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RESEARCH ARTICLE

Metaheuristic-Based Model Optimization of a Steam-Filled Chamber

HUBERT GUZOWSKI[1], ROMAN SENKERIK[2], (Member, IEEE), MACIEJ SMOŁKA[1], FRANTIŠEK GAZDOŠ[3], MIROSLAV PÁLKA[3], LIBOR PEKAŘ[4], (Member, IEEE), MICHAL PLUHACEK[5], (Member, IEEE), ADAM VIKTORIN[2], TOMAS KADAVY[2], ALEKSANDER BYRSKI[1], ZUZANA KOMÍNKOVÁ OPLATKOVÁ[2], RADEK MATUŠŮ[6], (Member, IEEE), AND JANUSZ KACPRZYK[1], (Life Fellow, IEEE)

[1]Faculty of Computer Science, AGH University of Krakow, 30-059 Kraków, Poland
[2]Department of Informatics and Artificial Intelligence, Tomas Bata University of Zlín, 760 01 Zlín, Czech Republic
[3]Department of Process Control, Tomas Bata University of Zlín, 760 01 Zlín, Czech Republic
[4]Department of Automation and Control Engineering, Tomas Bata University of Zlín, 760 01 Zlín, Czech Republic
[5]Center of Excellence in Artificial Intelligence, AGH University of Krakow, 30-059 Kraków, Poland
[6]Centre for Security, Information and Advanced Technologies (CEBIA – Tech), Tomas Bata University of Zlín, 760 01 Zlín, Czech Republic

Corresponding author: Hubert Guzowski (guzowski@agh.edu.pl)

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ABSTRACT Steam-filled chambers are an important part of many technological processes, among others, in tire manufacturing and electricity production from thermal power plants. This work proposes a chamber model as a strongly nonlinear process with time-delays, where parameters depend on operating conditions and may vary in time. To identify system parameters, a parametric optimization task is formulated that minimizes the fit of the model to factory-measured data under varying valve opening conditions. Two significantly different approaches were used to solve this nonlinear optimization task. The first utilized local and semi-local optimization with prior knowledge derived from solving a simplified variant of the task. The second used global optimization methods without any prior knowledge. The obtained parametric models were compared based on the quality of fit and the sensitivity and stability analysis of the obtained solutions. The achieved models reflect real data with high accuracy, with mean squared errors as low as 0.0138 on output values ranging from 0.0 to 20.0, representing less than 0.1% of the output range. The solutions differ significantly in the values of the obtained parameters. The use of multiple methods has thus made it possible to obtain a diverse set of solutions, which is particularly valuable in applications for difficult engineering problems. Results of this work can be further used e.g. for subsequent step - optimal control system design for the given process and operating conditions.

INDEX TERMS Evolutionary algorithms, metaheuristics, parametric model optimization, time-delay systems.

I. INTRODUCTION

In today's research and industry, optimizing complex systems is a common challenge, especially when dealing with continuous single-objective optimization problems. Metaheuristic algorithms [1] are crucial in this area because they effectively handle high-dimensional problems and are robust against noise and uncertainty. These algorithms are particularly valuable for complex problems where traditional methods fall short.

Control engineering plays a critical role in ensuring the efficient operation of complex systems. A significant challenge in this field is dealing with time delays - the gap between an action and its effect [2]. These delays complicate system control and parameter identification because they add infinite dimensions to the system, due to the infinite spectra of system's poles and zeros [3], [4].

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Process modeling is fundamental to control engineering, especially for model-based control designs [5], [6]. Accurate models need detailed information on system characteristics like gain, time constants, and especially time delays. For nonlinear processes, it's also vital to understand how parameters change under different conditions. This understanding allows for the application of adaptive, robust or predictive control methods that can adjust to these changes. Getting this model right can involve a combination of analytical [7] and empirical methods [8]. Analytical methods require a deep understanding of the system's sub-processes and their mathematical descriptions, which can be challenging for complex systems. Empirical methods, based on real-world measurements, might take more time but often result in more accurate and simpler models, which are easier to use in control systems design.

The intersection of metaheuristic optimization, control engineering, and process modeling offers a promising approach to tackle the challenges of systems with time delays. Despite disadvantages associated with using these algorithms, like closed-box nature, scalability, and the need for hyperparameters setting, using metaheuristic algorithms in control engineering for time-delay systems offers a promising approach for developing more efficient control strategies and precise model identification methods. By leveraging the strengths of these algorithms and developing optimization frameworks, researchers and practitioners can develop more robust, scalable, and effective control/identification algorithms.

This paper provides a case study of a metaheuristic-based parametric optimization of a nonlinear system affected by time delays, which is represented by an industrial application of a steam-filled chamber with a flexible material to be heat-treated. At the same time, a comparison was made between the local metaheuristic optimization method using prior knowledge and global methods.

The paper is organized as follows: We begin with the research motivation and related works, then describe the optimization task for time-delay system model identification. Next, we present the selected metaheuristic algorithm variants, followed by our experimental setup. The results section includes both performance evaluation, sensitivity analysis, and uncertainty measures, before concluding with final remarks.

A. MOTIVATION AND ORIGINALITY

Solving parametric optimization problems remains a challenging field. There is no clear answer as to which classes of algorithms work best for this type of problem, without even considering the different possibilities of selecting their parameters or introducing adaptation mechanisms. Regardless of the method chosen, there remains a set of challenges in optimizing the real-world problem, such as wrongly measured data and selected fitting points, which can cause very low sensitivity to the changes in optimized model parameters and obtained results consequently do not satisfy quality validation. Among the real-world parametric optimization problems, the time-delay systems introduce additional issues affecting the outcome. If feedback loops inside the process include delays (i.e., the so-called state or internal delays), the system is infinite-dimensional because of an infinite number of its modes. Only a limited set of model parameters determines its properties driven by an infinite set of model-free response components. For most time-delay systems, only a subset of the so-called dominant modes has a decisive impact on system features in the time and frequency domains [3]. This poses a challenge for metaheuristics, as there is a need to search a multimodal constrained space. Moreover, certain optimized parameters may be very close to the domain borders and also may dynamically change. All this imposes demands on the metaheuristic algorithm's selection, configuration, and core/adaptive internal mechanisms.

To address these challenges, we propose a comprehensive optimization framework for real-world time-delay system optimization tasks, by introducing different problem formulations, which lead to competing solution strategies. A range of advanced metaheuristics algorithms is then specifically selected for each of the formulations, levereging their unique strengths to handle non-convexity, high-dimensionality, and uncertainty inherent in time-delay systems. By comparing the results obtained by these methods both in terms of the quality of the solution fit and the sensitivity to changes in parameters, we are able to provide a set of representative solutions that can then serve as the basis for creating controllers with different properties. In this way, we advance the understanding of metaheuristics in time-delay systems and obtain more robust insight about the nature of the problem being solved.

In summary, the goals of this research paper can be clearly defined as follows:

- to obtain a relatively simple and control-relevant model of a non-linear industrial process,
- to provide insights into the problem's multimodal solution space through parameter sensitivity analysis and performance benchmarking across a representative set of solutions,
- to compare and evaluate the effectiveness of local/semi-local optimization approaches (utilizing prior knowledge) against global metaheuristic methods for parameter identification
- to propose a comprehensive metaheuristic framework that integrates multiple optimization algorithms and problem formulations for non-static parameter identification, enabling more robust and versatile modeling solutions across varied operating conditions

B. RELATED WORKS

Similar industrial modeling and simulation problems have been addressed in recent studies and surveys dealing with numerical modeling of the curing processes, high-pressured chambers, and rubber vulcanization processes related mainly to the tire industry [9], [10], [11]. Artificial intelligence methods have been used in [12], specifically a combination of a neural network and evolutionary algorithm for modeling and optimization of a boiler steam temperature system.

Metaheuristic algorithms are widely used to solve parametric optimization problems in mechanical engineering in real world applications [13], [14]. In recent years algorithms, such as particle swarm optimization (PSO), artificial bee colony (ABC), genetic algorithms (GA), differential evolution (DE), and hybrid versions with other metaheuristic algorithms have been proposed for optimizing the control of a complex system with time delays [15], [16], [17].

This presented research builds on the foundations presented in an earlier study [18] where open-loop identification has been reported for steam-filled chamber. Here, we are using the same measured datasets but different model optimization approach. Considering the aforementioned goals mainly in the metaheuristic domain, we further built this research on the findings from another metaheuristic optimization of the model parameters with time delay. The result of metaheuristic algorithms with mechanisms supporting exploratory behavior and knowledge sharing [19], [20], [21], [22] demonstrated effectiveness compared to classical evolutionary algorithms, such as genetic algorithms (GA). Another study with the same optimization problem is presented in [23]. Another observation was that the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) algorithm [24] could also handle the optimization problem better than the classical GA, and the Nelder-Mead [25] optimization method as a baseline technique. This explains the selection of metaheuristics algorithms for the experiments.

II. NON-LINEAR TIME-DELAYED SYSTEM

This section describes a suggested model for optimizing the identification of a nonlinear industrial time-delayed system. It also discusses the challenges that need to be dealt with in this area, especially when the parameters of the model are dependent on the system's state and input. Firstly, a simplified version of the optimization task is explained, followed by the more complex and challenging task, which is the subject of research reported in this paper mainly. The effective and precise identification of dependencies based on the experimentally measured open-loop responses of the process and the metaheuristic algorithms' provided outputs may further help to design a suitable (e.g. robust or optimal) controllers for the process.

A. GENERAL DESCRIPTION

The real industrial system can be described as a closed-tempered pressure chamber with a raw (rubber-based) material to be processed by higher pressure and temperature. There is a single control input $u(t)$ (manipulated variable) - the system is driven by the opening of a valve with saturated steam in the range from 0 to 100 % (steam pressure in the main supply line is approximately 20 bar, i.e., 2 MPa). The system output may be observed by one controlled variable $y(t)$ which is the pressure inside the chamber in [bar], related to the temperature inside (See Figure 1 below [18]).

TABLE 1. Nomenclature.

Symbol	Description
$u(t)$	Control input (valve opening) [%]
$y(t)$	System output (chamber pressure) [bar]
$y_u(t)$	Output y dependent on control u
$G_m(s)$	Model transfer function
$G_{m,\mathbf{p}}(s)$	Model transfer function with parameter vector $\mathbf{p}$
k	Process gain
A_1	First-order coefficient of the transfer function denominator
A_2	Second-order coefficient of the transfer function denominator
T_d	Time delay [s]
s	Laplace transform variable
$\mathbf{p}$	Parameter vector $[k, A_1, A_2, T_d]$
$\mathbf{p}^*$	Optimal parameter vector
$\mathbf{p}(y, u)$	Parameter vector as function of pressure and valve opening
$x_1(t)$	First state variable (equal to $y(t)$)
$x_2(t)$	Second state variable
$x_1'(t)$	Time derivative of $x_1(t)$
$x_2'(t)$	Time derivative of $x_2(t)$
$\mathcal{C}(\mathbf{p})$	Cost function for parameter identification
$\mathcal{D}$	Set of admissible parameters
$\mathcal{U}_{data}$	Set of control inputs used to produce experimental data
$u_i(t)$	Step function control input
$\overline{u}_i$	Valve opening level for step function i [%]
$\overline{y}_j$	Discretization node for pressure [bar]
y_u^i	Experimentally measured value at time t_i
$\hat{y}_{u,\mathbf{p}}^i$	Simulated value at time t_i using parameters $\mathbf{p}$
t_i	Observation time point
t_{end}	End time of identification interval
n_u	Number of observation points for control u
m	Number of valve opening levels
p	Number of pressure discretization nodes

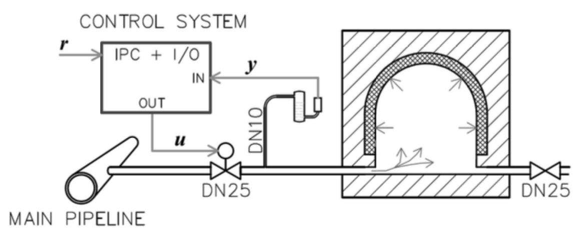

FIGURE 1. Scheme of the technological process.

The process is strongly nonlinear in nature including time-delay(s) present; parameters, such as gain k, time-constants, and time-delay T_d generally depend on the operating conditions (i.e. pressure/temperature inside the chamber + valve opening state) and they may also vary in time. Based on the initial screening of the measured process responses, the considered model transfer function defines a general time-delay system identification problem, $G_m : \mathbb{C} \to \mathbb{C}$ (1),

$$G_{m,\mathbf{p}}(s) = \frac{k}{A_2 s^2 + A_1 s + 1} e^{-T_d s}, \tag{1}$$

which can be re-written into a state-space description

$$\begin{bmatrix} x_1'(t) \\ x_2'(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\dfrac{1}{A_2} & -\dfrac{A_1}{A_2} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} 0 \\ \dfrac{k}{A_2} \end{bmatrix} u(t - T_d) \tag{2}$$

where output $y(t) = x_1(t)$. Hence

$$y(t) = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} 0 \end{bmatrix} u(t - T_d). \tag{3}$$

Hereafter if we need to highlight the dependence of the output y upon the control u we shall use the notation y_u.

Remark 1: It is worth pointing out a possible difference between processing and communication delays. In [26], the scaled consensus (tracking) problems, wherein all agents reach an agreement but with different assigned ratios in the asymptote, were studied. It was found there that the underlying communication network contained a spanning tree, and the scaled consensus could be achieved independent of the transmission delays, while the specified consensus values in the asymptote depended on the initial history of the agents over a period of time. However, despite our investigated process being nonlinear in nature, its simplified approximate model is linear. Especially, the model input-output delay (i.e., the dead time) is linear and constant (i.e., fixed) for given operating conditions. From this viewpoint, both processing and communication delays can be assumed together. Roughly speaking, only a sum of these two effects can be considered. The problem would be more complicated in case of time-varying delays, nonlinear models, and feedback-loop delays. The latter indicates infinite dimensionality, and such delays must be considered separately from the dead times. Such a research problem is planned to be investigated in the future.

B. MODEL PARAMETERS

Model (2) contains some real-valued parameters to be identified. These are k, A_2, A_1 and also the time-delay term T_d. The quantities generally depend on the process conditions, i.e. on the actual value of the pressure/temperature inside the chamber y and on the state of the control valve u. Therefore, in general the model parameters

$$\mathbf{p} = [k, A_1, A_2, T_d]\,. \tag{4}$$

form in fact a vector-valued mapping

$$\begin{aligned} \mathbf{p} : \mathbb{R}^2 &\ni (y, u) \\ &\longmapsto [k(y, u), A_1(y, u), A_2(y, u), T_d(u)] \in \mathbb{R}^4 \end{aligned}$$

More precisely (besides the condition of the valve), the properties depend on the difference between the pressure in the main supply line (which is approximately constant) and the pressure inside the chamber. Hence, the model is in general nonlinear but it has a relatively simple structure suitable for the further research, e.g. for the robust control system design or similar approaches.

In order to achieve appropriate properties of solutions, we use the following constraints, which were defined based on the preliminary screening of the process, its nature and responses. This setting will guarantee stability of the obtained models, feasibility of the solution and, at the same time, it enables to have enough flexibility to optimize all the parameters.

$$\begin{aligned} &A_2 > 0, A_1 > 0, \\ &0.1 < k < 20, \\ &0 < T_d < 1. \end{aligned} \tag{5}$$

C. PARAMETER IDENTIFICATION

Our task (a follow-up of the study [18]) is to find the parameter values $\mathbf{p}^*$ for which the identified model will fit with the measured data. It can be formulated as the following global optimization problem.

$$\mathcal{C}(\mathbf{p}^*) = \min_{\mathbf{p} \in \mathcal{D}} \mathcal{C}(\mathbf{p}), \tag{6}$$

where $\mathcal{D}$ is the set of all admissible $\mathbf{p}$, that in particular satisfy (5). The choice of the admissible set $\mathcal{D}$ determines a concrete identification task to be solved (see the sequel).

The cost function $\mathcal{C}$ measures the mismatch between the data and the observations of the simulated state. Here we use the weighted square error

$$\mathcal{C}(\mathbf{p}) = \sum_{u \in \mathcal{U}_{data}} \frac{1}{n_u} \sum_{i=1}^{n_u} \left(y_u^i - \hat{y}_{u,\mathbf{p}}^i \right)^2 \tag{7}$$

where:

- $0 < t_1 < \cdots < t_{n_u} \leq t_{end}$ are the moments which we observe y at,
- y_u^i is an experimentally measured value of y_u at t_i,
- $\hat{y}_{u,\mathbf{p}}^i$ is the value of $y_u(t_i)$ simulated using a model with parameters $\mathbf{p}$,
- t_{end} is the end of the time-interval used for the identification,
- $\mathcal{U}_{data}$ is the set of all controls u used to produce the data.

In the sequel we consider two different versions of the parameter identification task.

1) SIMPLE STATIC OPTIMIZATION TASK

In this case we assume that the model parameters A_1, A_2, k and T_d are constants for a given measured step-response, which means that here $\mathbf{p}$ can be identified with a vector in $\mathbb{R}^4$. Consequently,

$$\mathcal{D} = \left\{ \mathbf{p} \in \mathbb{R}^4 : \mathbf{p} \text{ satisfies (5).} \right\}$$

As the admissible controls (i.e., the valve opening strategies) we take step functions of the following form

$$u_i(t) = \begin{cases} \overline{u}_i & \text{for } t \geq 0, \\ 0 & \text{for } t < 0, \end{cases} \tag{8}$$

for some selected valve opening levels

$$0 \leq \bar{u}_1 < \cdots < \bar{u}_m \leq 100\%.$$

Therefore, in this case we have simply

$$\mathcal{U}_{data} = \{u_1, \ldots, u_m\}$$

In the actual experiments we had $m = 10$ and

$$\bar{u}_1 = 10\%, \bar{u}_2 = 20\%, \ldots, \bar{u}_{10} = 100\%.$$

The resulting 4-dimensional identification problem is relatively simple. However, its results may serve as a starting point for a more challenging non-static optimization task of model parameter identification considering the dependence on both variables: the pressure inside the chamber and the valve state.

2) COMPLEX NON-STATIC OPTIMIZATION TASK

As explained in the general description of the model the parameters of the state equation (2) depend on both the valve opening condition u and the actual state of the system, i.e. on the actual pressure inside the chamber y. Hence, in the second, more challenging, identification task we assume that $\mathbf{p}$ is a mapping from $\mathbb{R}^2$ to $\mathbb{R}^4$ with components satisfying (5) and with the last component, i.e. the time delay T_d, dependent only on u, i.e.

$$\mathbf{p}(y, u) = [k(y, u), A_1(y, u), A_2(y, u), T_d(u)] \,.$$

To avoid problems with solving (2) we assume that $\mathbf{p}$ is continuous with respect to y. Note that with feasible $\mathcal{U}_{data}$ we need not impose such an assumption on the dependence on u (see below). To make the problem of identifying $\mathbf{p}$ finite-dimensional we introduce the following discretization.

- We take $\mathcal{U}_{data}$ as in the previous case. Then it is sufficient to determine values of $\mathbf{p}$ over $\mathbb{R} \times \{\bar{u}_1, \ldots, \bar{u}_m\}$.
- We assume that the range of pressure inside the chamber $y(t)$ extends from 0 to approximately 20 bar and similarly as in the previous case we divide the range using nodes

$$0 \leq \bar{y}_1 \leq \cdots \leq \bar{y}_p \leq 20[\text{bar}].$$

  In the actual computations we took $p = 10$ and

$$\bar{y}_1 = 0, \bar{y}_2 = 2.22222222, \ldots, \bar{y}_{11} = 20.$$

  If the simulated pressure inside the chamber exceed 20bar, we treat it as if it was equal to 20bar for the purpose of parameter mapping.
- The set $\mathcal{D}$ of admissible $\mathbf{p}$ consists of mappings from $\mathbb{R} \times \{\bar{u}_1, \ldots, \bar{u}_m\}$ to $\mathbb{R}^4$ that is continuous with respect to y and such that:
  - $A_1(\cdot, \bar{u}_k), A_2(\cdot, \bar{u}_k)$ and $k(\cdot, \bar{u}_k)$ are simple 1D linear splines over the grid with nodes $\bar{y}_1, \ldots, \bar{y}_p$ for all $k = 1, \ldots, m$;
  - $\mathbf{p}(y, u)$ satisfies (5) for every $y \in [0, 20]$ and $u \in [0, 100]$.

  Such $\mathbf{p}$ are determined by their values in the node points $(\bar{y}_j, \bar{u}_k)$, hence in this case our problem is $(3mp + m)$-dimensional. In the actual experiments we have

$$3mp + m = 3 \cdot 10 \cdot 10 + 10 = 310$$

  free parameters. It should be noted that it does not suffice to check constraints (5) over the grid nodes, i.e. there are cubic splines that satisfy (5) at the nodes and fail to do it in between. This was one of the reason behind the usage of linear interpolation for defining the resulting surface.

The resulting non-static identification problem brings various limitations and challenges for the selection and execution of metaheuristics. However, their successful application will allow us to obtain higher dimensional dependencies of the optimized model parameters k, A_1, A_2, T_d with respect to both, control input (valve opening) and actual pressure inside the chamber and to fit measured responses more accurately. Hence, the goal is to find a surface for each of the parameters k, A_1, A_2, T_d that provides the best approximation of the measured data, and consequently to lay foundations for constructing, e.g., a robust controller and better understanding of the process itself.

III. METAHEURISTIC ALGORITHMS

In the selection of metaheuristics, we used both widely recognized methods and algorithms we are developing specifically for solving difficult real-world problems.

Firstly, we chosen the more local algorithms to tackle a version of the task with prior knowledge. L-BFGS-B algorithm was chosen to serve as a baseline method, as a well-known representative of quasi-Newton optimization algorithms designed for solving large-scale nonlinear optimization problems [27]. As a metahuristic alternative, we chosen CMA-ES [24], which is a widely used, advanced optimization algorithm that excels in continuous, non-linear, and high-dimensional optimization problems. It has become popular among researchers and practitioners due to its robustness, efficiency, and adaptability.

Secondly, for the global optimization approach, the main choice of algorithms belonged to the modern variants of established Differential Evolution algorithm, and to the Success-History-based Adaptive Differential Evolution (L-SHADE) family in particular [28]. We have selected both the main SHADE algorithm and the DISH [29] variant, due to it's very good results in time delay system parametric optimization [21]. The algorithm includes the distance-based approach, keeping the exploration ability and higher population diversity. The modern approaches considering the distance of solutions in the search space should lead to avoidance of premature convergence in complex search spaces [30]. Last algorithm used in the comparison is the Hierarchic Memetic Strategy [31]. It was designed specifically to tackle real-world multimodal optimization tasks, and was already applied in time-delay paremetric optimization setting [32].

Detailed descriptions of the L-BFGS-B, CMA-ES, and SHADE algorithms are widely available in the literature. In the following subsections, we instead focus on introducing the DISH and HMS algorithms, which are under development by our research team.

A. DISH ALGORITHM

The DISH algorithm represents the modified jSO [33], an adaptive DE-based algorithm from the L-SHADE family [28]. In the SHADE/L-SHADE core functionality, the mutation strategy is "current-to-*p*best/1" and uses four parent vectors:

- current i-th vector $\mathbf{x}_{i,G}$;
- vector $\mathbf{x}_{pbest,G}$ randomly selected from $NP \cdot p$ best vectors (in terms of objective function value) from current generation G; the value of p is sampled from the uniform probability distribution $\mathcal{U}([p_{min}, 0.2])$, where $p_{min} = 2/NP$;
- third parent vector $\mathbf{x}_{r1,G}$ randomly selected from the current generation;
- the last parent vector $\mathbf{x}_{r2,G}$ also randomly selected, but from the union of the current generation G and external archive A.

The mutated vector $\mathbf{v}_{i,G}$ is generated by (9).

$$\mathbf{v}_{i,G} = \mathbf{x}_{i,G} + F_i \left(\mathbf{x}_{pbest,G} - \mathbf{x}_{i,G}\right) + F_i \left(\mathbf{x}_{r1,G} - \mathbf{x}_{r2,G}\right) \quad (9)$$

L-SHADE algorithm uses a crossover scheme to create the trial vector $\mathbf{u}_{i,G}$ with the help of the current vector $\mathbf{x}_{i,G}$ and the mutated vector $\mathbf{v}_{i,G}$, similar as generic DE with the following differences. Control parameters scaling factor F and crossover rate CR are not static. Instead, the normal distribution is used to sample CR_i whereas the i-th scaling factor F_i is generated from a Cauchy distribution. In both cases, the historical memories with a size of H storing successful values of parameters F and CR are used.

$$\mathbf{u}_{j,i,G} = \begin{cases} \mathbf{v}_{j,i,G} & \text{if } r \leq CR_i \text{ or } j = j_{rand} \\ \mathbf{x}_{j,i,G} & \text{otherwise,} \end{cases} \quad (10)$$

where $r \in [0, 1]$ and $j_{rand} \in \{1, \ldots, D$ are sampled using appropriate uniform distributions. j_{rand} is the index of a feature which has to be updated. D is the dimensionality of the problem.

Also, the selection process is almost identical to the original DE, with the addition of a historical archive.

$$\mathbf{x}_{i,G+1} = \begin{cases} \mathbf{u}_{i,G} & \text{if } f\left(\mathbf{u}_{i,G}\right) \leq f\left(\mathbf{x}_{i,G}\right) \\ \mathbf{x}_{i,G} & \text{otherwise.} \end{cases} \quad (11)$$

If the objective function value of the trial vector $\mathbf{u}_{i,G}$ is better than that of the current vector $\mathbf{x}_{i,G}$ the trial vector will become the new individual in new generation $\mathbf{x}_{i,G+1}$ and the original vector $\mathbf{x}_{i,G}$ will be moved to the external archive of inferior solutions A. Otherwise, the original vector remains in the population in the next generation, and the external archive remains unchanged.

Another operation in L-SHADE algorithm is the linear population decrease. The basic idea is to reduce the population size to promote exploitation in later phases of the evolution. Therefore, a new population size is calculated after each generation based on the available budget of fitness function evaluation, user-predefined initial population size, and the end population size.

Finally, the idea distinguishing DISH from the jSO/L-SHADE algorithm is that the original adaptation mechanism for parameters F and CR values uses weights based on the improvement of the objective function value, thus promoting exploitation over exploration. The DISH approach is based on the Euclidean distance between the trial and the original individual (please, see details in [29]).

Due to the limited space here, for detailed information about historical memory update processes for F and CR parameters, population linear decrease calculation, please refer to [28]. Used Python implementation can be found at the TBU A.I.Lab GitHub repository.[1]

B. HIERARCHIC MEMETIC STRATEGY

The Hierarchic Memetic Strategy (HMS) is a stochastic global optimization strategy able to solve hard real-world inverse problems [31], [34], [35], [36] including identification problems originating from the control theory [32]. The core of HMS (utilized in this paper) is a multi-population evolutionary strategy, with the component populations forming a dynamically developing tree-like hierarchy. The level of the tree corresponds to the range of the search performed by populations at that level: the deeper into the hierarchy (i.e., the closer to leaves) the more focused and accurate the search becomes. The strategy starts with a single root population that seeks for optima in the broadest and most chaotic way. The further development of the tree is based on an operation called *sprouting*. It consists of starting new child populations by a non-leaf level population around a found solution deemed to be in the neighborhood of a potential optimum. In order to use the computational budget efficiently, the operation of populations can be stopped when the solutions they find do not improve significantly, or when they exhaust their allocated computational budget. More details on the HMS can be found [37] and references therein.

The HMS provides a hierarchical structure at the levels of which different algorithms can be used. In this work, we use a 2-level HMS with Simple Evolutionary Algorithm (SEA) at the root level and CMA-ES at the leaf level. This high-level configuration proved to be effective for multimodal problems in previous works [37].

We applied the sprout mechanism based on Nearest Better Clustering method [38], which determines the sprout individuals based on their quality and distance from the nearest better solutions. The detailed description of this approach is described in the article [32].

[1] https://github.com/TBU-AILab/DISH_python

IV. EXPERIMENT DESIGN

The purpose of conducting the experiments was both to obtain the best possible solution to the optimization task and to compare several approaches to it that differ in the way the problem was posed and the algorithm used.

A. STATIC TASK

First, we solved a static variant II-C1 of the task, by identifying the values of k, A_1, A_2, T_d for each of 10 levels of valve opening. To solve the task, we used a representation of the system in the form of a transfer function. A key element of this task was to identify the value of the time delay T_d based on both expert knowledge and empirical model fitting. This undertaking was made more difficult by the small extent of the overall process time, where the delay was identifiable. Thus, we applied a two-step approach in which we first optimized the parameters for the first two seconds of the process with a lower bound on the value of delay set at 0.1 based on expert knowledge. Then, with the delay value determined, we optimized the remaining parameters based on the fitting to the entire process. Other value constraints were set according to stability and feasibility constraints given in 5 with upper limits of A_1, A_2 being set liberally to 1000.

Due to the relative simplicity of the static task, two local methods were chosen to solve it. L-BFGS-B as a proven representative of quasi Newton methods and CMA-ES, which is a well recognized semi-local evolutionary optimization method. The starting point for both algorithms and each of the openings was the same and was determined by the preliminary screening to be $k = 0.2$, $A_2 = 15$, $A_1 = 45$, $T_d = 0.5$. In both cases, due to the task relative simplicity, both algorithms stopped execution due to the inbuilt stopping condition for stagnation of cost function value rather than the upper limit of cost function evaluations equal to 10000.

B. DYNAMIC TASK

The dynamic task represented a greater challenge in terms of both parameter identification and implementation of the system itself. Due to the unavailability of functionality for modeling the given system based on both input and internal state in popular control theory toolboxes available, we used a differential equation solver directly to simulate the system using a state description. To address the observed stiffness of the solved differential equation, we used the Backward Differentiation Formula (BDF) solver, which ensures stable integration and reliable parameter optimization in such cases.

To solve the dynamic task II-C2, we used both a semi-local CMA-ES and a local L-BFGS-B methods starting around the solution obtained in the first step, and a set of global methods searching the entire solution space. The purpose of such a comparison was to see if we could find a significantly different solution of similar quality. The portfolio of global algorithms used consists of a recognized variant of differential evolution: SHADE, and the previously described DISH and HMS algorithms.

To employ global search methods, box constraints were required. We determined them in accordance with feasibility and stability constraints given in 5 and knowledge about the result ranges in the static task. Missing upper limits of the parameters A_1, A_2 were set to 160.0 and k parameter upper limit was brought down to 1.5 as the highest k value determined in static task reached 1.235 2. Due to the varying parameter ranges, we applied parameter scaling to the (0,1) range for the purpose of facilitating the optimization process.

To reconcile the need for a fair comparison of methods with the high computational cost of the dynamic task, for each algorithm we performed 10 runs with a computational budget of 10000 evaluations of the cost function. Performing parametric optimization for each algorithm was computationally unachievable, so parameters were determined according to recommended default values for given problem dimensionality and domain size. Parameters and full experimental code can be found in [39].

V. RESULTS

The results descriptions are organized in two subsections corresponding to the two tasks stated in section IV. At the same time, the goal of both tasks is to fit the model to the same data, which allows comparing the quality of solutions obtained by both routes. For this reason, the results are included in common graphs and tables.

A. STATIC TASK

We achieved the same best solutions for both CMA-ES and L-BFGS-B algorithms. Their visualization is shown in Figure 2. The achieved value of total squared error for all optimized openings with unit weights was 0.3442. Sample fit of thus achieved model against the results of the dynamic task for the valve-opening of 40% is included in Figure 5.

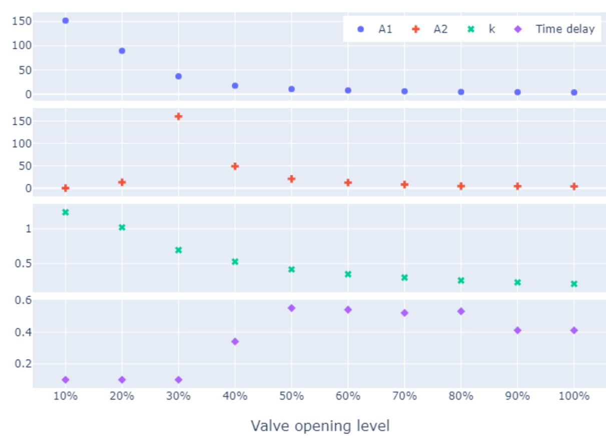

FIGURE 2. Final parameter values obtained for different openings by static task optimization.

Due to the fast and consistent convergence of the algorithms to the same solution, we conclude the potential unimodality of the solved problem.

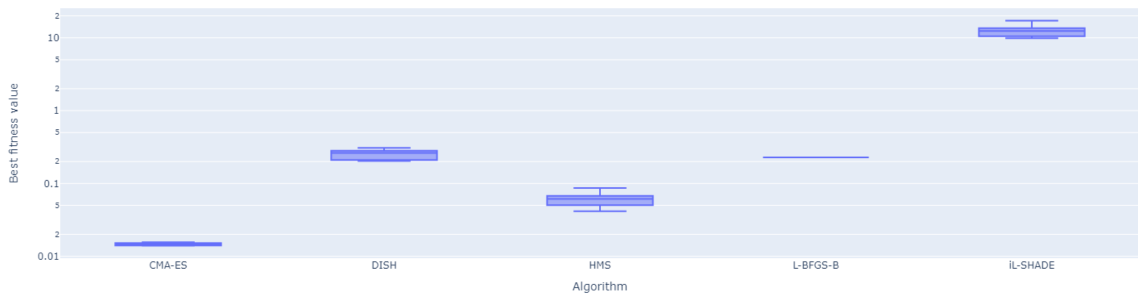

FIGURE 3. Box-whisker plot of the best solutions found for 10 runs of each algorithm. Results for each opening considered were summed on the basis of the random seed used.

TABLE 2. Ranges of the best solutions found for 10 runs of each algorithm. Results for each opening considered were summed on the basis of the random seed used.

Alg.	min	max	median	mean	std.dev.
CMA-ES	1.38e-2	1.61e-2	1.45e-2	1.48e-2	8.7e-4
L-BFGS-B	2.28e-1	2.28e-1	2.28e-1	2.28e-1	0.0
DISH	2.03e-1	3.08e-1	2.63e-1	2.52e-1	3.67e-2
HMS	4.15e-2	8.66e-2	6.13e-2	5.96e-2	1.34e-2
SHADE	9.89e0	1.72e1	1.24e1	1.26e1	2.24e0

B. DYNAMIC TASK

Dynamic task proved to be significantly more complex. Unlike the static task, the results of the algorithms used were significantly different, both in terms of the solution quality achieved and the values of the model parameters. As can be seen in Table 2, CMA-ES, which started with prior knowledge derived from the first task, achieved the best fit to physical data. L-BFGS-B was converging before reaching its maximal evaluation budget due to solution stagnation or inability to compute the next better step. Between global methods, both DISH and HMS outperformed the solution from the static task, while SHADE did not achieve as good a result. It is worth noting the very low standard deviation of solutions for CMA-ES, highlighting the more local nature of its application compared to global methods. L-BFGS-B results do not deviate, as the method is fully deterministic. A visual comparison of the ranges of results is included in Figure 3.

Figure 4 showing the convergence of solution quality for each algorithm gives us additional perspective on the results. SHADE and especially L-BFGS-B methods clearly converge prematurely and the majority of their evaluation budgets is spend on only slight improvements. Meanwhile global methods HMS and DISH mostly retain their tempo of solution improvement over the whole optimization process. Despite it's more local nature, CMA-ES does not converge as fast, as L-BFGS-B and instead is characterized by a steady improvement of solution quality during the first half of it's runtime.

The achieved quality of solutions should be analyzed in the context of the actual measured data and the considered mathematical model. Figure 5 shows the differences in fit to the real process data for the models obtained during the simulation experiments. The model runs reflect the actual data well. Zooming in on a key slice of the process allows one to see how well the best fit is and, in particular, the model obtained using CMA-ES. In further result analysis we focus on CMA-ES, HMS and DISH, as these methods obtained good quality solutions, that are different from each other and from starting parameters.

We can draw further conclusions about the nature of the matching error from Figure 6, where the aggregate error for all available valve-openings during the process operation is shown. Note the pronounced drops in values around times equal to 90 and 430, among others. These are due to different running times for different openings. When one process ends, its error is not measured for higher time intervals. The noisy nature of the error is clearly visible and is due to the measurement noise in the very data to which the models were fitted. Particularly for the best-fit models, we see that a large part of the error remains irreducible due to the aforementioned noise.

Finally, we tested whether the use of global methods would indeed lead to significantly different parameters for the resulting models. A comparison of the parameters k, A_1, A_2 of the best solutions for CMA-ES, DISH and HMS is provided in Figure 7, while obtained time delays are visualized in Figure 8. We can see that CMA-ES largely retained the general shape of the duplicated original solution obtained from the static task, which can be seen in Figure 2. Meanwhile, DISH and HMS obtained distinctly different solutions. In particular, the values of the parameters A_1, A_2 seem to take on values with no apparent pattern, while for the parameter k the obtained surfaces more closely resemble those obtained by CMA-ES. This proves the high capacity of the model so stated and the multimodality of the obtained cost function.

C. POST-OPTIMAL ANALYSIS

To evaluate the sensitivity of the solutions identified by evolutionary algorithms, a post-optimal sensitivity analysis was performed using the Morris Elementary Effects method [40].

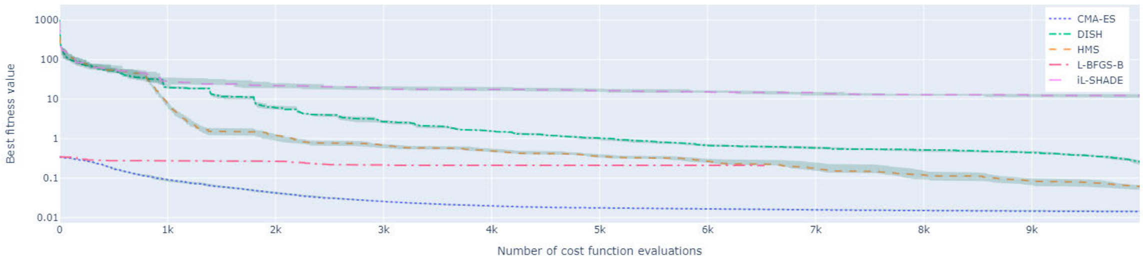

FIGURE 4. Convergence plot for algorithms used in the non-constant parameters problem variation. The gray traces around the lines correspond to the quartile ranges for the values achieved.

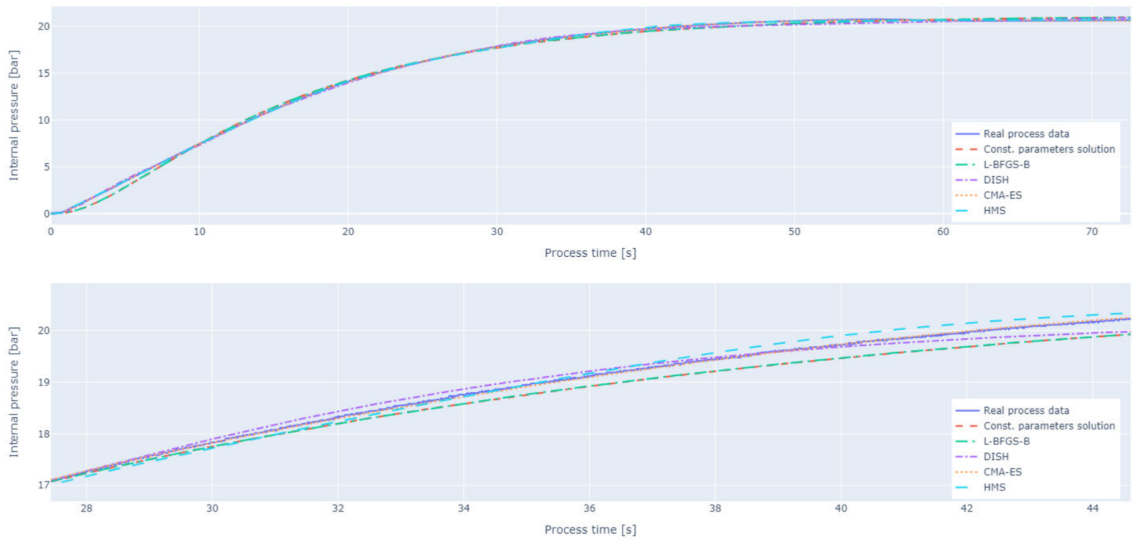

FIGURE 5. Comparison of real process data and resulting simulation models on valve opening level of 40%. The top panel shows the complete view, while the bottom panel presents a zoomed-in version to highlight the differences in fit quality.

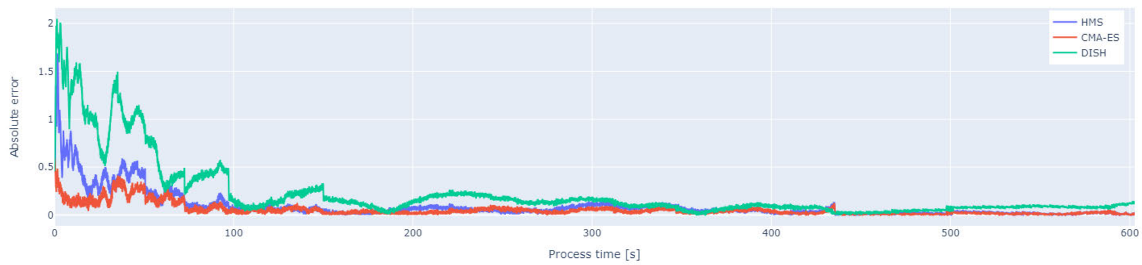

FIGURE 6. Sum of fit errors for each valve opening over total process time.

This method is specifically well-suited for our task, as it is designed to tackle problems for which classical mathematical analysis is impractical and that have a moderate-to-large number of inputs. Furthermore, since the problem parameters are clearly grouped, we employed a group analysis variant among other enhancements introduced in later works [41], [42]. The implementation of the method is sourced from SALib [43]. For each parameter scaled to the interval [0,1], sensitivity was estimated in the neighborhood of $\pm$ 0.01 with a constraint to the original limits. Using 20 optimal trajectories, the overall sensitivity measure μ^* was produced for each of the four parameter groups (A_1, A_2, k, T_d) along with bootstrapped confidence intervals. The results are provided in Table 3.

The results of the sensitivity analysis highlight the two solutions obtained by CMA-ES and HMS algorithms. The HMS optimum appears to be the most robust with consistently low variations among all of the parameters. CMA-ES optimum has the lowest sensitivities for A_1, A_2, T_d parameters and tight confidence intervals, but is moderately

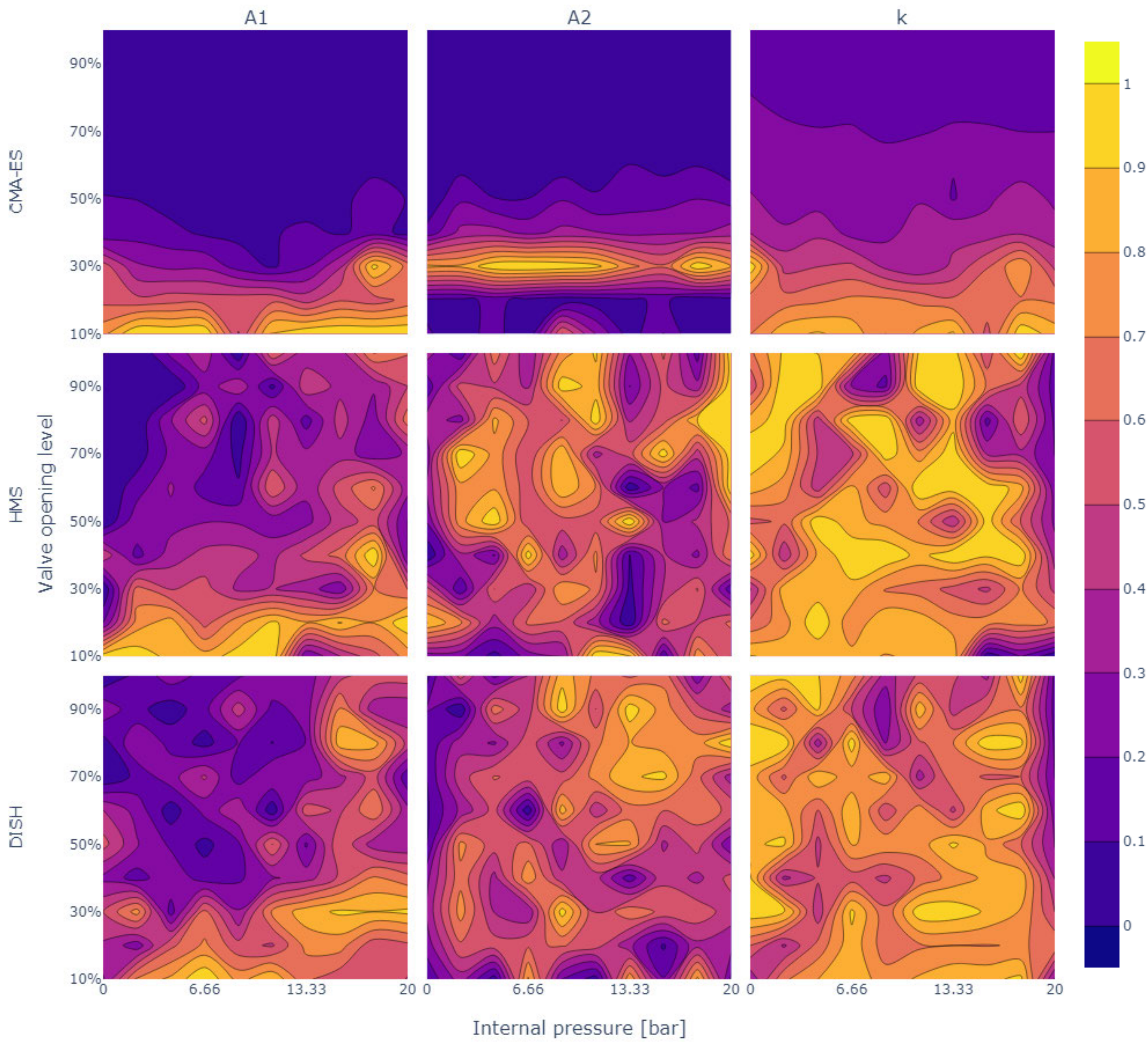

FIGURE 7. Parameter values obtained with different algorithms scaled to the same range of (0.0, 1.0).

sensitive to changes in k parameter value. The importance of parameter groups varies between algorithms, but for each solution besides SHADE, the parameter k shows the highest importance, with the parameter A_1 showing second.

D. UNCERTAINTY ANALYSIS

The output value of the scoped system is obtained by measuring the pressure by electrical means. The measurement method, limitations of the instruments, physical constraints of the measurement process, and human error bring uncertainty to the final value Y, which consists of measured value y and uncertainty Δy

$$Y = y + \Delta y.$$

The expanded standard uncertainty Δy is defined as

$$\Delta y = c\Delta y_c$$

where:

- c is the expansion coefficient,
- Δy_c is the combined uncertainty.

Combined uncertainty Δy_c is calculated as the geometric sum of partial uncertainties. It consists of two main groups: A-uncertainty and B-uncertainty

$$\Delta y_c = \sqrt{(\Delta y_A)^2 + (\Delta y_B)^2}.$$

The A-uncertainty calculation is based on repeated measurements. It is defined as the standard deviation of the sample averages. The B-uncertainty represents the effect of measurement instruments, used methods, human error, ambient, and other influences. The expansion coefficient c defines the range of the probability of occurrenence taken from the normal (Gaussian) distribution. In most cases,

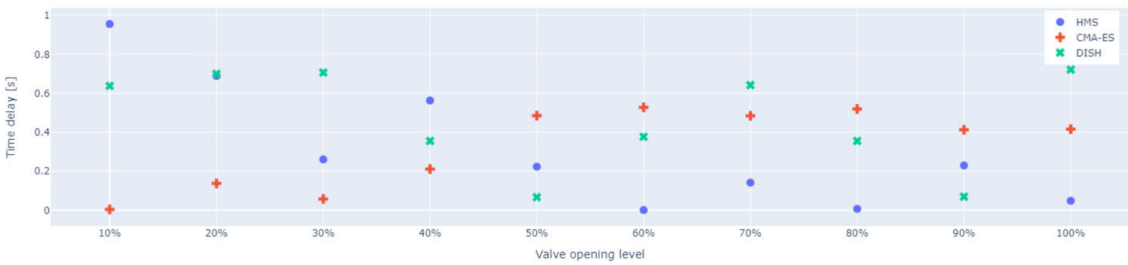

FIGURE 8. Time delay values obtained with different algorithms.

TABLE 3. Results of the Morris elementary effects sensitivity analysis method by algorithm and parameter groups.

Algorithm	Parameters	Normalized μ^*	Confidence Interval
HMS	A_1	0.008026	0.002282
	A_2	0.003035	0.000862
	k	0.023484	0.008050
	T_d	0.001076	0.000460
SHADE	A_1	0.144914	0.062974
	A_2	0.100642	0.031455
	k	0.134867	0.051252
	T_d	0.039787	0.008865
CMA-ES	A_1	0.004968	0.002026
	A_2	0.002292	0.000572
	k	0.073069	0.022986
	T_d	0.000876	0.000235
DISH	A_1	0.011837	0.003429
	A_2	0.005496	0.001820
	k	0.023969	0.007478
	T_d	0.003998	0.001221
L-BFGS-B	A_1	0.009908	0.003658
	A_2	0.004212	0.001142
	k	0.081622	0.023670
	T_d	0.002096	0.000799

TABLE 4. Expansion coefficient *c*.

c	σ	Probability of occurrence
1	± 1	68 %
2	± 2	95 %
3	± 3	99.7 %

it is defined as 2, to cover the 95% probability of occurrence, see Table 4 where σ means the standard deviation.

In our case, the A-uncertainty cannot be defined as the obtained output values are in the form of a range of values sampled with a period of 0.1 s. The properties of the used pressure transducer and input card define the B-uncertainty. The partial B-uncertainty is calculated from the measuring error a for standard devices.

$$\Delta y_B = a/\sqrt{3}$$

Table 5 shows the properties of the used components defined by the producers, measurement range, calculated measurement error, partial uncertainties, and overall B-uncertainty Δy_B.

Hence, since A-uncertainty cannot be defined, the overall uncertainty equals B-uncertainty.

$$\Delta y = \Delta y_B = \sqrt{0.0450^2 + 0.1351^2} = 0.1424[\text{bar}]$$

VI. DISCUSSION AND CONCLUSION

Building on the foundation established by previous studies [18], [19], [20], [23], this research aims to enhance our understanding of metaheuristic algorithms in the area of control engineering and investigate their potential for optimizing the parameters of time delay system models.

In this paper, parametric optimization of a suggested control-relevant model of a steam-filling chamber process in two stages of different complexity was performed. The solution obtained in the first stage was used in the second one as a starting point for local L-BFGS-B and semi-local CMA-ES optimization methods, while a portfolio of global methods searched the whole space to check for different solutions of comparable quality. For a budget of 10000 evaluations each, CMA-ES with prior knowledge produced the best solution with a high-quality match to the original process data, achieving a minimum MSE of 1.38e-2 and a consistent performance (mean MSE of 1.48e-2 with standard deviation of only 8.7e-4). Meanwhile, global methods DISH and HMS made up for the starting advantage of local methods and located completely different solutions of comparable quality in terms of the model fit. Particularly noteworthy is HMS, which achieved a minimum MSE of 4.15e-2 without prior knowledge. The limited improvement by the L-BFGS-B method, which consistently converged to a solution with MSE of 2.28e-1 despite having the same evaluation budget, highlights the advantages of metaheuristic stochastic optimization methods over local quasi-Newtonian optimization for real-world multimodal problems. The significant performance gap between the best (CMA-ES: 1.38e-2) and worst (SHADE: 9.89e0) performing algorithms underscores the importance of algorithm selection for these types of optimization problems. It remains an open question whether the global methods would achieve better results than CMA-ES when assigned a higher computational budget, especially considering HMS's promising performance, which remains to be the subject of future research and analysis.

TABLE 5. B-uncertainty calculation.

Component	Producer	Type	Scale [bar]	Measurement error [%]
pressure transducer	Endress+Hauser	PMC51	39	0.1
analog input card	Beckhoff	KL3052	39	0.3

Component	Measurement error a	Component uncertainty Δy_B	Expansion coefficient c	Uncertainty Δy
pressure transducer	0.039	0.0225	2	0.0450
analog input card	0.117	0.0675	2	1351

The application of optimization by means of several algorithms and problem formulations simultaneously made it possible to obtain significantly different solutions in terms of both the quality of the fit to the data and the values of the parameters and the sensitivity of the solution to their changes. Thus, such a method carries significant practical benefits, providing a more representative set of solutions as candidates for further implementation steps.

The presented parameter identification approach is generally applicable to the entire class of nonlinear dynamic processes with input-output delays. It only requires a possibility to measure the process input-output data in several operating points. On the top of that, the procedure can be extended to processes with state delays, which then represent additional optimization parameters. This would be a task of the future research.

The results presented in this study can be also used for the subsequent step - designing an optimal controller for the given process. The suggested relatively simple structure of the model with the parameters changing with the operation conditions allows using e.g. the robust control theory apparatus to find a suitable controller(s). The possible ranges of model coefficients provided by the metaheuristic algorithms are the basis for this synthesis. However, a limitation of robust control under parametric uncertainty is generally the risk of conservatism, meaning that controllers designed to guarantee stability and meet certain performance requirements for all possible parameter values within the uncertainty set can become overly conservative. This issue is also related to the fact that robust control methods typically optimize for worst-case scenarios. Another potential problem can be seen in the fact that real-world uncertainties can be even more complex (including, e.g., unmodeled dynamics, nonparametric disturbances, etc.) and might not fit neatly into parametric descriptions.

Another contribution of this paper can be seen in the dependencies of the optimized model parameters obtained on both the control input and inner state of the system making it possible to build a relatively simple simulation model of the process, which can be used in the tuning phase of the designed controller(s) as well as for better understanding of the behavior of the whole process itself. The potential of optimizing controllers using the employed metaheuristic algorithms will also be a subject of further investigation.

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HUBERT GUZOWSKI was born in Kraków, Poland, in 1998. He received the M.S. degree in computer science from the AGH University of Krakow, in 2022, where he is currently pursuing the Ph.D. degree with the Faculty of Computer Science. His research interests include stochastic global optimization, meta-learning, and industrial applications of metaheuristics.

ROMAN SENKERIK (Member, IEEE) received the master's and Ph.D. degrees in technical cybernetics from the Faculty of Applied Informatics, Tomas Bata University in Zlín, in 2004 and 2008, respectively. In 2013, he habilitated as an Associate Professor in informatics, and received the title of Full Professor in informatics with the VŠB—Technical University Ostrava, in 2022. He is a Professor and the Head of the A.I.Lab (https://ailab.fai.utb.cz/), Department of Informatics and Artificial Intelligence, Tomas Bata University in Zlín. He is also a Professor with the Department of Computer Science, Faculty of Electrical Engineering and Computer Science, VŠB—Technical University Ostrava. He has authored over 50 journal articles, 300 conference papers, several book chapters, and editorials. His primary research interests include generative artificial intelligence, bio-inspired optimization methods, and distributed systems. Specifically, his work focuses on the development of evolutionary algorithms, machine learning models and their modifications, benchmarking, generative AI (LLMs), AutoML, neuroevolution, data science, and interdisciplinary applications of soft computing and machine learning methods. His secondary research interests include chaos theory, complex systems, and cybersecurity. He is a member of IEEE CIS and IEEE SMC groups and the IEEE Task Force on Benchmarking Metaheuristics. He is a respected reviewer of many leading journals in computer science and computational intelligence. He has been and is part of many teams for special sessions/symposia and event organizations related to AI and metaheuristics at conferences, such as IEEE WCCI, IEEE CEC, IEEE SSCI, and GECCO. He has been a guest editor of several special issues of journals and edited the proceedings of several conferences.

MACIEJ SMOŁKA received the dual M.S. degrees in mathematics and in computer science and the Ph.D. degree in mathematics from Jagiellonian University, Kraków, Poland, in 1996, 1997, and 2000, respectively, and the Habilitation degree in computer science from the AGH University of Krakow, Poland, in 2017. From 1999 to 2012, he was with Jagiellonian University. Since 2012, he has been with the AGH University of Krakow, Poland, where he is currently an Associate Professor. His research interests include stochastic global optimization algorithms, inverse problems, and applications of metaheuristics and machine learning in music.

FRANTIŠEK GAZDOŠ was born in Zlín, Czech Republic, in 1976. He received the M.Sc. degree in automation from Brno University of Technology, in 1999, and the Ph.D. degree in technical cybernetics from Tomas Bata University in Zlín, in 2004. In 2012, he became an Associate Professor of machine and process control and currently the Head of the Department of Process Control, Faculty of Applied Informatics, Tomas Bata University in Zlín. He is the author or co-author of more than 90 journal contributions and conference papers, giving lectures at foreign universities, such as the University of Strathclyde, Glasgow, the Instituto Politécnico do Porto, the Università di Cagliari. His research activities cover the area of process modeling, simulation, and control.

MIROSLAV PÁLKA was born in Zlín, Czech Republic, in 1978. He received the B.Sc. degree in automation from Brno University of Technology in 1999, and the M.Sc. degree in automation from Tomas Bata University, Zlín. In 2020, he has started Ph.D. degree in automatic control and informatics with the Department of Process Control, Faculty of Applied Informatics, Tomas Bata University. His dissertation thesis focuses on the methods of optimal control loop setting with respect to the required control quality and actuators lifetime. His research interests cover also the area of process modeling, simulation, and algebraic approach to control system design.

LIBOR PEKAŘ received the B.S. degree in automation and informatics, the M.S. degree in automation and control engineering in consumption industry, and the Ph.D. degree in technical cybernetics from Tomas Bata University (TBU) in Zlín, in 2002, 2005, and 2013, respectively.

In 2018, he was appointed as an Associate Professor of machine and process control with TBU in Zlín. From 2006 to 2013, he was a Junior Lecturer with TBU in Zlín, where he became a Senior Lecturer, in 2013. Since 2020, he has been a Senior Lecturer with the College of Polytechnics Jihlava, Czech Republic. He is the author of one book and eight book chapters and the (co-)author of more than 50 journal articles and 80 conference papers. His research interests include analysis, modeling, identification, and control of time-delay systems; algebraic control methods; heat-exchanger processes; autotuning; and optimization techniques. He has served as a Reviewer for over 20 WoS MJL journals. He serves as an Academic Editor for *Mathematical Problems in Engineering*, a Topical Advisory Panel Member and a Lead Guest Editor for *Mathematics*, an Editorial Board Member for *AppliedMath*, an Advisory Board Member for *Applied Thermal Engineering*, and an Associate Editor for *Frontiers in Energy Research* and *International Journal of Robotics and Control Systems*.

MICHAL PLUHACEK (Member, IEEE) received the Ph.D. degree in information technologies from Tomas Bata University in Zlín, Czech Republic, in 2016. His Ph.D. dissertation topic was Modern Method of Development and Modifications of Evolutionary Computational Techniques. In 2019, he finished six-months long research stay with New Jersey Institute of Technology, USA, focusing on swarm robotics. In 2023, he became an Associate Professor, after successfully defending his habilitation thesis on the topic "Inner Dynamics of Evolutionary Computation Techniques: Meaning for Practice." Currently, he is a Researcher with the Center of Excellence in Artificial Intelligence, AGH University of Krakow. His research interests include evolutionary computing and swarm intelligence (theory and applications), artificial intelligence in general, and generative AI.

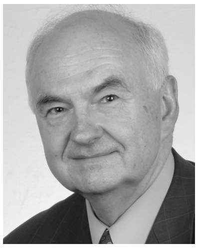
ADAM VIKTORIN was born in Czech Republic. He received the M.Sc. and Ph.D. degrees in computer and communication systems from the Faculty of Applied Informatics, Tomas Bata University in Zlín, in 2015 and 2021, respectively. His Ph.D. thesis topic was Control Parameter Adaptation in Differential Evolution. His professional interests include the development and analysis of adaptive strategies for differential evolution in the area of numerical optimization and the application of such algorithms to real-world problems, data analysis, and development and applications of AI/ML models and LLMs.

TOMAS KADAVY was born in the Czech Republic, in 1990. He received the M.Sc. and Ph.D. degrees in information technologies from the Faculty of Applied Informatics, Tomas Bata University in Zlín, in 2016 and 2024, respectively. His research interests include swarm-based algorithms, computational intelligence and optimization, machine learning, SW engineering, high-performance computing, and the application of AI/LLMs.

ALEKSANDER BYRSKI is a Full Professor with the Faculty of Computer Science, AGH University of Krakow. His research interests include nature-inspired computing, agent-based distributed computation, artificial intelligence, parallel and distributed computing, and simulations.

ZUZANA KOMÍNKOVÁ OPLATKOVÁ received the Ph.D. degree in technical cybernetics from the Faculty of Applied Informatics, Tomas Bata University in Zlín, Czech Republic, in 2008. In 2023, she was appointed as a Professor with Tomas Bata University in Zlín. Since 2018, she has been the Vice-Head of the A.I.Lab (https://ailab.fai.utb.cz/) Research Group, Department of Informatics and Artificial Intelligence, Tomas Bata University in Zlín. She is the author of more than 30 journal articles, 200 conference papers, and several book chapters. Her research interests include evolutionary computation, artificial neural networks, chaos control, classification techniques, pseudo neural networks, evolutionary symbolic regression methods, and large language models. She serves as a guest editor for highly-respected journals; and a member for journal editorial boards and conference international program committees, journal reviewers, and guest editor of books published by Springer. She had lectures at European universities and South Africa under the program Erasmus.

RADEK MATUŠŮ (Member, IEEE) was born in Zlín, Czech Republic, in 1978. He received the M.S. degree in automation and control technology in consumer goods industry from the Faculty of Technology, Tomas Bata University (TBU) in Zlín, in 2002, and the Ph.D. degree in technical cybernetics from the Faculty of Applied Informatics (FAI), TBU in Zlín, in 2007. He was appointed as an Associate Professor of machine and process control with FAI TBU in Zlín, in 2018. He has been holding various research or pedagogical positions with TBU in Zlín, since 2004, where he is currently a Senior Researcher and a Project Manager. He has (co-)authored more than 50 scientific journal articles and over 110 conference contributions. His research interests include analysis and synthesis of robust control systems, fractional-order systems, and algebraic methods in control design. He has served as a Reviewer for over 50 scientific journals, including but not limited to *Automatica*, IEEE Transactions on Automatic Control, and *IEEE Control Systems Magazine*. He serves as an Academic Editor for *Journal of Control Science and Engineering*, a member of Topical Advisory Panel for *Mathematics* and *Fractal and Fractional*, and a Guest Editor for *Mathematic Problems in Engineering*.



JANUSZ KACPRZYK (Life Fellow, IEEE) is a Professor of Computer Science with the Systems Research Institute, Polish Academy of Sciences, and the WIT–Warsaw School of Information Technology, AGH University of Science and Technology, Kraków. He is also a Professor of automatic control with the PIAP—Industrial Institute of Automation and Measurements, Warsaw, Poland. He is an Honorary Foreign Professor with the Department of Mathematics, Yli Normal University, Xinjiang, China. He has authored seven books, (co)edited more than 150 volumes, (co-)authored more than 650 papers, including ca. 150 in journals indexed by WoS. He is listed in 2020 and 2021 "World's 2% Top Scientists" by Stanford University, Elsevier (Scopus), and ScieTech Strategies and published in *PLOS Biology*. His main research interests include the use of modern computation computational and artificial intelligence tools, notably fuzzy logic in systems science, decision making, optimization, control, data analysis, and data mining, with applications in mobile robotics, systems modeling, and ICT. He is fellow of IET, IFSA, EurAI, IFIP, AAIA, AIIA, I2CICC, and SMIA. He is a Full Member of the Polish Academy of Sciences; a member of the Academia Europaea, European Academy of Sciences and Arts, European Academy of Sciences, and the International Academy of Systems and Cybernetics (IASCYS); and a Foreign Member of Bulgarian Academy of Sciences, Spanish Royal Academy of Economic and Financial Sciences (RACEF), Finnish Society of Sciences and Letters, Flemish Royal Academy of Belgium of Sciences and the Arts (KVAB), Russian Academy of Sciences, the National Academy of Sciences of Ukraine, Lithuanian Academy of Sciences, and the Accademia Nazionale di Scienze, lettere e Arti, Palermo. He received the eight honorary doctorates. He is the President of the Polish Operational and Systems Research Society, the Past President of the International Fuzzy Systems Association; and a member of the Administrative Committee (Adcom) of the Computational Intelligence Society of IEEE, and the Board of Governors of the Systems, Man and Cybernetics Society of IEEE. He is the Editor-in-Chief of eight book series at Springer and two journals. He is on the editorial boards of ca. 40 journals.