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IMPROVEMENT OF QUALITY OF THE EVALUATION OF MODEL PARAMETERS BY INTEGRATED METHOD OF LEAST SQUARES

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Abstract*—Modern systems of management, optimization and forecasting of production require new algorithms of work and evaluation of systems and processes. When solving problems, in the absence of a priori information, there is a need for the use of effective methods of parametric identification. The accuracy of the existing classical methods of identification depends on the availability of certain information regarding the characteristics of the signals, in particular, on the law of the distribution of random error of measurement, and therefore in the real processes are ineffective. There is a need to apply methods that provide more accurate estimates of the parameters of a mathematical model of the object under study in time-limited and non-sensitive data, about noise variables and control impacts. The estimation of parameters is carried out using the integrated method of least squares, which provides smoothing of the external influences of the model under study on the results. The effectiveness of the method under consideration is confirmed by comparison with the least squares method. The optimization of the parameters of the weight function according to the external criterion has been made, at least the norm of the difference between the estimates of the parameters of the pair and odd sequences. The analysis of the dependence of the accuracy of the estimations of parameters on the choice of coefficients of the weight function is carried out.*

Index Terms—Parametric identification; ordinary least squares; unbiasedness; estimation efficiency; modification of ordinary least squares; weight function.

I. INTRODUCTION

The development of science is characterized by the significant development of methods and means of identification from simple approximate manual [1] to more complex and accurate [2], which use modern automated data acquisition and processing systems (ACID) using powerful computers and intelligent primary transducers (sensors). This allows you to significantly increase the frequency of questioning sensors, the speed and accuracy of information processing, increase the informativeness of data in limited time samples. However, the natural properties of real objects (not autonomy, non-stationary, non-linearity of the interconnections of the changing states, infinite dimensionality, etc.) do not allow the construction of models that are identical to the real object. The most advanced ACID has the ability to observe only a limited set of variables of the state $X(t)$ of the object. Any model only approximates the interconnection of the components $x_i(t)$, $i=\overline{1, n}$, n-dimensional vector of the function $X(t)$ and the m-dimensional vector function $U(t)$ of the input effects:

$$\dot{X}^*(t) = f\left(X^*(t),\ U^*(t),\ t\right), \qquad (1)$$

where $\dot{X}^*(t)$ is the velocity vector of the change.

For the limited deviations ΔX^*, ΔU^* from the basic mode $(X_0,\ U_0)$ and the presence of natural smoothness of the map f, the model (1) can be supplied with the error $\varepsilon^*(t)$ of the linear stationary:

$$\Delta\dot{X}^*(t) = A_0 X^*(t) + B_0 U^*(t) + \varepsilon^*(t), \qquad (2)$$

or its scalar representation:

$$\Delta\dot{x}_i^*(t) = \sum_{j=1}^{n} a_{ij}\Delta x_j^*(t) + \sum_{k=1}^{m} b_{ik}\Delta U_k^*(t) + \varepsilon_i^*(t), \qquad i=\overline{1, n}. \qquad (3)$$

II. PROBLEM STATEMENT

The task of parametric identification consists in determining the estimates $\hat{a}_{ij}$, $\hat{b}_{ik}$ of coefficients a_{ij}, b_{ik} with a minimum of the error $\varepsilon_i^*(t)$ functional I_i. It is logical to take as the average square error $\varepsilon_i^*(t)$ in the interval T of observation as I_i where the exact values of the corresponding variables appear in (1), (2), (3). Then, as the best model (2), there will be one whose coefficients a_{ij}, b_{ik} are calculated by the least squares method

(LSM) for the exact data, $\dot{X}*(t)$, $X*(t)$, $U*(t)$. If it is possible to directly measure or calculate $\dot{X}*(t)$, then formally dynamic models (2) and (3) can be represented as regression ones. For example, each ith line (3) of system (2) is represented as:

$$y*(k)=\sum_{i=1}^{n+m}\beta_i x_i*(k)+\varepsilon*(k), \qquad (4)$$

where $y*(k)=\Delta\dot{x}_i*(k)$, $x_i*(k)$ includes a set $\Delta x_j*(k)$, $\Delta U_k*(k)$, β_i includes a set a_{ij}, b_{ik} in equation (3), k is the number of the discrete t_k of time t, $k=\overline{1,\ m}$.

Thus, theoretically, the best estimate of the vector β of the parameters a_{ij}, b_{ik} of the simplified model (3) will be the LSM estimate [5] under the condition of accurate measurement of variables:

$$\hat{\beta}*=\left((X*)^{\mathrm{T}}X*\right)^{-1}(X*)^{\mathrm{T}}Y*. \qquad (5)$$

However, the LSM evaluation of the parameters is not without disadvantages, especially in a situation of random perturbations that arise in all real processes. The LSM estimates are the coordinates of the minimum point of the functional $\varepsilon^{\mathrm{T}}\varepsilon$. Since the functional is a square value of ε that is averaged over the finite interval T, which is a mixture of a useful signal $Y^*-X^*\beta$ and random perturbation $N_y-N_x\beta$, it is not a precise function as a function of β. Therefore, the operation of differentiating $\frac{\partial}{\partial\beta}(\varepsilon^{\mathrm{T}}\varepsilon)$ a noisy function $\varepsilon^{\mathrm{T}}\varepsilon$ is incorrect [4]. This is precisely due to the low accuracy of LSM estimates on short, very noisy data samples Y, even (as required by LMS) for exact X*.

III. The Method Proposed to be Used in Real Conditions

The disadvantage of LSMs is the spread of functional values of I. This can be done by additional averaging over the set of quasi-statistically independent functionals close to the mean square value for the exact data. Such functions can be mean products

$$\frac{1}{T}\int_0^T\varepsilon(t)\varepsilon(t+\theta)dt,$$

shifted in time t to the interval θ average product range. Averaging them in the interval $[-\tau_1,\tau_1]$, let's obtain the following functional:

$$I=\int_{-\tau_2}^{\tau_1}\eta(\theta)\int_0^T\varepsilon(t)\varepsilon(t+\theta)dtd\theta, \qquad (6)$$

where $\eta(\theta)$ is the weight function.

From the necessary condition for a minimum with respect to β_k, $k=\overline{1,n}$ of the exponent (6):

$$\frac{\partial I}{\partial\beta_k}=\int_{-\tau_1}^{\tau_1}\eta(\theta)\int_0^T\left[\frac{\partial\varepsilon(t)}{d\beta_k}\varepsilon(t+\theta)+\varepsilon(t)\frac{\partial\varepsilon(t+\theta)}{\partial\beta_k}\right]dtd\theta=\int_{-\tau_1}^{\tau_1}\eta(\theta)\int_0^T(-x_k(t))\left[y(t+\theta)-\sum_{i=1}^{n}\beta_i x_i(t+\theta)\right]$$
$$+(-x_k(t+\theta))\left[y(t)-\sum_{i=1}^{n}\beta_i x_i(t)\right]=0,\quad k=\overline{1,n}. \qquad (7)$$

Let's obtain a system of equations:

$$A\cdot\hat{\beta}=B, \qquad (8)$$

where A is the matrix $n\times n$ with elements a_{ik}; B is matrix-column $n\times 1$ with the elements b_k:

$$a_{ik}=\sum_{1=-p}^{p}\eta(l)\sum_{j=1}^{M}\left[\left(x_i(j+l)\right)x_k(j)+x_i(j)x_k(j+l)\right],$$

$$b_k=\sum_{1=-p}^{p}\eta(l)\sum_{j=1}^{M}\left[\left(y(j+l)\right)x_k(j)+y(j)x_k(j+l)\right].$$

The solution of system (8) gives the required estimate $\hat{\beta}$:

$$\hat{\beta}=A\cdot B. \qquad (9)$$

The weight function $\eta(m)$ can be found in the class of finite functions that are symmetric with respect to m = 0 (such that $\eta(0)=\eta(\pm m_{kr})$. For example:

$$\eta(m)=\eta(m,\gamma,\theta)=(1+|m|)^{\theta}\left(1-\cos\frac{|\pi m|}{m_{kr}}\right)^{\gamma} \qquad (10)$$

where $\theta\in(\pm\infty)$, $\gamma\in(0,\infty)$, m_{kr} is determined when:

$$\det\left[X^{\mathrm{T}}\left(X_{m_{kr}}+X_{-m_{kr}}\right)\right]\cong 0. \qquad (11)$$

The parameters θ and γ are optimized for the main (external) exponent I [3], [5]. The parameter γ affects the width of the pulse $\eta(m)$, and θ its asymmetry relative to the maximum (Fig. 1).

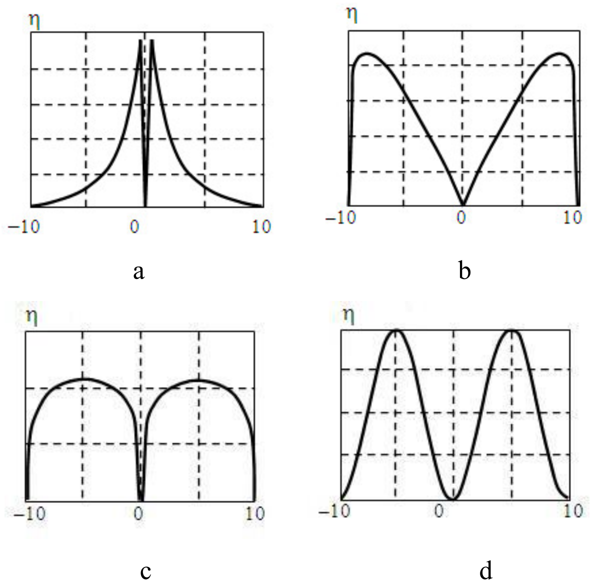

Fig. 1. Dependence $\eta(m, \theta, \gamma)$: (a) is $\theta = 0$, $\gamma = 0.1$; (b) is $\theta = 0$, $\gamma = 1$; (c) is $\theta = -2$, $\gamma = 0.1$; (d) is $\theta = 2$, $\gamma = 0.1$

IV. COMPARISON OF LSMS AND THE PROPOSED METHOD IN THE IDENTIFICATION TASK

The quality of parametric estimation is affected by the degree of interrelation of the variables $x_i(t)$, $i = \overline{1, n}$ and not by their number. Therefore, let's confine ourselves to a simple example. The equation describing the process is presented in the form (4), where:

$$y^*(k) = \beta_1 {}^* x_1{}^*(k) + \beta_2{}^* x_2{}^*(k);\ k = \overline{1, 1000};$$

$$\beta_1{}^* = \beta_2{}^* = 1;\ x_1{}^* = \sin\frac{\pi k}{500};\ x_2{}^* = \sin\left(\frac{\pi k}{500} + \frac{\pi}{6}\right).$$

On measurements $y(k)$, $x_1(k)$, $x_2(k)$ white noise is imposed – random numbers with uniform distribution in the range [±1]. For an objective estimation of the displacement and spread of estimates β_1, β_2 ten statistically independent realizations of noise are generated. The results of identifying the coefficients β_1, β_2 for the least squares method and the proposed method are given in Table I. Estimates of β_1 and β_2 by LSM (Table I) are underestimated by almost 50% (9). However, there is a regularization [6]: the spread $\sigma_{\beta i}$ of estimates β_i is 0.02 and 0.05. In the proposed method (Table I), the estimates are almost unchanged: 1.005 and 0.943, but the spread is greater than in a regularized LSM (0, 15, 0.16). Reducing the spread is possible due to a compromise between displacement and dispersion by changing the parameters θ and γ weight functions.

TABLE I

THE RESULTS OF ESTIMATING THE PARAMETERS FOR NOISINESS OF INPUT AND OUTPUT VARIABLES

No	Least squares method		Estimations by the proposed method	
	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$
1	0.4790	0.4981	1.0282	0.9094
2	0.4607	0.4493	1.0179	0.8844
3	0.4843	0.5663	1.0916	0.8435
4	0.5024	0.5401	1.0020	0.9290
5	0.5246	0.4659	1.0313	0.9798
6	0.4997	0.5058	1.2904	0.7437
7	0.4849	0.5255	0.7093	1.2307
8	0.4919	0.4431	0.8283	1.1910
9	0.4676	0.4856	1.0825	0.7197
10	0.4642	0.6015	0.9653	1.0112
$\bar{\beta}$	**0.4860**	**0.5082**	**1.0047**	**0.943**
$\sigma^2_{\beta i}$	**0.00038**	**0.0026**	**0.0241**	**0.0283**
σ_{β_i}	**0.0197**	**0.0511**	**0.1551**	**0.1682**

In the case of noise only in the original variable (Table II) (ideal situation for least squaresmethod), the estimates are unbiased, but the spread of the estimates for this method (0.07 and 0.09) is greater than the spread (0.05 and 0.08) optimization of parameters θ and γ of the function $\eta(m)$. In the case that there is an opportunity to optimize $\eta(m)$ [4], the gain of the proposed method in the sense of unbiasedness and the effectiveness of estimates relative to least squares method is much larger.

TABLE II

THE RESULTS OF ESTIMATING THE PARAMETERS WITH NOISINESS OF ONLY THE ORIGINAL VARIABLES

No	Least squares method		Estimations by the proposed method	
	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$
1	0.9781	0.9212	0.9497	1.1019
2	1.0541	0.9371	1.0234	0.8554
3	0.9329	1.0817	0.9825	1.0618
4	1.1181	0.8819	1.0111	0.9132
5	0.9847	1.0327	1.1907	0.9807
6	1.0009	1.0192	1.1018	0.9823
7	1.1549	0.8258	0.9866	1.1244
8	0.9407	1.0765	1.0216	0.9879
9	0.9578	1.0823	0.9639	1.0861
10	1.0007	0.9412	1.0961	0.9946
$\bar{\beta}$	**1.0123**	**0.9800**	**1.0280**	**1.0089**
$\sigma^2_{\beta i}$	**0.0055**	**0.0083**	**0.0027**	**0.0073**
σ_{β_i}	**0.0744**	**0.0911**	**0.0522**	**0.0854**

V. Optimization of Parameters of Weight Function by External Criterion

The accuracy of the estimation β_1 and β_2 depends on the choice of the parameters θ and γ of the weight function. To select the parameters of the weight function we use an external criterion [5] to verify the stability of the model. To do this, we break down the resulting sequence of data into two sequences containing paired and odd values of *k* respectively. The external criterion for evaluating the parameters of the weight function is the minimum of the norm of the difference between the estimates β_1 and β_2, respectively, of the pair and odd sequences:

$$\Lambda = \sqrt{\left(\beta_{11} - \beta_{12}\right)^2 + \left(\beta_{21} - \beta_{22}\right)^2}. \qquad (12)$$

The results of choosing the parameters of the weight function in the situation of noisiness of the input variables are presented in Table III. According to research $\Lambda \to \min$ at $\theta = -1, \gamma = 0{,}1$ (No11). Estimating the parameters across the sample gives the following results: $\beta_1 = 0.9868$ and, $\beta_2 = 1.0416$ which confirms the approximation of the estimates β_1 and β_2 to the given unit parameters.

TABLE III

THE RESULTS OF ESTIMATING THE PARAMETERS FOR NOISINESS OF INPUT VARIABLES

No	θ	γ	Λ	β_{11}	β_{12}	β_{21}	β_{22}
1	1	1	0.3319	0.8670	0.6582	0.9056	0.9879
2	0.1	1	0.8235	0.8515	0.5313	0.8777	–0.291
3	0.1	0	0.1508	0.8429	1.1969	0.8978	1.0565
4	–1	0	0.1817	0.6988	0.5461	0.6651	0.7246
5	–2	0	0.2342	0.7337	0.4244	0.5566	0.5570
6	0	0.1	0.2748	0.8421	1.2088	0.8495	1.4835
7	0	1	4.9171	0.8458	0.4847	0.8850	5.4016
8	–2	1	0.1711	1.3970	0.9374	1.2481	1.0217
9	–1	1	0.1516	0.8216	1.2855	0.7816	1.1393
10	–1	0.1	0.4302	0.9215	0.7130	0.9832	1.1388
11	1	0.1	0.1058	0.8990	1.0929	0.9157	1.1974
12	2	0.1	0.2276	0.9163	1.0363	0.9328	1.2634
13	–2	0.1	0.2576	0.8727	0.7765	0.8848	1.0339
14	2	1	0.4176	0.8737	0.6426	0.9209	1.0576

In the case of noise only in the output variable (Table IV) $\Lambda \to \min$ at $\theta = 2, \gamma = 0.1$. Accordingly, the estimates are equal to $\beta_1 = 0.9889$ and $\beta_2 = 0.9515$.

TABLE IV

THE RESULTS OF ESTIMATING THE PARAMETERS FOR NOISINESS OF OUTPUT VARIABLES

No	θ	γ	Λ	β_{11}	β_{12}	β_{21}	β_{22}
1	1	1	0.7335	0.8363	0.8277	0.9961	0.1118
2	0.1	1	1,7781	0,7760	2,0047	0,5531	2,7688
3	0.1	0	1,0880	1,2146	0,3031	1,1657	0,3876
4	-1	0	0,6070	0,7356	1,3892	1,0588	0,9541
5	-2	0	0,6471	0,7220	1,3979	1,1571	0,8663
6	0	0,1	2,1720	1,9175	-5,985	2,1598	-8,143
7	0	1	3,2159	0,7330	2,5885	0,3594	5,7827
8	-2	1	0,4904	1,2884	1,3455	1,1805	0,8671
9	-1	1	0,7651	0,9306	1,0297	1,0057	0,2683
10	-1	0.1	0.6040	0.7329	1.3817	1.1592	0.9538
11	1	0.1	0.5567	0.9800	0.7347	1.2018	1.2453
12	2	0.1	0.3439	0.9479	1.0210	1.1673	1.2858
13	-2	0,1	0.5835	0.7432	1.3776	1.1514	0.9606
14	2	1	1.0899	1.0149	1.0823	1.4338	0.0762

In the case of noise in the input and output variables (Table V) $\Lambda \to \min$ at $\theta = -1, \gamma = 1$. Accordingly, the estimates are equal to $\beta_1 = 1.12$ and $\beta_2 = 1.09$.

TABLE V

THE RESULTS OF ESTIMATING THE PARAMETERS FOR NOISINESS OF INPUT AND OUTPUT VARIABLES

No	θ	γ	Λ	β_{11}	β_{12}	β_{21}	β_{22}
1	1	1	0.4755	1.4865	1.1689	1.1667	0.8170
2	0.1	1	1.1601	1.3682	1.2027	1.1277	0.0678
3	0.1	0	0.3754	1.2932	1.2396	1.1364	0.8985
4	-1	0	0.1780	0.7635	0.7344	0.9407	0.7515
5	-2	0	0.1715	0.4964	0.6020	0.609	0.5535
6	0	0,1	2.5027	1.3128	1.2043	1.0437	-1.283
7	0	1	1.8355	1.3581	1.2075	1.0881	-0.608
8	-2	1	0.1594	1.1643	0.9791	1.2125	1.1311
9	-1	1	0.0888	1.2805	1.3208	1.2072	1.2707
10	-1	0.1	0.1801	1.0825	0.9912	1.2152	1,1130
11	1	0.1	1.0191	2.1536	1.0670	1.1378	0.9848
12	2	0,1	0.9161	0.207	1.2066	1.1006	1.0250
13	-2	0.1	0.2679	0.9700	0.9981	1.2258	1.0771
14	2	1	0.6050	1.7284	1.1353	1.1641	0.9170

VI. Conclusions

As shown in the theoretical [3], [2] and experimental calculations, the proposed method allows, in the real situation, the noise measurements of the input and output signals of the primary converters, obtain unobstructed estimates of parameters close to the estimates for the LSM for accurate measurements, as well as the spread of estimates, a lower spread for LSMs. Choosing the parameters of the weight function on the external (main) indicator Λ [7] increases the accuracy of the estimates obtained. This enables more efficiently than the LSM to use the proposed method in adaptive control systems, diagnostics and prediction of the behavior of real objects.

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А. М. Сільвестров, Г. І. Кривобока. Підвищення якості оцінок параметрів моделі інтегрованим методом найменших квадратів

Сучасні системи керування, оптимізації та прогнозування виробництвом потребують нових алгоритмів роботи та оцінки систем і процесів. При розв'язуванні поставлених задач, в умовах недостатньої апріорної інформації, виникає потреба в застосуванні ефективних методів параметричної ідентифікації. Точність існуючих класичних методів ідентифікації залежить від наявності певних відомостей стосовно особливостей сигналів, зокрема щодо закону розподілу випадкової похибки вимірювань, тому в реальних процесах малоефективні. Існує потреба в застосуванні методів, які забезпечують отримання більш точних оцінок параметрів математичної моделі досліджуваного об`єкта з обмежених у часі і діапазоні, зашумлених вибірок даних про змінні стану і керуючі впливи. Проведено оцінювання параметрів за допомогою інтегрованого методу найменших квадратів, що забезпечує згладжування зовнішніх впливів досліджуваної моделі на результати. Підтверджено ефективність розглянутого методу шляхом порівняння з методом найменших квадратів. Здійснено оптимізацію параметрів вагової функції за зовнішнім критерієм, як мінімум норми різниці оцінок параметрів парної і непарної послідовностей. Проведено аналіз залежності точності оцінок параметрів від вибору коефіцієнтів вагової функції.

Ключові слова: параметрична ідентифікація; МНК-оцінювання; незміщеність; ефективність оцінок; інтегрований метод найменших квадратів; вагова функція.

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А. Н. Сильвестров, Г. И. Кривобока. Улучшение качества оценки параметров модели интегрированным методом наименьших квадратов

Современные системы управления, оптимизации и прогнозирования производства требуют новых алгоритмов работы и оценки систем и процессов. При решении проблем при отсутствии априорной информации необходимо использовать эффективные методы параметрической идентификации. Точность существующих классических методов идентификации зависит от наличия определенной информации о характеристиках сигналов, в частности, от закона распределения случайной ошибки измерения, а потому в реальных процессах неэффективны. Необходимо применять методы, которые обеспечивают более точные оценки параметров математической модели исследуемого объекта в ограниченных по времени и нечувствительных данных, о шумовых переменных и контрольных воздействиях. Оценка параметров осуществляется с использованием интегрированного метода наименьших квадратов, который обеспечивает сглаживание внешних воздействий исследуемой модели на результаты. Подтверждена эффективность рассматриваемого метода сравнением с методом наименьших квадратов. Сделана оптимизация параметров весовой функции по внешнему критерию, по крайней мере, норма разницы между оценками параметров пары и нечетными последовательностями. Проведен анализ зависимости точности оценок параметров от выбора коэффициентов весовой функции.

Ключевые слова: параметрическая идентификация; МНК-оценивание; несмещенность; эффективность оценок; интегрированный метод наименьших квадратов; весовая функция.

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