Algorithms for improving models of optimal control for multi-parametric technological processes based on artificial intelligence

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Abstract. This article highlights scientific approaches to solving problems that arise in the development of models for optimal control of multi-parameter technological processes. In particular, at the modeling specification stage, the necessity of developing artificial intelligence algorithms aimed at creating derivative parameters and ensuring their effectiveness for the optimal parametric and structural formulation of the problem is revealed. It is justified that the creation of neural rules is a relatively simple process in improving the formal model of complex systems using combinatorial derivatives of the relationships of significant elements over the full range. Usually, in the modeling of sufficiently complex, multi-parameter, uncertain technological systems, it is impossible to fully cover all the elements of the system that can have a strong influence on its reaction. There are several reasons for this. Nevertheless, the main scientific idea of the research is that it is possible to develop mathematical models that preserve the general effect of all elements and allow for its multi-level assessment, which are tasked with making management decisions.

1 Introduction

Improving models of optimal control of multi-parameter technological processes using artificial intelligence (AI) is an active research area with significant potential for practical applications. The goal is to develop models that can optimize control actions in complex processes with multiple inputs and outputs, while taking into account constraints, uncertainties, and other factors that may affect the performance of the system. In the works where this scientific goal is advanced, the most important aspect is that the problems of choosing structural variables of the model have a large scale [1, 2].

One approach to achieving this goal is to use machine learning (ML) techniques to learn models of the process dynamics from data. “For example, deep learning methods such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs) have been used to learn nonlinear, high-dimensional models of complex processes from time-series data” [3].

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Another approach is to use optimization algorithms to find the best control actions based on the learned models. Reinforcement learning (RL) is a popular technique for learning optimal control policies from interaction with the environment. RL algorithms can learn to maximize a reward signal that reflects the performance of the system, while taking into account the state of the system, the actions taken, and the resulting outcomes.

A key challenge in applying AI to optimal control of multi-parameter technological processes is the need for data. In many cases, it may be difficult or expensive to collect sufficient data to train accurate models. In such cases, it may be necessary to combine data-driven models with physics-based models, which incorporate knowledge of the underlying physical laws governing the process.

In addition, is an important aspect to consider limitations and constraints of the control system, such as actuator saturation, sensor noise, and communication delays. This requires the development of algorithms that can handle these constraints, while still providing effective control actions.

These problems require the development of approaches and modern methods for improving the modeling process.

2 Materials and method

A number of scientists have written papers on its improvement using artificial intelligence in the simulation process. In particular, in the works of the researcher Yu.V.Prus, one can observe the ideas of improving the management system modeling methodology using artificial intelligence based on big data. In it, the results of the experiment conducted according to this methodological approach were positively evaluated. The effectiveness of the modeling process based on big data is explained by the use of artificial intelligence in the system. In the author's proposals of the researcher, it is noted that the structural formation and mathematical structure of the model is the most difficult object of research, and the process of their development can be solved using large-scale, accurate algorithms that control artificial intelligence [4].

Also information on object analysis, G.G. Malinesko [5], N.K. Nagwani and J.S. It can be seen in the scientific works of Suri [6] and other scientists. On algorithms for conducting information analysis of model parameters [7], on simplification of parametric inference algorithms [8, 9], on methods of improving the specification process for ensuring model quality [10, 11], on improving modeling processes it can be noted that there is significant information in the sources [12, 13] on the technologies of using artificial intelligence.

Methods such as factor analysis, correlation analysis, factor analysis, mathematical analysis, and mathematical programming were used in the research.

3 Results

In the study, we focus on the effectiveness of artificial intelligence-based consideration of all input parameters' combinatorial options when creating the optimal form of the model's structural variables at the specification stage of modeling.

In our case, we will consider the process of working out the rules for the formation of neurons using the example of a 3-zone reactor in a stationary mode. In the reactor, let the parameters of influence be the temperature in 3 zones and the concentration of the substance at the inlet to the reactor, the main indicator is the concentration of the substance at the outlet of the reactor.

Correlation link indicators obtained according to the results of the corresponding regulatory experiment with 3,7,10 sessions of the production process are given in the table...
below (Table 1). From the data in the table, it can be seen that there is a discrepancy between the levels of correlation density obtained for different sessions of the production process. Of course, the main focus here is on the importance of the results of the 10-session experiment. Because \( k = 10 \) for 3-session information, \( k = 20 \) for 7 sessions and \( k = 50 \) for 10 sessions are appropriate. According to the calculation results, it is not possible to build a model depending on the main indicator for the selected system elements in all cases. Let's assume that there are derived indicators generated from these indicators, so that this model can be created as a result.

**Table 1.** Correlation indicators obtained from the results of 3, 7, 10 sessions of the corresponding normative experiment of the production process

<table>
<thead>
<tr>
<th></th>
<th>1</th>
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<th>3</th>
<th>4</th>
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<th>3</th>
<th>4</th>
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<tbody>
<tr>
<td><strong>10 sessions</strong></td>
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<td>1.00</td>
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<td></td>
<td>1.00</td>
<td></td>
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<td></td>
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<tr>
<td><strong>7 sessions</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.34</td>
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<td></td>
<td></td>
<td></td>
<td>0.64</td>
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<tr>
<td><strong>3 sessions</strong></td>
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<td>0.32</td>
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<td>0.09</td>
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<td><strong>4</strong></td>
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<td></td>
<td></td>
<td>0.51</td>
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<td></td>
<td></td>
<td>0.27</td>
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<td></td>
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<tr>
<td><strong>5</strong></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td>0.52</td>
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<td></td>
<td>0.28</td>
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</tr>
</tbody>
</table>

Calculated by the authors

Here: 1 – temperature in the lower zone 1 of the reactor (°C), 2 – temperature in the middle zone 2 of the reactor (°C), 3 – temperature in the upper zone 3 of the reactor (°C), 4 – substance concentration at the reactor inlet (%), 5 - the concentration of the substance at the outlet of the reactor (%).

It is here that the main set of rules for the neuron is formed. The algorithm for generating these rules should be simple in nature. Then the following would be appropriate:

**Rule 1.** For expression (2) with all exogenous factors, the relation is true

\[
R_{[5]} h_1 h_2 ... h_L \to 1, \quad R_{[5]} h_j \geq 0.7 \quad (1)
\]

Here \([5]\) is the response of the system, \( R_{[5]} h_1 h_2 ... h_L \) – plural correlation index, \( R_{[5]} h_j \) – pair correlation index, \( h_j \) – is the \( j \)-derivative factor \( h_j \in S, j=1,2,...,L \), \( L \) – is the number of derivative factors. Here, the derivative factors are determined by the following equation:

\[
h_j = \alpha_0^{(j)} + (\alpha_1^{(j)} \cdot f_j([1],[2],[3],[4]))^{(2)} \quad (2)
\]

Here \( \alpha_0,1,2^{(j)} \) – parameters of Eq.

**Rule 2.** \( f_j \) - the response function should be formed in the most optimal system of mathematical operations and structurally positively identified. In this case, the following equations are checked for optimality:

\[
\begin{align*}
f_j^{(N)} &= \left( \beta_0^{(1)} + \sum_{i=1}^{4} \beta_1^{(1)} \cdot G_i^{(N)}([i]) \right)^{\theta_1^{(1)}} \\
f_j^{(N)} &= \left( \beta_0^{(2)} + \left( \beta_1^{(2)} \prod_{i=1}^{4} \theta_i^{(i)} \cdot [G_i^{(N)}([i])] \right)^{\gamma_0^{(2)} \theta_1^{(2)}} \right)^{\theta_1^{(2)}} \quad (3)
\end{align*}
\]
Here \( (N) \) – number of all operations, \( \beta, \theta, \gamma \) – parameters, \( G_i^{(N)} \) – all combinatorial expressions that can be considered. This selection combination is measured in a sufficiently large amount. It is precisely this aspect that dictates the optimality of the artificial intelligence algorithm. For example, for a 4-input parametric, we check the sum of all possible combinations. Then we get the corresponding values from the following relation:

\[
C_1(4) \ast C_2(4) \ast C_3(4) \ast V_1(4) \ast V_2(4) \ast V_3(4) \ast V_4(4) = 2654208
\]

So, the number of expressions formed by addition, multiplication, and leveling operations based on the ratio of even exogenous pairs is more than 2 million. This requires a machine review.

### 4 Discussion

So, the most important complex aspect here is to determine the optimal one in all combinatorial conditions of \( G_i^{(N)} \), and the most important thing is the existence of such an optimum. Here, the optimum always exists, and at least the initial observation is repeated. Let's check it out. We choose an optional combinatory case. In accordance with it, the following expression is appropriate, i.e.

\[
f_j^{(1)} = \left( \beta_0^{(2)} + \left( \beta_1^{(2)} \prod_{i=1}^{4} \sum_{j=1}^{i} \theta_j^{(i)} \cdot \left[ \frac{1+i^4}{1+\prod_{i=1}^{4} t_i} \right] \right) \right) \beta^{(2)}
\]

Then, according to the results of calculations, the following results are obtained (Table 2).

**Table 2.** Optimal values of response function parameters

<table>
<thead>
<tr>
<th>( \beta_0^{(2)} )</th>
<th>( \beta_1^{(2)} )</th>
<th>( \beta^{(2)} )</th>
<th>( \theta_1^{(1)} )</th>
<th>( \theta_2^{(2)} )</th>
<th>( \theta_3^{(1)} )</th>
<th>( \theta_4^{(2)} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.330478</td>
<td>0.14751</td>
<td>1.00784</td>
<td>-0.127814</td>
<td>-0.002571</td>
<td>0.810191</td>
<td>0.000547</td>
</tr>
<tr>
<td>( \theta_3^{(1)} )</td>
<td>( \theta_4^{(1)} )</td>
<td>( \theta_3^{(2)} )</td>
<td>( \theta_4^{(2)} )</td>
<td>( \gamma_1^{(1)} )</td>
<td>( \gamma_2^{(1)} )</td>
<td>( \gamma_2^{(2)} )</td>
</tr>
<tr>
<td>-1.887124</td>
<td>1.654170</td>
<td>-0.001473</td>
<td>0.722543</td>
<td>-0.008147</td>
<td>1.392894</td>
<td>0.000001</td>
</tr>
<tr>
<td>( \gamma_3^{(1)} )</td>
<td>( \gamma_3^{(2)} )</td>
<td>( \gamma_3^{(3)} )</td>
<td>( \gamma_4^{(1)} )</td>
<td>( \gamma_4^{(2)} )</td>
<td>( \gamma_4^{(3)} )</td>
<td>( \gamma_4^{(4)} )</td>
</tr>
<tr>
<td>0.333000</td>
<td>1.781204</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.587452</td>
</tr>
</tbody>
</table>

Calculated by the authors.

We create a model for determining derived factors in accordance with the calculated optimal values.

\[
\begin{align*}
    h_1(f_1) &= 5.72 - 0.811 \cdot f_1^{5.991} \\
    h_2(f_2) &= -0.61 + 2.33 \cdot f_2^{6.007} \\
    h_3(f_3) &= 0.39 + 1.764 \cdot f_3^{5.928} \\
    h_4(f_4) &= 0.97 - 0.028 \cdot f_4^{6.001}
\end{align*}
\]

As a result of processing the values of 10 sessions according to the values of the model (6), it can be seen that these relationships are valid:
Thus, it is possible to improve the methodology of the factorial approach at the stage of specification in the development of the most optimal structural-parametric revealed response function when making optimal control decisions for multi-parameter technological processes under uncertainty. In this case, it suffices to take as a necessary condition that each neuron stores a purposeful derived factor.

It should be noted that this estimate is important at the stage of model building specification [14, 15]. The validity of this opinion can be observed in other sources [16].

5 Conclusions

Based on the research results and some scientific sources [17, 18, 19], we draw the following important conclusions:

1. In the absence of a functional link, if the density of linking the factor of influence to the main indicator is known, the possibility of increasing it according to the principle of a selected set is limited. In this case, it may not be enough to consider all combinations of choices;

2. In the absence of functional linkage, if the density of linkage of an influencer to the main indicator is known, it is always possible to increase it using various mathematical operations on this factor, but this may not increase the quality and significance of the model;

3. In the absence of functional connection, if the interconnection density of arbitrary two influencers of the system is known, the possibility of reducing it based on the principle of a selective set is limited. In this case, it may not be sufficient to consider all the choice combinations;

4. In the absence of a functional connection, if the density of the relationship between arbitrary two factors of system influence is known, it can always be reduced using various mathematical operations on these factors, but this may not improve the quality and significance of the model;

5. In the absence of functional linkage, there is an unlimited number of combined scenarios of increasing the linkage density of all selected influencers of the system to the key indicator;

6. Optimal modeling of complex technological processes with many parameters requires big data. At the same time, the simplification of these information processing algorithms is of great importance, and this aspect should be the main task of developing neural rules.

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