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Optimization of Machining on the Basis of Artificial Intelligence

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Abstract—Often, in the assessment of a technological system, attention focuses on quantitative characteristics reflecting aspects of the machining quality. The assessment may be subjective for each machine tool and each implementation of flexible technology. If characteristics corresponding to the quality of control are considered, the system may be assessed at the design stage. Various engineering and economic parameters may be adopted as the criteria in optimization. The system corresponding to a minimum of the optimization criterion only provides the best results in the worst operating conditions.

Keywords: neural network modeling, applied fuzzy systems, process control systems, control, quality, optimization, machining

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INTRODUCTION

Quantitative assessment of a technological system on the basic of specific criteria entails establishing a model of the relation between the machining conditions and the requirements N on the product, assuming that the state of the system in the course of operation is M

$$R^m \in M;$$

$$R^m \in N,$$

where R^m is the state vector of the technological system.

The characteristics R^m may be significantly different, depending on the current state of the system. For example, the dynamic state may be modeled in the Fourier time or frequency domain. Given the set of states of the system, incorrect assessment of the quality of control is probable.

Characteristics directly associated with the quality of control were presented in [1–3]. Their analysis permits the assumption quantitative assessment of the technological system is possible at the design stage in terms of characteristics such as the operational quality attainable by adjustment of the system parameters; the energy consumption; the speed; and the conditions corresponding to the final state.

ANALYSIS

As a rule, the number of quality indices $J_1(t)$, ..., $J_l(t)$ depends on the complexity of the problem to be solved [4]. With increase in the number of indices, the solution of the problem becomes extremely complex. To eliminate such complexity, we must use generalized indices (J) depending on the particular indices $J_1(t)$, ..., $J_l(t)$ and the transient state functions

$$\varphi_i(t_0, t, z, x) \quad (i = 1, \ldots, N),$$

where z is the internal state of the system; and X is the input.

The structural function characterizing the system depends on the inputs $X(t)$, the operator W, and the parameter vector K. On that basis, we state the following conclusion regarding the quality of the system

$$J = J\{J_1, \ldots, J_l, Y_1, \ldots, Y_n, X_1, \ldots, X_m, t_1, t_0\},$$

where X is the set of input data; and Y is the set of output data.

Thus, analysis and modeling of technological systems is possible on the basis of the change in state of the system and the quality index J.

The numerical value of the generalized index J corresponding to a specific state of the system is a characteristic of the system. When using the time domain for various structural operators of the system, the real values of J correspond to specific operational processes of the system over time. Hence, the functional relation allows the characteristic to be regarded as a functional.

All sets of characteristics may be categorized as regular or statistical. Analysis of a system that only contains determinate processes is possible by means of regular characteristics [4].

The characteristic J is regular and may be represented by the structural parameters K of the system, omitting the stochastic component

$$J = J(K).$$

Optimization may be based on characteristics such as the reliability, the productivity, the cost of raw materials and energy, and the product quality. On the basis of the conditions of the problem, we need to find the minimum or maximum values of the target function (Q) corresponding to optimal control of the system

$$Q(\bar{X}_{\text{out}}, \bar{X}_{\text{in}}, \bar{U}, \bar{F}, t) = \text{min/max},$$

where $\bar{X}_{\text{out}}$ are the output data; $\bar{X}_{\text{in}}$ are the input data; $\bar{U}$ are the control signals; and $\bar{F}$ are the perturbations.

When stochastic process $X(t)$ acts on the system, the state vector Z and hence the output data $\bar{X}_{\text{out}}$ will be random. To eliminate this problem, a statistical index representing the determinate characteristic of the stochastic process must be introduced. The statistical index selected is the conditional mathematical expectation [4, 5]

$$J = \int_x^0 Q(\chi, K) f(\chi) d\chi,$$

where Q is the functional of vectors $\chi = \chi(X, Y, Z)$ and K; f is the distribution of the random process; X denotes the input data; Y denotes the output data; Z is the internal state of the system; and K consists of the system's design parameters.

For dynamic control systems, the problem becomes more complex; as a rule, it is necessary to determine the statistical index of the system in integral form [6]

$$J = \int_{a_1}^{b_1} \dots \int_{a_n}^{b_n} \Phi(\lambda_1, \dots, l_m, t) f(\lambda_1, \dots, \lambda_m) d\lambda_1, \dots, \lambda_m,$$

where Φ is a function determined by a specific type of characteristic and expressing the reaction of the system; $\lambda_1, \dots, \lambda_m$ denotes a set of random values; and f is the distribution density of the set of m random values $\lambda_1, \dots, \lambda_m$.

In creating systems that may be parametrically optimized, it is preferable to use a single index [6] in assessing the quality of control. For example, for continuous systems, we may select an integral quality index. (For a discrete system, we take the sum, rather than the integral.) On that basis, mathematical considerations indicate that the sum of squares of the control errors is preferable. The index may be represented as the mean power, and so may be used in modeling the regulators for other methods.

For parametric optimization, we use quadratic quality indexes in the form [7]

$$S_{lu}^2 = \int_{k=0}^{m} \left(l^2(k) + r\Delta U^2(k)\right),$$

where $l(k) = W(k) - Y(k)$ is the control error; $\Delta U(k) = U(k) - \bar{U}$ is the deviation of the controlled variable from the steady value $\bar{U} = E\{U(k)\}$ in the case of stochastic perturbations; and r is a weighting factor for the controlling variable.

In this quadratic index, the ratio of the mean square control error

$$S_l^2 = \overline{l^2(k)} = \frac{1}{M+1} \sum_{k=0}^{m} \Delta U^2(k)$$

to the mean square deviation of the controlling variable or the mean input power

$$S_u^2 = \overline{\Delta U^2(k)} = \frac{1}{M+1} \sum_{k=0}^{m} \Delta U^2(k)$$

depends on the weighting factor r.

To attain the minimum value of S_{lu}^2 in optimization of the regulator parameters, we need to determine the parameters $q^r = [q_0 q_1 \dots q_v]$ such that

$$\frac{dS_{lu}^2}{dq} = 0.$$

Comparison of the quality of control is possible by means of the mean square control error S_l', the mean square variation in the controlling variable (the costs of control) S_u', the overregulation Y_m, and the time to determine the output data and the initial value of the controlling variable $U(0)$ with stepwise variation in the signal $W(0)$

$$S_l' = \sqrt{\overline{l^2(k)}} = \sqrt{\frac{1}{M+1} \sum_{k=0}^{m} \Delta U^2(k)};$$

$$S_u' = \sqrt{\overline{U^2(k)}} = \sqrt{\frac{1}{M+1} \sum_{k=0}^{m} \Delta U^2(k)};$$

$$Y_m = Y_{\max}(K) - W(K).$$

A method exists for determining the optimality criterion on the basis of a penalty function, which reflects the distance between the elements of metric space (Fig. 1) [7].

At time t, the state of the system (Fig. 1) is determined by the group of vectors $X(t)$, $Y(t)$, $U(t)$, with the penalty $C(X,Y,U)$, where $C(X,Y,U)$ is a specified nonnegative function of its arguments. If $C(X,Y,U)$ corresponds to specific penalties in unit time, the operational quality of the system in time segment [0, T] may be assessed by means of an integral of the form

$$\int_0^T C(X(t),Y(t),U(t))\,dt.$$

Since the processes $X(t)$, $Y(t)$ are random, the integral is a random quantity with absolutely any fixed control law $U(t)$, $0 \le t \le T$. With repeated use of the control algorithm, the mean costs or losses in control are determining. Thus, optimization may be based on the integral index

$$I_1[U] = M\int_0^T C(X(t),Y(t),U(t))\,dt. \quad (1)$$

In many cases, it is only important to know the state of the system at the final time T (terminal control); the transient processes when $0 \le t \le T$ are insignificant. On that basis, we may obtain the terminal optimality criterion by means of a specific penalty function $\varphi[X(t),Y(t)]$

$$I_2[U] = M\Psi(X(T),Y(T)). \quad (2)$$

With expansion of the phase vector X, the integral criterion in Eq. (1) may be written in the form in Eq. (2). Consequently, we may regard Eq. (1) as a particular case. Nevertheless, the consequences of the criteria in Eqs. (1) and (2) will be different, since they have very different engineering interpretations. In addition, it is not unusual to encounter criteria in which these approaches are combined and the outcome depends on both the transient process and the final state of the system

$$I_3[U] = M\left[\int_0^T C(X(t),Y(t),U(t))\,dt + \psi(X(T),Y(T))\right].$$

If the worst state of the system (in terms of the selected penalty function) in fixed time interval [0, T], we obtain the following expression instead of the integral

$$\max_{0\le t\le T} C(X(t),Y(t),U(t)).$$

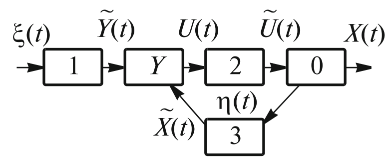

Fig. 1. Functional diagram of the penalty assessment system.

Averaging, we obtain the optimality criterion

$$J_4[U] = M\max C(X(t),Y(t),U(t)).$$

The quality of operation with a quadratic penalty function is estimated by means of an integral function of the form

$$J(U) = M\int_0^T\left[qx^2(t) + hU^2(t)\right]dt.$$

For a set of systems, calculation of the optimal regulator (damper) is required. On the basis of the mean square error, it best suppresses the fluctuations due to random perturbations $\xi(t)$. The optimization criterion may be taken in the form [8]

$$J(U) = M\int_t^T\left[x^2(t) + x^2(t)dt\right].$$

Optimal damping largely involves selecting the mean square criterion in assessing the quality of the system.

We assume that the observable signal $\{Y_t\}$ takes the form

$$Y_t = S_t(\tau,K) + V_t,$$

where S_t is the useful signal, which varies over time and depends in a known manner on the set τ of significant informational parameters and the set K of parasitic parameters; and V_t is the noise of the observation, which varies over time (t = 1, 2, ...).

We need to assess the informational parameters (τ). Often, the parameter sets τ and K are specified stochastically with specified statistical properties. They may also be determinate. It is important to find optimal estimates corresponding to extrema in the quality functional

$$W_t(\tau') = M\left\{\sum_{t=1}^T \left|Y_t - S_t(\tau',k)\right|^2/\tau\right\},$$

where T is the time of signal observation; and M signifies averaging over the ensemble of iterations of the signals {Yt}, {S_t} corresponding to a specific value of the parameter g. Determining W-rfr entails understanding the statistics of the signals {Yt}, {S_t}.

A similar problem concerns the disorder occurring when, say, the tool is worn

$$Y_t = S_t(\tau_t) + V_t,$$

where the parameter τ_t corresponds to the determination of the statistical properties of the useful signal. Although τ_t varies over time, it is constant over long intervals. We need to determine the time intervals in which τ_t passes from a variable to a constant state.

CONCLUSIONS

The proposed method permits the solution of many mathematical and applied problems that are variational in character but cannot be addressed by traditional variational calculus. On the other hand, many nonclassical problems arise specifically from engineering problems. The optimal characteristics of a system correspond to its optimal behavior in dynamic optimization and in determining optimal steady characteristics during static optimization. Optimization is possible in designing the system and the regulator.

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CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

1. Trotsenko, V.V., Fedorov, V.K., Zabudskii, A.I., et al., *Sistemy upravleniya tekhnologicheskimi protsessami i informatsionnye tekhnologii: Uchebnoe posobie dlya vuzov* (Technological Process Control Systems and Information Technologies: Manual for Higher Education Institutions), Moscow: Yurait, 2023. https://urait.ru/bcode/515149. Accessed January 30, 2023.
2. Borodin, I.F. and Andreev, S.A., *Avtomatizatsiya tekhnologicheskikh protsessov i sistemy avtomaticheskogo upravleniya* (Automation of Technological Processes and Automatic Control Systems), Moscow: Yurait, 2023.
3. Lazarev, V.L. and Travina, E.A., *Sintez i raschet sistem avtomaticheskogo upravleniya* (Synthesis and Calculation of Automatic Control Systems), St. Petersburg: Univ. ITMO, 2018.
4. Bondarenko, Y.A. and Bestuzheva, O.V., Multicriterion optimization of processing of mill trunnion based on hierarchy analysis method, *IOP Conf. Ser.: Mater. Sci. Eng.*, 2019, vol. 560, p. 012007.
5. Sergeev, A.P. and Tarasov, D.A., *Vvedenie v neirosetevoe modelirovanie: Uchebnoe posobie (Introduction to Neural Network Simulation: Manual)*, Sergeev, A.P., Ed., Yekaterinburg: Ural. Univ., 2017.
6. Duyun, T.A., Grinek, A.V., and Sakharov, D.V., Modeling and optimization of manufacturing processes using the method of dynamic programming, *Vestn. Belgorod. Gos. Tekhnol. Univ. im. V.G. Shukhova*, 2013, no. 3, pp. 61–65.
7. Lisitsyna, L.S., *Osnovy teorii nechetkikh mnozhestv* (Basics of Fuzzy Set Theory), St. Petersburg: Univ. ITMO, 2020.
8. Asai, K., Vatada, D., Ivan, S., et al., *Prikladnye nechetkie sistemy* (Applied Fuzzy Systems), Terano, T., Asai, K., and Sugeno, M., Eds., Moscow: Mir, 1993.

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