Data processing to determine the parameters of a mathematical model of dynamic objects*

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Abstract

Mathematical modeling is essential for control system design, yet identifying parameters remains difficult due to uncertainty and noise. Traditional approaches typically rely on estimating parameters from system responses to standard inputs, such as step signals, but these methods often exhibit reduced robustness under practical conditions. This study proposes a unified data-processing framework for determining the parameters of dynamic object models represented by transfer functions. The approach combines classical identification techniques with polynomial approximation and structural modeling concepts inspired by the Group Method of Data Handling. A key feature of the proposed method is the transformation of exponential transient responses into reduced-order polynomial representations, effectively regularizing the estimation problem and mitigating numerical instability caused by ill-conditioned matrices. Unlike conventional strategies, this framework ensures stable parameter recovery under limited and noise-perturbed data. Simulation results using a high-performance UAV motor model demonstrate that the proposed approximation achieves significantly higher accuracy (MSE 0.0004573) than direct identification or GMDH-based methods. These findings provide a robust foundation for real-time parameter refinement in adaptive control systems operating in uncertain environments. The obtained results highlight the potential of combining response transformation and data-driven modeling as a foundation for future integration with adaptive and learning-based control strategies.

Keywords

System identification, Group Method of Data Handling (GMDH), adaptation, polynomial approximation, transient response analysis, parametric uncertainty, UAV motor dynamics

1. Introduction

Mathematical modeling involves describing the processes occurring within a system using formulas and dependencies, which allows for a more precise study of certain properties of objects or processes without resorting to their physical implementation [1]. The advantage of this approach lies in its resource savings during routine testing, the detailed study of system behavior in critical situations during the design stage, and the improvement of decision-making mechanisms. Currently, mathematical modeling is a universal approach to studying technological processes, enabling significant advances in understanding their behavior, identifying a wide range of system responses to changes in their parameters, formulating quantitative hypotheses for experimental testing, and, ultimately, predicting and identifying fundamentally new classes of phenomena and processes.

The main problems in constructing a mathematical model of dynamic objects are considered to be the a priori parametric uncertainty of the adopted form of the mathematical model and the conditions for measuring the output values of their characteristics; the imperfection of sensors and measurement methods; and the limited time for studying the characteristics of the dynamic model.

*ITS-2025: Information Technologies and Security, December 11, 2025, Kyiv, Ukraine

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CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073

published 2026-11-26

CEUR-WS.org/Vol-4337/paper4.pdf

The aim of the study is to reduce the impact of these problems when obtaining the parameters of a mathematical model in the form of a transfer function used to obtain a response to a typical impact that would be adequate for the real measurement process by expanding the research capabilities through the integration of several approaches, including artificial intelligence-based approaches.

The main contribution of this work is not limited to comparing existing parameter estimation techniques for dynamic objects. Instead, the study introduces a unified data-processing framework that combines classical identification, polynomial approximation, and evolutionary modeling concepts inspired by the Group Method of Data Handling.

Unlike traditional approaches that rely on a single estimation paradigm, the proposed framework:

- Enables reduction of parameter uncertainty under limited measurement data.
- Improves approximation accuracy through structural transformation of the dynamic response.
- Provides an alternative low-complexity representation of system dynamics.
- Creates a foundation for future integration with adaptive and learning-based control strategies.

A key novelty of the proposed approach lies in transforming the dynamic response identification problem into a reduced polynomial approximation form, which allows for the efficient estimation of system parameters while preserving essential dynamic properties.

2. Paper review

Mathematical modeling for the design of dynamic systems is an interesting research area, where a wide variety of methods are employed, ranging from traditional methods based directly on identification to complex combinational approaches that utilize artificial intelligence and time series processing.

The most straightforward approach for quickly finding the parameters of a dynamic object is to identify them based on their response to a typical stimulus by estimating the rate of rise of the output value, its delay, and the rise time interval. This is the so-called direct identification, the application of which can be found in the work of Qian et al. [2], where the authors used this approach to identify the main and physical parameters of a robot, taking into account friction and joint loads. However, for a more detailed overview of existing identification methods, one should refer to the book by J.P. Norton [3]. Inspired by the basic idea of identification, D. Kucherov et al. [4] proposed an approach to estimating unknown coefficients of the characteristic polynomial by numerically integrating the area under the curve of the error function, which can serve as a basis for further decisions.

Probabilistic methods remain an established approach to constructing mathematical models under statistical uncertainty, one of which is regression, which involves taking into account various factors influencing the processes under study. For example, Wang and Barry [5] used regression to construct a kinematic model of the wrist, into which constraints on the rotation of the control object were introduced based on quaternions. Further, an extended Kalman filter was used to refine the model parameters in real time. Fei and Bai [6] used statistical learning and mean and autocovariance recognition methods in constructing an autoregressive model based on non-stationary time series measurements. Castano et al. [7] synthesized a nonlinear autoregressive model for a discrete dynamic system.

The possibility of using artificial intelligence elements to determine the model parameters is demonstrated in [8 – 12]. The application of genetic algorithms to determine the parameters of a linear fuel cell model is presented by Ohenoja et al. [8]. Grasev [9] used a genetic algorithm to identify the parameters of a gas turbine engine with an objective function in the observed

Koopman subspace. Zakaria et al. [10] proposed a genetic algorithm to detect and identify problematic vibration defects in unmanned aerial vehicles (UAVs). Machado and Givigi [11] present obtaining the parameters of a dynamic system impulse response model using a convolutional neural network. A general solution to the problem of selecting a model of a complex system under a priori uncertainty can be found in the study of Gu and Wei [12].

Popular methods for constructing a mathematical model of a dynamic object that allows predicting its changes are recurrent methods that use the analysis of current data, which include the group data processing method [13 – 15] and time series analysis methods [16 – 21]. The group data processing method for predicting changes in the river bed was used by Ma et al. [13]. Pournasir et al. [14] presented the possibility of using the group data processing method to improve the accuracy of modeling and forecasting the number of kanban cards in just-in-time systems. Mohammad and Davidrajuh [15] presented the process of obtaining a mathematical model from data obtained in real time during drilling operations in the oil and gas industry, based on the group data processing method.

An algorithm for segmenting a multivariate time series into subsequences at change points in the dynamics, which is based on recursive merging of adjacent subsequences using a bottom-up heuristic procedure, was proposed by Lu and Huang [16]. Puri et al. [17] proposed a method for learning a Gaussian process by predicting a time series based on test data and studied a selected subset. Ruble et al. [18] presented a Bayesian time matching method and a machine-learning algorithm that matches signals from two time sequences containing inserted, deleted, or distorted elements. Yang and Yang [19] proposed machine learning-based data change prediction methods that decompose a complex time series into several subsequences. Koulali and Clarke [20] studied a Gaussian process for modeling quasi-periodic signals in geodetic time series using the Monte Carlo method. Ali et al. [21] presented a review of methods and technologies for accurate assessment of object identification in motion and its localization.

As noted earlier, a single approach to constructing a mathematical model, whether based on identification or statistics, is insufficient. Therefore, the most extensive list of studies is focused on the combined use of different approaches to construct a satisfactory mathematical model. Thus, Wei et al. [22] combined multivariate signal analysis with smoothing methods based on group data processing and a genetic algorithm to construct a mathematical model for the regression assessment of the state of lithium-ion batteries. Yuniarti et al. [23] proposed a combination of the wavelet transform and the group data processing method for forecasting the load of the electrical grid. Zhou et al. [24] proposed a model for integrating the Kalman filter and the state space model to improve the accuracy of forecasting long-term time series. Yu et al. [25] proposed a combination of an adaptive genetic algorithm with a particle filter for predicting the service life of a nonlinear mechatronic system with multiple faults. Aghili-Ashtiani and Menhaj [26] to synthesize a model of an asynchronous DC-DC buck converter proposed fuzzy logic and online identification. Hsiao and Chan [27] presented the integration of Newton-Euler and least squares methods for the identification of robotic arm parameters. A combined approach to motor parameter identification based on the least-squares method and Li and Ma [28] presented selective control in the study. Şen et al. [29] presented a combination of the Elman-Jordan recurrent neural network model with the extended Kalman filter.

The presented analysis of modern methods in the field of constructing mathematical models shows that it is advisable to continue research in the direction of finding effective solutions for identifying dynamic objects under conditions of a priori parametric uncertainty.

3. Methodology

In research, the object under study is typically treated as a "black box," in which a priori information about its structure, properties, and response to typical stimuli is unknown. Its response

may be similar to previously studied objects, which can somewhat simplify its description. However, nonlinearity, delays, environmental influences, and the dynamic nature of the object complicate the research process. In this case, both direct and indirect research methods can be useful.

Unknown parameters of a mathematical model can be obtained through identification, a direct research method based on experimental data measurements. An example of this is shown in [4], where measurement results were used to calculate the coefficients of the transfer function's denominator polynomial by numerically integrating the error function, which is obtained as the difference between the input signal and the system's response to that signal.

An alternative approach to the studied identification method is the Group Method of Data Handling (GMDH), proposed by the distinguished Ukrainian scientist A.G. Ivakhnenko [30, 31], a pioneer in deep learning methods. This approach also allows one to find unknown coefficients for a polynomial function composed of a series of measurements, based on least-squares estimation.

Indirect methods eliminate the need to estimate the parameters of a dynamic object's mathematical model and instead adjust the controller's parameters in a closed control loop based on adaptation or learning algorithms, where the performance criterion is the system error functional. The appeal of this approach lies in its applicability during system operation, where, over several trial runs, the controller adjusts to the best transient response parameters and monitors their changes, accounting for sensor errors and measurement noise. This allows these latter methods to be considered elements of artificial intelligence.

4. Problem formulation

A mathematical model of the dynamic object under study is considered in the form of a polynomial with unknown coefficients. This model can be represented either as a differential equation or as a transfer function, since there is a one-to-one correspondence between these two representations, obtained by replacing the differentiation symbols with the Laplace operator, i.e., $p = d/dt$, and representing it as the ratio of the Laplace images of the output and input quantities. In this case, the differential equation is transformed into an algebraic equation of the same order, and the polynomial with unknown coefficients becomes the denominator of the transfer function.

Let the mathematical model of the dynamic object under study, taking into account the above-mentioned remark, be represented in the form of a transfer function of the type

$$W(s)=\frac{k}{a_n s^n + a_{n-1} s^{n-1} + \ldots + a_1 s + 1}. \quad (1)$$

In model (1), the coefficients of the denominator polynomial, a_n, a_{n-1}, ..., a_1, and the coefficient of the numerator k are considered unknown.

The coefficients of the system under study must be non-negative, i.e., they cannot all be equal to zero simultaneously; that is, $a_i \geq 0$, which corresponds to most real objects.

It is assumed that measurement data are affected by bounded additive noise. The estimation procedure is therefore required to provide parameter values that ensure acceptable approximation accuracy under measurement uncertainty.

The task is to determine the parameters of the model, a_n, a_{n-1}, ..., a_1, and k such that the model's response to a typical impact and the object under study meets the proximity criterion.

The criterion for assessing the model approximation is the mean square error of the deviation of the measurement data from the response of the mathematical model in the form

$$I(n)=\frac{1}{n}\sum_{i=1}^{n}\left(y^*[i]-y[i]\right)^2 \varepsilon, \quad (2)$$

where $y^*[i]$ and $y[i]$ are the reaction of the object and the model at the i-th moment of time, n is the number of measurements, ε is the permissible accuracy of approximation.

5. Problem solution

The solution to this problem is supposed to be accomplished by two methods of data processing, namely, the Group Method of Data Handling [30, 31] and the identification method [4].

5.1. Identification

We will use the method proposed in [4], in which the coefficients of the denominator polynomial (1) are found recursively. The identification algorithm itself includes the following steps.

1. The coefficient k of the model (1) is determined on the linear section of the acceleration curve trajectory, specified by the interval of measurement points, i.e.
$$k = \frac{\Delta y}{\Delta t}. \quad (3)$$
2. The measurement data $y[n]$, obtained from the points of the acceleration curve, are brought to the interval [0, 1] by normalizing to the steady-state value.
3. The deviations $\theta[n] = 1 - y[n]$ are calculated within the established observation interval.
4. The weighting coefficients μ_i of the power series of the image expansion by error are determined by numerically integrating the expression relative to the error over the study interval T_n, the general form of which is given by the formula
$$\mu_i = \frac{1}{i!}\int_0^{T_n} (-t)^i \theta(t)\, dt, \quad (4)$$

where $\theta(t)$ is a function on the interval $[m - 1, m]$, approximated by a trapezoid or a parabola depending on the integration method, $m \in [0, T_n]$.

5. The coefficients of the denominator polynomial (1) are obtained using the formulas
$$a_k = \mu_{k-1} + \sum_{i=0}^{k-2} \mu_i a_{k-i-1} \quad (5)$$

limited to positive values, $a_1 = \mu_0$.

5.2. Group Method of Data Handling

To build a polynomial model based on data, you can use the group argument accounting method, which allows you to find unknown coefficients by evolutionary selection of the best combinations of variables. In this case, the unknown coefficients of the polynomial model are found by the least squares method.

The algorithm for solving the problem of constructing a mathematical model in accordance with this method involves performing the following sequential actions [30, 31]:

1. The existing data sample should be divided into two parts: training and validation.
2. Given a training set of measured data, adjacent pairs of arguments are linked to form unique pairs of values without repetitions to obtain an initial representation of the model in the form of a polynomial.
3. A polynomial model is constructed through the parallel connection of components by summing the coefficients of the polynomial description with the same indices.
4. The model is evaluated using the validation data set; if the evaluation is unsatisfactory according to the adopted criterion (2), the model with the smallest error is selected, which serves as the basis for the second round of calculations, forming a new structural layer.
5. The procedure for creating structural layers of calculations is repeated until the quality of the model becomes satisfactory.

5.3. Approximation

An alternative approach to studying the numerical characteristics and qualitative properties of an object, which reduces a complex problem to simpler or more convenient objects. Let's consider a possible approach to solving this problem for a second-order dynamic object, as in the GMDH version, based on least-squares approximation.

Let operations (1)-(3) described in Section 5.1 be performed. Then the transition function for the deviations ε[*n*] of the second-order object can be represented in the form of a time function based on the inverse Laplace transform [32], of the form

$$\varepsilon(t) = A e^{-\alpha_1 t} + B e^{-\alpha_2 t} \tag{6}$$

where $A = \frac{\alpha_1^2}{\alpha_1 - \alpha_2}$, $B = \frac{\alpha_2^2}{\alpha_2 - \alpha_1}$, and the quantities α_1 and α_2 are the roots of the characteristic equation of the dynamic object to be determined on the basis of experimental data.

For practical identification problems, direct estimation of exponential components in (6) is numerically sensitive and poorly conditioned under noisy measurements. Therefore, a reduced-order polynomial representation is introduced. Using a second-order truncated series expansion of the exponential terms, the response is approximated within the dominant transient interval. This transformation preserves the principal dynamic behavior while enabling stable least-squares estimation. Such reduction is justified for systems where the dominant dynamics are governed by the initial transient phase, which is the most informative for parameter estimation.

Due to the difficulty of directly applying the least squares method directly to (6), it is proposed to reduce this equation to quadratic form by representing the exponentials of the first three terms of the expansion in a power series.

After applying the transformations, we obtain a quadratic equation

$$\varepsilon(t) = a t^2 + bt + c, \tag{7}$$

where

$$a = \frac{1}{2}(\alpha_1 + \alpha_2)(\alpha_1^2 + \alpha_2^2), \tag{8}$$

$$b = -(\alpha_1^2 + \alpha_1 \alpha_2 + \alpha_2^2), \tag{9}$$

$$c = (\alpha_1 + \alpha_2). \tag{10}$$

The coefficients *a*, *b*, *c* are found from experimental data by solving a system of equations

$$M_{t^4} a + M_{t^3} b + M_{t^2} c = M_{t^2 x}, \tag{11}$$

$$M_{t^3} a + M_{t^2} b + M_t c = M_{tx} \tag{12}$$

$$M_{t^2} a + M_t b + c = M_x \tag{13}$$

The following notations are used here:

$$M_{t^4}=\frac{1}{n}\sum_{i=1}^{n} t_i^4, M_{t^3}=\frac{1}{n}\sum_{i=1}^{n} t_i^3, M_{t^2x}=\frac{1}{n}\sum_{i=1}^{n} t_i^2 x_i, M_x=\frac{1}{n}\sum_{i=1}^{n} x_i',$$

The solution of system (11) – (13) yields the values of parameters a, b, c for function (7). Parameters α_1 and α_2 (6) are found by solving the system of equations (8) – (10). Then the coefficients of the denominator polynomial of the object under study are found from the expressions $a_2=\alpha_1\alpha_2$, and $a_1=\alpha_1+\alpha_2$.

6. Simulation

The problem of determining the parameters of a mathematical model in the form (1) for a dynamic object is considered using the methods described in Section 5. The mathematical model of the RCINPOWER SmooX 2306 Plus 2280KV motor is proposed as a reference model, with its parameters calculated based on the technical characteristics presented in [33]. Based on the calculation results, we have a transfer function of the dynamic object in the form:

$$W(s)=\frac{0.0042}{2.04\cdot 10^{-8}s^2+8.2\cdot 10^{-6}s+1.764\cdot 10^{-5}}, \quad (14)$$

The experimental data were obtained by calculation using the transition function for (14)

$$y(t)=247.056\left(1+0.00542\,e^{-399.7979\,t}-1.0055242\,e^{-2.1629\,t}\right), \quad (15)$$

To avoid biased evaluation, the generated data were additionally perturbed by bounded stochastic noise, simulating measurement uncertainty typical for real sensor systems.

The results of data processing obtained from n = 50 measurements performed with a time resolution of t = 0.1 using the specified methods are presented in Table 1.

Table 1
Comparative analysis of methods

Method	MSE
Identification	0.0047
Group method of data handling	0.061614
Approximation	0.0004573

An analysis of the results in Table 1 allows us to give preference to the approximation method, which showed the highest accuracy, all other things being equal.

7. Discussion

This study addressed the problem of determining the parameters of mathematical models of dynamic objects under conditions of parametric uncertainty and limited measurement data. A unified data-processing framework was developed that combines classical identification,

polynomial approximation, and structural modeling principles inspired by the Group Method of Data Handling.

A key result of the work is the introduction of a transformation-based approximation of transient responses, which allows reducing the original exponential representation of system dynamics to a polynomial form suitable for stable parameter estimation. This approach enables efficient recovery of model parameters while preserving the dominant dynamic characteristics of the system.

The comparative analysis demonstrated that polynomial approximation based on response transformation provides improved estimation accuracy relative to direct identification and GMDH-based modeling, particularly when measurement data are limited or affected by uncertainty.

The proposed framework does not replace classical identification methods but complements them by offering a computationally efficient alternative for reduced-order modeling. In this sense, the results contribute to the development of hybrid parameter estimation strategies that combine interpretability with numerical robustness.

The superior performance of the transformation-based approximation (MSE 0.0004573) compared to direct identification and GMDH-based modeling is primarily due to the reduction of numerical sensitivity inherent in exponential regression. While GMDH provides powerful structural selection for complex datasets, its application to limited, noise-perturbed transient responses can lead to overfitting or unstable polynomial structures. By contrast, the proposed method regularizes the identification problem by mapping the exponential response into a quadratic form within the dominant transient interval. This approach effectively mitigates the issues of ill-conditioned matrices often encountered in high-order dynamic systems. Furthermore, the successful application of this framework to the RCINPOWER SmooX motor model suggests that providing stable, low-complexity representations of system dynamics is critical for real-time adaptive control in UAV applications, where computational resources and measurement time are limited.

Future work will focus on extending the proposed approach to noisy and non-stationary environments, as well as exploring its integration with adaptive and learning-based control mechanisms for real-time parameter refinement.

Acknowledgements

The work has been carried out on an initiative basis. The authors thank both the authorities of the National University “Kyiv Aviation Institute” and the especially leadership of the Faculty of Computer Science and Technologies for their support during the preparation of this paper.

Declaration on Generative AI

During the preparation of this work, the authors used GPT-4.0 and Grammarly in order to: Grammar and spelling check. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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