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IDENTIFICATION OF THE MACHINING TOOL WEAR MODEL VIA MINIMAX COMBINING AND WEIGHTING SUBSEQUENTLY SPECIFIC MODELS

The paper states that for a set of mathematical models, describing the same object, there primarily can be determined a meta-model, which is the result of evolution of convex combinations of those models. The evolution is actually the identification process that starts at the convex combination by coefficients, guaranteeing minimum of lacks. The purpose is to identify the machining tool wear theoretically under ultimate uncertainties, when there are no anticipatory data, determining how and in what ratio the abrasive, adhesive, diffusive, and oxidizing wear components constitute the wear value. The machining tool wear is considered as a time function of the single geometrical coordinate. There are four wear models, focusing on such specific features of the complicated wear process as abrasion, adhesion, diffusion, and oxidation. The aggregate of those four specificities of wear can be found as their convex combination, whose coefficients evolve as time goes by along with evolving values of wear models. Initially, these coefficients are set at minimaxed probabilities of applying the abrasive, adhesive, diffusive, and oxidizing wear models. Using a measure of accuracy for each wear model, the evolution through sampled time of the convex combination coefficients in every point of the single geometrical coordinate is expressed. That measure establishes the relative correspondence between a model wear value and the wear convex combination in the current time sample for any value of the geometrical coordinate. The stated procedure of weighting the wear models on their accuracy may be found as an identification process under uncertainties or unavailable anticipatory data. This will be used for identifying the model structure of a system or process primarily, when there are several approaches to model it, having unknown or uncertain significances.

***Keywords:** machining tool wear, abrasive wear, adhesive wear, diffusive wear, oxidizing wear, ultimate uncertainties, wear aggregate, measure of accuracy, convex combination, minimaxed probabilities.*

Introduction

Machining metals is an important part of engineering and machine-building. Tools for machining are usually applied as being more endurable, and metals are machined with sturdier metals. As machining process runs, tools of machining are worn out. It is needful to know how much or deep the tool is worn for using it rationally, not longer when the tool is off usage and not to waste the tool early.

In machining metals, there generally are four models of the machining tool wear, where each of them focuses on specific features [1, 2] of the complicated wear process [3, 4]: on the abrasive wear [5, 6], on the adhesive wear (could have been based on Usui's model) [7, 8], on the diffusive wear (derived from Takeyama – Murata model) [9, 10], and on the oxidizing wear [11, 12]. For controlling the wear process entirely, there should be developed an approach, which would let aggregate [10, 13, 14] those four specificities of wear. Some attempts have been done in that way [14, 15], but they depend strongly on the anticipatory data, determining actually the leading specificity of wear [7, 16]. Under conditions of severe uncertainties, however, such data are unavailable or unreliable [16]. Such conditions are generated on prior stages of a tool usage when there is poor information about the tool material properties.

1. Assumptions and investigation methodology

Whatever the machining tool geometry is, may L be the tool wearing curve length. Will consider the wear that spreads out according to the single coordinate x by $x \in [0; L]$. Denote by T the interval duration of theoretical observation of the machining tool job, assuming that this duration is not greater than the tool life cycle (duration of the tool usage).

Implicitly, the j-th tool wear model is an equation

$$\tilde{w}_j(x, t) = \psi_j \tag{1}$$

with the function $\tilde{w}_j(x, t)$ describing the tool wear evaluation in the moment $t \in [0; T]$ on the location $x \in [0; L]$. The equation (1) is determined by the rightside member operator ψ_j, having arguments

$$\frac{\partial \tilde{w}_j(x, t)}{\partial x}, \ \frac{\partial \tilde{w}_j(x, t)}{\partial t}, \ \frac{\partial^2 \tilde{w}_j(x, t)}{\partial x^2},$$

and Wiener process $\xi(t)$, $j = \overline{1, 4}$. The coordinate x and time t may be included into arguments of the operator ψ_j also [17]. The rightside member in equation (1) is the known operator (function), giving the j-th partial differential equation with initial condition [17]:

$$\tilde{w}_j(x, 0) = 0 \quad \forall\ j = \overline{1, 4} \ \text{ by } \ x \in [0; L] \tag{2}$$

and some other boundary conditions, whose desired solution has been stated implicitly as the leftside member in (1) under Wiener process $\xi(t)$. So, even after having solved stochastic equations (1) $\forall\ j = \overline{1, 4}$ the tool wear $\tilde{w}(x, t)$ over segment $[0; T]$ along the dimension x remains uncertain due to complicated wear process, generating the four models mentioned above.

Obviously, the tool wear could be found as a convex combination

$$\tilde{w}(x, t) = \sum_{j=1}^{4} \lambda_j(x, t) \tilde{w}_j(x, t) \quad (3)$$

using $\forall\ x \in [0; L]$ and $\forall\ t \in [0; T]$ some functional weights

$$\lambda_j(x, t) \in (0; 1) \text{ by } \sum_{j=1}^{4} \lambda_j(x, t) = 1. \quad (4)$$

But there opens the question of how to find these weights (4) for (3) under ultimate (multivariate) uncertainties. It cannot be answered with operations research as there is no minimization or maximization problem. That question can be answered with applying the decision making theory, suggesting criterions for solving a decision making problem, whereupon weights (4) are going to be determined subsequently. However, under multivariate uncertainties the decision estimator should be found only with methods, reckoning upon any possible situations. Such methods include either criterion, tolerating any probability distribution over states. Here, both the minimax and Savage criterions can be unified [18] for minimizing lacks in the worst situation.

2. Subsequent weights of wear models

It is clear that adjustment of weights $\{\lambda_j(x, t)\}_{j=1}^{4}$ cannot be continual, as the adjustment can be fulfilled only in discrete time. For this, substitute the observation segment $[0; T]$ with the set $\{t_n\}_{n=1}^{N+1}$ by $t_n = \dfrac{(n-1)T}{N}$. The time point t_1 corresponds to the initialization, so $\{\lambda_j(x, 0)\}_{j=1}^{4}$ cannot be evaluated due to conditions (2). But once the machining process started, there appear different types of wear. Then, the weights $\{\lambda_j(x, 0)\}_{j=1}^{4}$ can be evaluated on the first observed-by-modeling wears $\{\tilde{w}_j(x, t_2)\}_{j=1}^{4}$.

The lack in evaluating the j-th weight $\lambda_j(x, 0)$ depends mainly on interrelationship between the j-th model wear value $\tilde{w}_j(x, t_2)$ and the rest three model wear values. Nevertheless, the weight $\lambda_j(x, 0)$ is influenced with other interrelationships. Thus, every weight is determined via interrelationship between every couple of model wear values [18, 19]. Evaluations of these interrelationships are given $\forall\ x \in [0; L]$ with elements [17]:

$$k_{ij}(x, t_2) = \rho_E\left(\tilde{w}_i(x, t_2), \tilde{w}_j(x, t_2)\right)$$
$$\text{by } i = \overline{1, 4} \text{ and } j = \overline{1, 4} \quad (5)$$

of the decision matrix

$$\mathbf{K}(x, t_2) = \left[k_{ij}(x, t_2)\right]_{4\times 4}. \quad (6)$$

Elements (5) for the matrix (6) are determined with a quasimetric ρ_E on the space E, regarding tool wear evaluations and their mutual interrelationship. This space particularly may be taken as ordinary absolute distance or relative distance between the i-th model wear value $\tilde{w}_i(x, t_2)$ and the j-th one $\tilde{w}_j(x, t_2)$.

If at $x \in [0; L]$ to regard the prevailing i-th wear model as manifestation s_i of multivariate uncertainties $\forall\ i = \overline{1, 4}$, while the investigator selects the j-th tool wear model $\forall\ j = \overline{1, 4}$, then there is being generated the game

$$\left\langle \{s_i\}_{i=1}^{4}, \{m_j\}_{j=1}^{4}, \mathbf{K}(x, t_2) \right\rangle. \quad (7)$$

The investigator, having solved the game (7), possesses its optimal strategy

$$\mathbf{Q}_{opt}(x) = \left[q_{opt}^{\langle 1\rangle}(x) \quad q_{opt}^{\langle 2\rangle}(x) \quad q_{opt}^{\langle 3\rangle}(x) \quad q_{opt}^{\langle 4\rangle}(x)\right] \in$$
$$\in \left\{ \begin{array}{l} \left[q^{\langle 1\rangle}(x) \quad q^{\langle 2\rangle}(x) \quad q^{\langle 3\rangle}(x) \quad q^{\langle 4\rangle}(x)\right] \in \mathbb{R}^4 \mid \\ q^{\langle j\rangle}(x) \in [0; 1] \ \forall\ j = \overline{1, 4}, \ \sum\limits_{j=1}^{4} q^{\langle j\rangle}(x) = 1 \end{array} \right\}, \quad (8)$$

where $q_{opt}^{\langle j\rangle}(x)$ is the optimal probability of selecting the j-th tool wear model, $j = \overline{1, 4}$. Particularizing, $q_{opt}^{\langle 1\rangle}(x)$ is the minimaxed probability of applying the abrasive wear model, $q_{opt}^{\langle 2\rangle}(x)$ is the adhesive model minimaxed probability, $q_{opt}^{\langle 3\rangle}(x)$ and $q_{opt}^{\langle 4\rangle}(x)$ are for the diffusive and oxidizing models, respectively. And the strategy (8) directs to assign

$$q_{opt}^{\langle j\rangle}(x) = \lambda_j(x, 0) \quad \forall\ j = \overline{1, 4}$$

for the first convex combination [17]:

$$\tilde{w}(x, t_2) = \sum_{j=1}^{4} q_{opt}^{\langle j\rangle}(x) \tilde{w}_j(x, t_2) \quad (9)$$

along the dimension x.

A measure of inaccuracy for the j-th tool wear model can be stated with (9) as

$$\delta_j(x, t_2) = \left| \frac{\tilde{w}(x, t_2) - \tilde{w}_j(x, t_2)}{\tilde{w}(x, t_2)} \right|$$

due to that $\tilde{w}(x, t) = 0$ is unlikely. Then accuracies

$$a_j(x, t_2) = \delta_j^{-1}(x, t_2) \quad \forall\ j = \overline{1, 4}$$

let get the weights

$$\lambda_j(x, t_2) = a_j(x, t_2) \left(\sum_{m=1}^{4} a_m(x, t_2) \right)^{-1} \quad \forall\ j = \overline{1, 4}$$

for evaluating the tool wear in the subsequent time point, $\tilde{w}(x, t_3)$. Here is assumed that

$$\tilde{w}(x, t_2) \neq \tilde{w}_j(x, t_2) \quad \forall\ j = \overline{1, 4}.$$

Generally, in the time point t_n $\forall\ n = \overline{2, N+1}$ the inaccuracies

$$\delta_j(x, t_n) = \left| \frac{\tilde{w}(x, t_n) - \tilde{w}_j(x, t_n)}{\tilde{w}(x, t_n)} \right| \quad \forall\ j = \overline{1, 4} \quad (10)$$

with

$$\tilde{w}(x, t_n) = \sum_{j=1}^{4} \lambda_j(x, t_{n-1}) \tilde{w}_j(x, t_n)$$

$$\forall\ n = \overline{2, N+1} \quad (11)$$

give the accuracies

$$a_j(x, t_n) = \delta_j^{-1}(x, t_n) \quad \forall\ j = \overline{1, 4} \quad (12)$$

letting get the weights

$$\lambda_j(x, t_n) = $$

$$= \sum_{r=2}^{n} a_j(x, t_r) \left(\sum_{m=1}^{4} \sum_{r=2}^{n} a_m(x, t_r) \right)^{-1}$$

$$\forall\ j = \overline{1, 4} \quad (13)$$

for evaluating the tool wear in the time point t_{n+1},

$$\tilde{w}(x, t_{n+1}) = \sum_{j=1}^{4} \lambda_j(x, t_n) \tilde{w}_j(x, t_{n+1})$$

$$\forall\ n = \overline{2, N}. \quad (14)$$

Again, here is assumed that the combined (expected) wear $\tilde{w}(x, t_n)$ in any time point cannot be equal to any of model wear values. Naturally, the set of wear evaluation functions $\left\{\tilde{w}(x, t_n)\right\}_{n=2}^{N+1}$ for $x \in [0; L]$ is predetermined with the space E quasimetric in (5). This quasimetric must reflect charges of lacks, originating from erroneous tool wear modeling.

3. Simulation of theoretical observation and aggregating four wear models

For simulating the procedure of observation and aggregating four wear models there is going to be applied the powerful environment Matlab®. Let the length of the tool wearing curve be 1 cm, and let there be 60 seconds for theoretical observation duration of the machining tool job. The surfaces of the exampled wear $\left\{\tilde{w}_j(x, t)\right\}_{j=1}^{4}$ plotted on the semi-open rectangle

$$[0; L] \times (0; T] = [0; 1] \times (0; 60]$$

are imaged in Fig. 1 – 4. Although it is just a simulation [20, 21], these surfaces hint that the tip of the machining tool is worn harder than any other places. However, the oxidizing wear model shows (Fig. 4) that the middle part of the tool has less resistance to its wear (substantiated mostly with the oxidation process). It is noteworthy that near the coordinate $x = 0$ (as if it is at the tool holder, where the machining or cutting contact is minimal) the tool wear is insignificant. So, this numerical simulation reflects a pretty standard tool wear shape [20, 22].

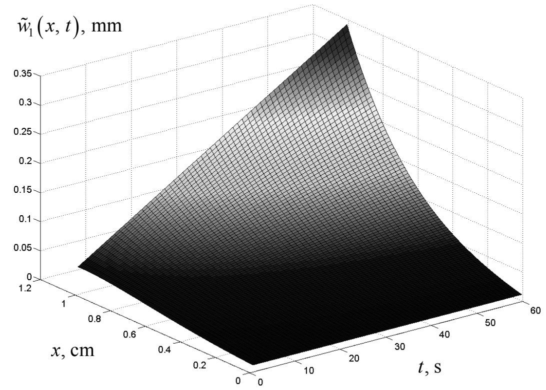

Fig. 1. Theoretical wear (mm) of the machining tool by the abrasive wear model (simulation of the tool tip, being worn hardest, while at the tool holder the tool wear is insignificant), giving the greatest prediction of the tool wear at its tip

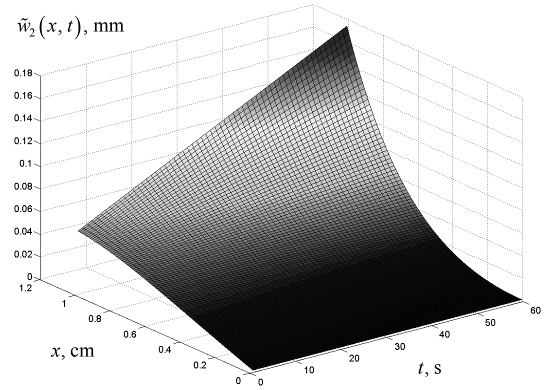

Fig. 2. Theoretical wear (mm) of the machining tool by the adhesive wear model (simulation of the tool tip, being worn harder, while at the tool holder the tool wear is insignificant), giving almost averaged (or combined, as in Figure 5) prediction of the tool wear at its tip (locally) and at all it is very similar to the combined wear surface in Fig. 5

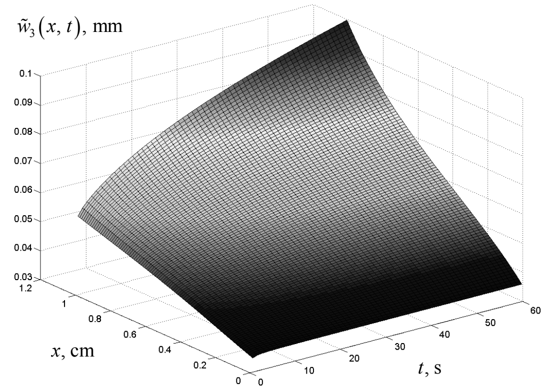

Fig. 3. Theoretical wear (mm) of the machining tool by the diffusive wear model (simulation of the tool tip, being worn harder, while at the tool holder the tool wear is insignificant, although this wear through passing time and along the coordinate x is increasing roughly linearly), giving the lowest prediction of the tool wear at its tip and the greatest at the tool holder

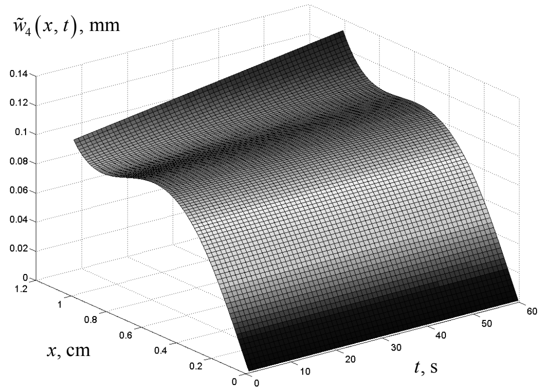

Fig. 4. Theoretical wear (mm) of the machining tool by the oxidizing wear model, giving the tool wear, not changing roughly through passing time and changing significantly along the coordinate x (simulation of the tool tip, being worn harder since the beginning of the observation process, while at the tool holder the wear is insignificant, and in the neighborhood of 8 mm the tool wear is decreased, probably, due to oxidation processes, "restoring" the tool shape partially)

Having substituted the observation segment [0, 60] with the set $\{t_n\}_{n=1}^{61}$ by $t_n = n-1$, there must be defined the quasimetric in (5) for to start aggregating four specificities of the machining tool wear. It may be taken as

$$k_{ij}(x, 1) = \max\left\{\frac{\tilde{w}_i(x, 1)}{\tilde{w}_j(x, 1)}, \frac{\tilde{w}_j(x, 1)}{\tilde{w}_i(x, 1)}\right\},$$

$$i = \overline{1, 4} \text{ and } j = \overline{1, 4} \qquad (15)$$

by $t_2 = 1$ s. The result of the aggregation process of wear models is shown in Fig. 5, whereas their plane projections are shown in Fig. 6. The maximal charge of lacks from erroneous tool wear modeling here is (Fig. 7)

$$\mathbf{U}(x)\cdot\mathbf{K}(x, 1)\cdot\left(\mathbf{Q}_{opt}(x)\right)^T, \qquad (16)$$

wherein $\mathbf{U}(x)$ is an assumed probability distribution over wear models at the coordinate x.

And although the mean wear

$$\bar{w}(x, t) = \frac{1}{4}\sum_{j=1}^{4}\tilde{w}_j(x, t) \qquad (17)$$

seems (Fig. 8) to be very similar to the wear in Fig. 5, its application is more inaccurate and incautious (Fig. 7) than weighting wear models with subsequently recalculated coefficients (13).

This is revealed because there are probable such probability distributions $\mathbf{U}(x)$ over wear models that, taking the equiprobable distribution instead of $\mathbf{Q}_{opt}(x)$, the resulting charge

$$\mathbf{U}(x)\cdot\mathbf{K}(x, 1)\cdot\left(\begin{bmatrix}0.25 & 0.25 & 0.25 & 0.25\end{bmatrix}\right)^T$$

of lacks appears greater than that one in (16).

Thus, Fig. 1 – 4 with Fig. 8 also relate to the given data $\{\tilde{w}_j(x, t)\}_{j=1}^{4}$ after having solved equations (1) $\forall\ j = \overline{1, 4}$, while Fig. 6 and 7 explain the preference of using the surface wear in Fig. 5 to the surface wear in Fig. 8. Now it is turn to summarize on the suggested procedure in (10) – (13) for evaluating the tool wear (3) through sampled time.

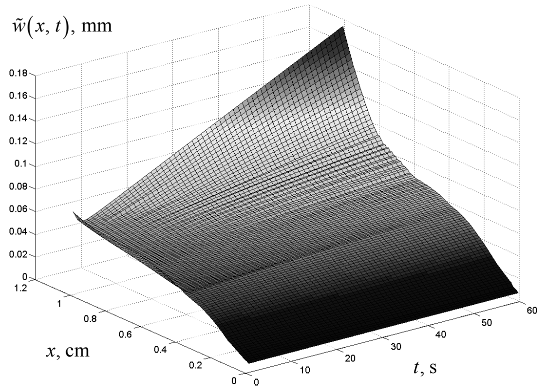

Fig. 5. Theoretical combined wear (mm) of the machining tool by (14) with (10) – (13) over the optimal strategy (8) in the game (7) by the quasimetric (15), where the obvious similarity to the wear surfaces in Fig. 1 and 2 can be exposed (and partially the present figure reminds Fig. 3), and it displays the tool tip, being worn hardest, while at the tool holder the tool wear is insignificant; some roughs of the surface along the coordinate x (especially at a few first time samples) are explained with rigid scattering of wears on four specificities, weighting them subsequently by different coefficients

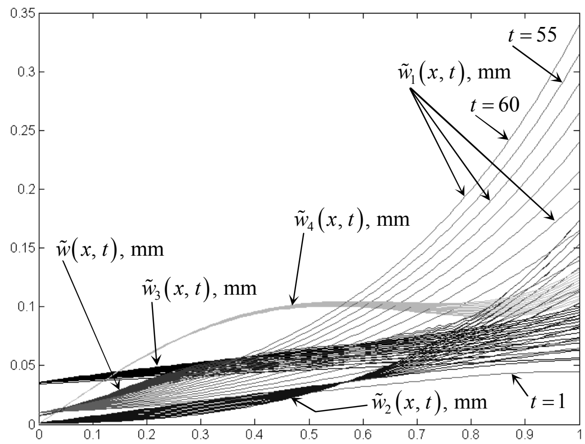

Fig. 6. Bundles of plane projections of theoretical wears of the machining tool and their convex combination (14) with (10) – (13) over the optimal strategy (8) in the game (7) by the quasimetric (15)

Conclusions

The procedure of taking the convex combination (14) with (10) – (13) assists in identifying the machining tool wear theoretically for the case, when the tool material properties are studied superficially and there are no anticipatory data, determining how and in what ratio the abrasive, adhesive, diffusive, and oxidizing wear components constitute the wear value along the coordinate x through time of the model observation.

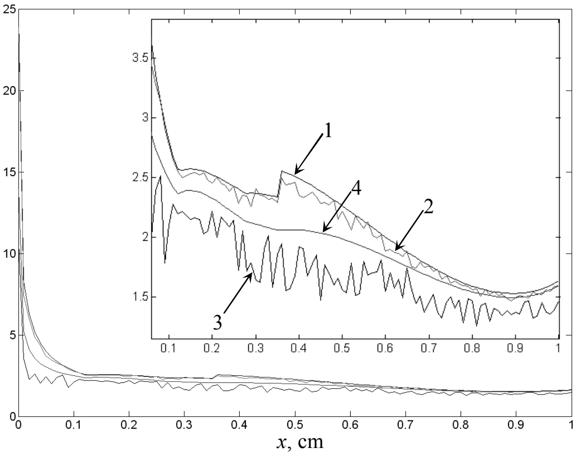

Fig. 7. Charge of lacks (in comparative ratio units) from erroneous tool wear modeling:
1 – the equiprobable distribution instead of $\mathbf{Q}_{\text{opt}}(x)$ is used, while the probability distribution $\mathbf{U}(x)$ over wear models stays the worst along every coordinate x;
2 – the equiprobable distribution instead of $\mathbf{Q}_{\text{opt}}(x)$ is used, and the probability distribution $\mathbf{U}(x)$ over wear models stays near the worst distribution along every coordinate x (being not the worst, whatsoever);
3 – the optimal strategy (8) in the game (7) by the quasimetric (15) is used, and the probability distribution $\mathbf{U}(x)$ over wear models is random along every coordinate x;
4 – the optimal strategy (8) in the game (7) by the quasimetric (15) is used, and the probability distribution $\mathbf{U}(x)$ over wear models is the worst along every coordinate x

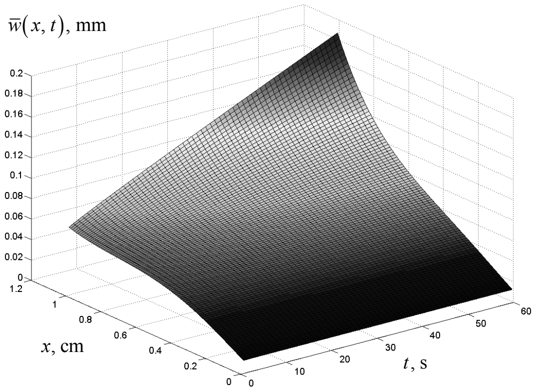

Fig. 8. The mean wear (17), that is the equiprobable distribution instead of $\mathbf{Q}_{\text{opt}}(x)$ is used

The practical gain lies in that such primal identification of the machining tool wear model allows to control its theoretical wear and to minimize the aftermath of the tool possible underuse or overuse. When real measurements become available during the further exploitation of the same type tool, its wear model will be re-identified, where the approach with weighting the specific components of the tool wear stays nevertheless in the form of the combination (14). And not only on real measurements the re-identification can be accomplished. There may be studied deeper the models, making the wear composite, what renders anticipatory data determining the leading specificity of wear or at least narrowing the primal ultimate uncertainty to a certain probability distribution over wear models at each coordinate of the wearing curve. In general, if there is a set of mathematical models, describing the same object, then a primal meta-model can be determined as the result of evolution of convex combinations of those models [4, 16, 20, 23]. The matter is just what coefficients for the starting convex combination must be fitted: minimaxed ones from the optimal strategy (8) in the game (7) by the quasimetric (15) are fitted riskless for the ultimate uncertainty case, and coefficients $\left\{\lambda_j(x, 0)\right\}_{j=1}^{4}$ should be taken some differently if there has appeared a supplementary information (data) about model components of the meta-model.

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ІДЕНТИФІКАЦІЯ МОДЕЛІ ЗНОСУ РІЖУЧОГО ІНСТРУМЕНТУ ЗА МІНІМАКСНИМ КОМБІНУВАННЯМ ТА ПОДАЛЬШИМ ЗВАЖУВАННЯМ СПЕЦИФІЧНИХ МОДЕЛЕЙ

В.В. Романюк

У статті стверджується, що для деякої множини математичних моделей, що описують один і той же об'єкт, першопочатково може бути визначена метамодель, котра є результатом еволюції опуклих комбінацій цих моделей. Цією еволюцією фактично є процес ідентифікації, що починається з опуклої комбінації з коефіцієнтами, котрі гарантують мінімум втрат. Мета полягає в теоретичній ідентифікації зносу ріжучого інструмента за граничних невизначеностей, коли немає попередніх даних, котрі б визначали як і у якому співвідношенні абразивна, адгезійна, дифузійна й окислювальна компоненти утворюють значення зносу. Знос ріжучого інструменту розглядається як функція часу однієї геометричної координати. Є чотири моделі зносу, що фокусуються на таких специфічних ознаках складного процесу зношування як абразія, адгезія, дифузія та окислення. Сукупність цих чотирьох особливостей зносу може бути знайдена як їх опукла комбінація, чиї коефіцієнти еволюціонують з плином часу з еволюціонуючими значеннями моделей зносу. На самому початку ці коефіцієнти встановлюються як мінімаксні імовірності застосування абразивної, адгезійної, дифузійної та окислювальної моделей зносу. Використовуючи міру точності для кожної моделі зносу, еволюція у часі коефіцієнтів опуклої комбінації виражається у кожній точці єдиної геометричної координати. Ця міра встановлює відносну відповідність між значенням моделі зносу й опуклою комбінацією зносу у поточній часовій вибірці для довільного значення геометричної координати. Викладена процедура зважування моделей зносу за їх точністю може бути покладена як деякий процес ідентифікації за умов невизначеностей або відсутності попередніх даних. Це використовуватиметься для першопочаткової ідентифікації структури моделі системи або процесу, коли існує декілька підходів до моделювання, значимості яких невідомі або невизначені.

***Ключові слова:** знос ріжучого інструменту, абразивний знос, адгезійний знос, дифузійний знос, окислювальний знос, граничні невизначеності, сукупний знос, міра точності, опукла комбінація, імовірності за мінімаксом.*

ИДЕНТИФИКАЦИЯ МОДЕЛИ ИЗНОСА РЕЖУЩЕГО ИНСТРУМЕНТА ПО МИНИМАКСНОМУ КОМБИНИРОВАНИЮ И ПОСЛЕДУЮЩЕМУ ВЗВЕШИВАНИЮ СПЕЦИФИЧЕСКИХ МОДЕЛЕЙ

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В статье утверждается, что для некоторого множества математических моделей, описывающих один и тот же объект, первоначально может быть определена метамодель, которая является результатом эволюции выпуклых комбинаций этих моделей. Этой эволюцией фактически является процесс идентификации, который начинается с выпуклой комбинации с коэффициентами, гарантирующими минимум потерь. Цель заключается в теоретической идентификации износа режущего инструмента при предельной неопределённости, когда нет предварительных данных, которые бы определяли как и в каком соотношении абразивная, адгезионная, диффузионная и окислительная компоненты образуют значение износа. Износ режущего инструмента рассматривается как функция времени одной геометрической координаты. Есть четыре модели износа, которые фокусируются на таких специфических признаках сложного процесса изнашивания как абразия, адгезия, диффузия и окисление. Совокупность этих четырех особенностей износа может быть найдена как их выпуклая комбинация, чьи коэффициенты эволюционируют с течением времени с эволюционирующими значениями моделей износа. В самом начале эти коэффициенты устанавливаются как минимаксные вероятности применения абразивной, адгезионной, диффузионной и окислительной моделей износа. Используя меру точности для каждой модели износа, эволюция во времени коэффициентов выпуклой комбинации выражается в каждой точке единственной геометрической координаты. Эта мера устанавливает относительное соответствие между значением модели износа и выпуклой комбинацией износа в текущей временной выборке для произвольного значения геометрической координаты. Изложенная процедура взвешивания моделей износа по их точности может быть положена как некоторый процесс идентификации в условиях неопределённостей или отсутствия предварительных данных. Это будет использоваться для первоначальной идентификации структуры модели системы или процесса, когда существует несколько подходов к моделированию, значимости которых неизвестны или неопределены.

***Ключевые слова:** износ режущего инструмента, абразивный износ, адгезионный износ, диффузионный износ, окислительный износ, предельные неопределённости, совокупный износ, мера точности, выпуклая комбинация, вероятности по минимаксу.*