1}}{K_{x_2}} \) is the transformation coefficient of the parameter distribution law. Methods for determining the values of a quantity \( k_{ke} \) are described. Expression (11) also uses the notation \( I_l = \ln k_{ke} \) intellectual component of information, \( I_p = \ln \frac{\sigma_1}{\sigma_2} \) energy component of information.

The choice of names is based on the following considerations. The quantity \( k_{ke} \) characterizes the change in the properties of the distribution law of the parameter, which is one of the factors of consideration and accounting in the problems of intellectual analysis. Therefore, the term \( \ln k_{ke} \) should be interpreted as an intellectual component.

According to (10) and (11), the quantity can take both positive and negative values. Negative values take place when the transition to the next stage is characterized by an increase in the state of uncertainty of the parameter \( H_{x_1} < H_{x_2} \). Proceeding from the fact that the real range of variation of \( K_e \) is within the \( 1 \leq K_e \leq 2.07 \) limits, it is possible to determine the maximum possible value of the intellectual component of information \( I_l(\text{max}) \)[7].

\[
I_l(\text{max}) = \ln k_{ke}(\text{max}) = \ln \frac{K_{\text{e}(\text{max})}}{K_{\text{e}(\text{min})}} = \ln 2.07 \approx 0.7[\text{nit}]
\]

(12)

By (12) it follows

\[
0 \leq |I_l| \leq \ln 2.07[\text{nit}]
\]

(13)

The units for measuring the amount of information and entropy are determined by the base of the logarithms used in expressions (9), (11) and (12). For example, when using natural logarithms, the amount of information is obtained in natural units - nit, when using binary logarithms - in binary units or bits, when using decimal logarithms - in dits. The relationship between different units of measurement is based on the relationship for the transition between logarithms with different bases. For the mentioned units of measurement, the corresponding dependencies will have the form

\[
1 \text{nit} \approx 1.455h \approx 0.43 \text{Hart}
\]

(14)

The upper range of \( \sigma \) variation is not limited. This implies

\[
0 \leq |I_p| < \infty
\]

(15)
In the case of dominance of one of the information components, model (13) can be simplified to this component. To characterize the ratio of these components a special value was introduced - the ratio of information.

\[ \eta = \frac{|I_p|}{|I|} \]  

(16)

From (15) and (16), we can conclude that the “power” of the set of energy models exceeds the power of the set of intelligent models. The signs of the absolute values are necessary to ensure the constancy of the sign of the value \( \eta \), since the values \( I_I \) and \( I_p \), according to the definitions, can take both positive and negative values. The choice of a variant of the model must be carried out based on the requirements for its adequacy, by setting the boundary level of the value of the quantity \([8]\).

Based on practical experience, as such, we can recommend the value of \( C \), which is in the range from two to five. If, \( \eta \leq 1/C \), then the determination of the value of \( I \) should be carried out using an intelligent model. If, \( \eta \geq C \), the problem can be solved using the expression of the energy model. If, \( 1/C < \eta < C \), then the general model should be used (16).

4. Conclusion

The resulting characteristics of the states of uncertainty are compact, informative and easy to perceive. Informational and entropy portraits make it possible to visualize and study the evolution of states of uncertainty. They should be considered as elements of cognitive graphics, with the help of which the "compression" of the initial information about the evolution of states of uncertainty is carried out. The use of such methods and approaches makes it possible to simplify research technologies and increase the efficiency of organizing the management of objects of various nature.

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