Application of the evolutionary approach to structural and parametric identification of dynamic objects

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Abstract. The paper examines the evolutionary approach to structural and parametric identification of dynamic systems in the form of differential equations. The approach is based on a genetic programming algorithm to determine a structure of the equation and differential evolution method for parameters selection. The author proposed approach based on such evolutionary algorithms as genetic programming and differential evolution. The search for the structure is carried out by genetic programming. The selection of numerical parameters and initial conditions is implemented by a method of differential evolution. The problem of finding a model that describes changes in the efficiency of a hydraulic system is solved with the help of this approach. The proposed approach is compared with a recurrent neural network and a nonparametric kernel regression estimation.

1 Introduction

The paper considers the inverse problem of mathematical modeling. It lies in searching the structure of a model applying numerical data of inputs and outputs that describe the behaviour of the object whose model needs to be built [1]. The investigation of dynamic systems often supposes the construction of its model. The task of searching for a model of a dynamic system is called identification according to the theory of mathematical modeling [2]. A lot of different methods have been developed to solve the identification problem. The main methods for solving identification problems are parametric and nonparametric algorithms. The essence of parametric methods is to select parameters for a predetermined structure. However, obtaining a model of the structure application of analytical methods is difficult in complex production processes. Nonparametric methods make it possible to obtain a response from a model. Though, a researcher will not be able to obtain an explicit model demonstrating the relationship between the characteristics of the system. Moreover, these methods demand more from the data since the quality of simulation depends significantly on the sample properties. Current artificial intelligence methods are also applied for the identification problem solving. It is worth highlighting recurrent neural networks designed to work with time series. They do provide highly accurate predictions, but do not provide an explicit model.

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The paper explores the approach to identify dynamic systems in a symbolic form from observational data. The representation of the model in the form of differential equations and their systems is the most convenient symbolic form. In this case, one could talk about reducing the identification problem to a symbolic regression problem. The paper discusses the application of such an evolutionary algorithm as genetic programming to solve the identification problem as a symbolic regression problem [3].

The author applied methods from the evolutionary class for the identification problem solving. However, in a number of works, evolutionary models are applied to search for model parameters with a linear structure known in advance [4]. The work [5] also sets restrictions on the structure of the resulting models. It is worth noting that the solution to the identification problem as a symbolic regression problem is considered in [6]. However, the proposed evolutionary approach differs from known methods in the minimum number of a priori requirements imposed on potential models.

The paper examines the application of the authors' evolutionary approach to solving practical problems.

2 Methods

The author of the paper applies the approach previously proposed to identify dynamic processes in the form of differential equations [7]. Consider its key features.

The initial identification problem is a mathematical modeling problem which involves the model generation of the object under study based on measurements of input variables x and output characteristics y. In general, stochastic noise operates in measurement channels.

In this work, the problem statement is the need to search for a model of a dynamic object in the form of a differential equation. A priori information about the structure and the values of the numerical parameters of the differential equation will be considered as unknown. The structure of a differential equation is searched with a genetic programming algorithm. The optimization of numerical coefficients including initial conditions is carried out by the method of differential evolution. It means that the work presents a method of structural and parametric identification. Известно, что качество применения эволюционных алгоритмов существенно зависит от подбора параметров алгоритма. However, a self-configuring procedure is applied to overcome this drawback [8]. In this work, self-configuring refers to the automated selection of algorithm parameters, both with a choice of operator type and with the assignment of a numerical value. Self-configuring is carried out applying the Success History Adaptation and Population-Level Dynamic Probabilities method.

Thus, the application of a self-configuring genetic programming algorithm in this approach implies encoding the differential equation in the form of a tree. The application of a genetic programming algorithm for the identification problem becomes possible by changing the terminal set (including in it a set of all input (x) and output (y) variables, a set of constants, derivatives $y',\ \dots,\ y^{(k-1)}$) and evolutionary steps of the algorithm.

The following fitness function is applied to evaluate the resulting models:

$$fitness = \frac{1}{1-error}, \tag{1}$$

$$error = \frac{\sum_{i=1}^{k}\sum_{j=1}^{n}\left(y_{ij}-\hat{y}_{ij}\right)^2}{kn}, \tag{2}$$

here *n* is a sample size, *k* is an order of the differential equation, y_{ij} is original sample points, $\hat{y}_{ij}$ are sample points obtained from the model.

The presented approach to solving the problem of dynamic objects identification in the form of a differential equation helps determine its order, structure and coefficients automatically.

3 Results and discussion

Consider the application of the presented approach in real process identification. Data were selected from the repository to study the approach of structural and parametric identification [9].

The problem being solved is related to monitoring the condition of hydraulic systems.

The studied data were obtained experimentally using a hydraulic test bench. This bench consists of a main working and secondary cooling-filtration circuits, which are connected through an oil tank. The system repeats constant load cycles (60 seconds long) and measures process parameters such as pressure, volumetric flow and temperature while the status of four hydraulic components (cooler, valve, pump and accumulator) is quantitatively varied. It is necessary to determine the change in coefficient of performance (efficiency) y for the given system.

The following variables were considered as input ones:

- readings of six pressure sensors (bar) (x_1, ..., x_6);
- engine power sensor readings (W) (x_7);
- readings of two volumetric flow sensors (l/min) (x_8, x_9);
- readings of four temperature sensors (°C) (x_{10}, ..., x_{13});
- vibration sensor readings (mm/s) (x_{14}).

The original dataset contains 1100 samples, but 300 points were used to generate the differential equation model using the evolutionary approach. The use of an incomplete amount of data is associated with the need to check the correctness of the model on data that was not used to find a solution. The resulting model helps track changes in efficiency depending on changes in input characteristics.

Present the model found by the proposed approach in the form of a differential equation. It makes it possible to track changes in efficiency depending on changes in input characteristics:

$$y' = \frac{-14{,}76x_5x_6(0{,}38 + 4{,}06x_1 + 1{,}44x_{11} + x_{12})}{(7{,}57x_3 - 82{,}11x_5x_6)(0{,}38 + 4{,}06x_1 + 1{,}44x_1 + x_{12}) + 3{,}21x_5x_6} - \frac{(x_1 + 2{,}47)(yx_1 + 19{,}37x_1 - 12{,}43x_1x_7 + 2{,}89x_7x_9)}{x_1}. \quad (3)$$

The error of the resulting model on test data was 5.4%. The graph obtained from the found model is presented in Figure 1.

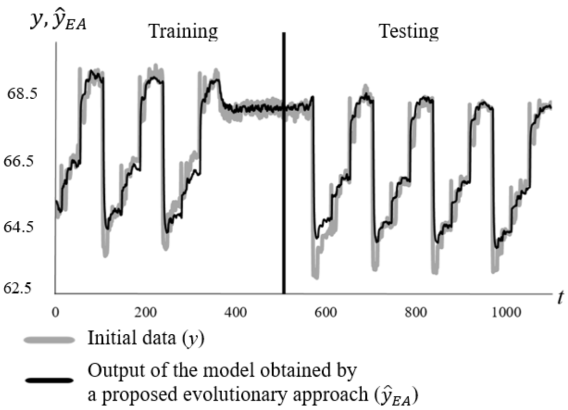

Fig. 1. Conformity of models to initial sample points for the problem of monitoring the condition of a hydraulic system: identification by the proposed evolutionary approach.

A comparison of a nonparametric kernel regression estimator and a recurrent neural network was made to prove the efficiency of the developed evolutionary approach.

Figure 2 presents graphs of the conformity of the models obtained by these methods to the points of the original sample. The model errors on the test data obtained by the recurrent neural network and nonparametric kernel regression estimation were 27.88% and 19.02%, respectively.

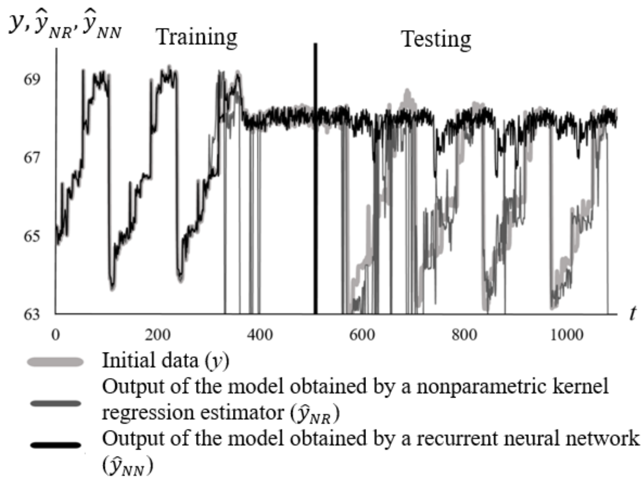

Fig. 2. Conformity of models to source sample points for hydraulic system condition monitoring problem: identification using recurrent neural network and nonparametric kernel regression estimation.

4 Conclusion

The paper considers the evolutionary approach to structural and parametric identification of dynamic systems in the form of a differential equation. Representation in the form of a differential equation enables to obtain a model in explicit form. It makes it possible to study it further. That is, a model is interpretable. The development of interpretable models is an important field, since making decisions based on such models carries a significantly less risk. The algorithmic basis of this approach is genetic programming and the differential evolution method. In the course of solving a practical problem, the author's approach was compared with a nonparametric kernel regression estimate and a recurrent neural network. Both approaches are designed to identify dynamic processes. However, a model obtained by the proposed evolutionary approach provided the smallest error. Also, it adequately describes not only training, but data testing as well.

This work was supported by the Ministry of Science and Higher Education of the Russian Federation (Grant № 075-15-2022-1121).

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