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Improved Cooperation Search Optimization Algorithm for Infinite Impulse Response System Identification

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ABSTRACT

This study addresses the challenges of infinite impulse response (IIR) system identification by introducing an improved cooperation search algorithm (ICSA). Improved cooperation search algorithm enhances the original cooperation search algorithm (CSA) through the integration of a pattern search algorithm and opposition-based learning, aiming to improve both exploration and exploitation capabilities. The algorithm's performance was evaluated against diverse IIR plants of varying orders using convergence analysis, scatter plots, and statistical metrics. Results demonstrate ICSA's superiority over CSA, achieving significantly lower mean squared error (MSE) values across different system orders and model types. Notably, ICSA outperformed CSA by up to 27 orders of magnitude for matched-order models and up to 95.85% for reduced-order models. The algorithm also exhibited more consistent performance, with substantially lower standard deviations in many cases. Statistical validation through the Wilcoxon signed-rank test further confirmed ICSA's enhanced performance. This research highlights ICSA's efficacy in producing efficient IIR systems, demonstrating its potential for more accurate system identification compared to existing methods.

***Index Terms*—**Cooperation search algorithm (CSA), infinite impulse response (IIR), opposition-based learning (OBL), pattern search algorithm, system identification.

I. INTRODUCTION

Adaptive filtering has emerged as a dynamic and crucial area of research with wide-ranging applications across various domains, including signal processing, audio/video/image processing, communication, and control systems. Its utility extends to noise and echo cancellation, channel equalization, spectrum analysis, and system identification tasks [1]. The field of adaptive filtering predominantly employs two categories of digital filters: finite impulse response (FIR) filters, also known as non-recursive filters, and infinite impulse response (IIR) filters, also referred to as recursive filters [2].

The fundamental distinction between these filter types lies in their response characteristics. Finite impulse response filters generate output-based solely on current and previous input values, resulting in a FIR. In contrast, IIR filters derive their output from both current and previous input values, as well as current and previous output values, leading to an IIR [3]. This inherent difference endows adaptive IIR filters with superior modeling capabilities for physical systems or plants compared to their FIR counterparts, while simultaneously requiring significantly reduced computational resources [4].

Despite these advantages, adaptive IIR filters present certain challenges. A primary concern is stability monitoring, as the filter's poles may potentially move outside the unit circle during the adaptation process, inducing instability. Several strategies have been proposed to address this issue, including parameter space limitation, alternative filter structures such as lattice configurations [5, 6], and real-time pole calculation to ensure they remain within the unit circle [8]. Another significant challenge is the multi-modal nature of the error surface with respect to the filter coefficients [2], necessitating the implementation of sophisticated learning algorithms.

Conventional gradient-based learning algorithms, such as the least mean square (LMS) method, attempt to locate the global minimum of the error surface by moving in the direction opposite to the gradient. However, these approaches are susceptible to convergence at local minima

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rather than the desired global minimum [8-10]. In response to these limitations, researchers have explored the application of contemporary global optimization algorithms to achieve global minimum solutions. These investigations have encompassed a wide array of metaheuristic techniques, including artificial bee colony (ABC) optimization [4, 11] that demonstrates its superior performance compared to traditional optimization techniques on benchmark functions and IIR filter design problems. Cat swarm optimization (CSO) [6] demonstrates superior performance in IIR system identification compared to genetic algorithms. Simple genetic algorithm (SGA) [12] demonstrated the superiority of evolutionary digital filters in finding global minima on multi-peak error surfaces. Improved artificial rabbits optimization (IARO) [13] incorporates advanced strategies for enhanced performance across various IIR system orders. Additionally, numerous other studies such as, average differential evolution with local search (ADE-LS) [14], firefly algorithm (FA) [15], grey wolf optimization (GWO) [16], harmony search (HS) algorithm [17], artificial immune algorithm (AIA) [18], particle swarm optimization (PSO) [19-27], inclined planes system optimization (IPSO) [28], weighted sum - variable length particle swarm optimization (WS-VLPSO) [29], artificial intelligent optimization (AIO) [30], Social Engineering Optimizer (SEO) [31], red deer algorithm (RDO) [32, 33], gravitational search algorithm (GSA) [34] indicate the usefulness of metaheuristic optimization algorithms in overcoming the challenges posed by IIR filter-based system identification.

The persistent quest for enhanced signal processing and system identification methodologies continues to drive innovation in the field. Researchers and practitioners seek novel approaches to effectively address the inherent challenges of IIR system identification. While conventional methods demonstrate some efficacy, they often encounter issues such as sensitivity to initial conditions, slow convergence rates, and limited accuracy, resulting in suboptimal performance. Recognizing these limitations, researchers are actively exploring new methodologies that aim to surpass the boundaries of existing techniques.

In this context, the development of artificial intelligence algorithms has played a pivotal role in addressing complex problems and systems. Motivated by these considerations, the present study proposes an enhanced version of the cooperation search algorithm (CSA), a recent addition to the meta-heuristic optimization landscape, as a novel optimizer for IIR system identification.

The CSA [35], while demonstrating promise with its rapid convergence characteristics, exhibits certain limitations when confronted with complex optimization problems. Research conducted by Cao et al. and Niu et al. highlights the algorithm's susceptibility to common pitfalls encountered by other metaheuristic approaches, particularly the tendency to become trapped in local optima and suffer from premature convergence. This phenomenon arises from the algorithm's reliance on leading individuals for population updates, which constrains its exploration capabilities and potentially overlooks superior solutions outside the immediate search space. The dependence on a single update mechanism can also result in reduced population diversity, further impeding the algorithm's ability to escape local optima [36].

To address these shortcomings and enhance the algorithm's effectiveness, this paper introduces an upgraded version of the CSA, designated as Improved Cooperation Search Algorithm (ICSA). The ICSA incorporates two key enhancements: opposition-based learning (OBL) and pattern search (PS) algorithm.

The present study employs four IIR filter-based systems, ranging from second to fifth-order, along with their corresponding matched and reduced-order models, as benchmark functions. It is well-established that matched-order system models serve as unimodal functions, while reduced-order system models function as multimodal functions from an optimization perspective. Consequently, these benchmark systems provide a comprehensive testbed for evaluating the exploration and exploitation capabilities of the proposed algorithm.

The primary contributions of this study are as follows:

1. Development of an improved version of the recently proposed ICSA to mitigate its limitations and enhance its accuracy.
2. Application of the newly proposed ICSA for identifying matched-order and reduced-order models of four IIR filter-based benchmark systems.
3. Implementation of the parameter space limitation method ensures modeled system stability, significantly reducing the computational burden on optimizers.
4. Comprehensive performance evaluation through convergence analysis, scatter plot visualization, and both parametric and nonparametric statistical tests demonstrates the superior performance of the proposed ICSA over the original CSA and other state-of-the-art optimizers reported in the literature.

The remainder of this paper is structured as follows: Section II elucidates the original CSA optimizer and introduces its improved version, the ICSA. Section III presents the problem formulation for IIR system identification and details the implementation of the proposed optimizer for identifying matched- and reduced-order models of the benchmark plants. This section also includes comparisons with other reported state-of-the-art optimizers. Finally, Section IV concludes the paper with a summary of findings and potential avenues for future research.

II. COOPERATION SEARCH ALGORITHM AND THE PROPOSED IMPROVED VERSION

A. Cooperation Search Algorithm

The Cooperation Search Algorithm (CSA) is conceptualized as a meta-heuristic optimization technique that draws inspiration from corporate organizational structures and dynamics. The algorithm's foundational principles are rooted in a corporate philosophy that emphasizes adaptability to dynamic environments, the maximization of operational efficiency, and the pursuit of excellence. These objectives are achieved through the continuous enhancement of knowledge, skills, and productivity across all organizational levels, from entry-level employees to executive leadership.

Central to the CSA's operational framework is the cultivation of a knowledge-sharing culture, coupled with a meritocratic approach to personnel management. This paradigm facilitates the replacement of underperforming individuals with more competent counterparts, thereby ensuring the continual optimization of the organization's human capital. The framework places significant emphasis on seamless team collaboration, extending this principle to the highest echelons of the corporate hierarchy. Notably, even top executives are subject to replacement by talented newcomers if such a transition is deemed beneficial to the organization's overall progress.

In the context of optimization problems, the CSA employs a metaphorical representation wherein each employee embodies a potential solution. These employees are aggregated into company teams, with the team's composition reflecting the collective performance of its constituent members. Within this hierarchical structure, executive managers represent optimal solutions derived from their respective teams, while the board of directors encapsulates globally recognized best solutions. The chairperson, selected randomly from the board members, serves as the current global optimum.

The algorithm's solution refinement process is facilitated through the application of three primary operators:

- Team Communication: This operator facilitates the exchange of information and strategies among team members, promoting collective problem-solving and innovation.
- Reflective Learning: This mechanism enables individual employees to introspect and refine their approaches based on personal experiences and observations of successful strategies within the organization.
- Internal Competition: This operator introduces a competitive element that drives continuous improvement and ensures that the most effective solutions are propagated throughout the organization.

The CSA's operational framework is outlined as follows:

1) Team-Building Phase

At this stage, all team members are randomly selected using (1). After evaluating the performance of all solutions, a subset of promising solutions, represented as M∈[1, I], is chosen from the initial pool to form the higher-ranking set.

$$x_{i,j}^{k} = \varnothing\left(\underline{x}_j, \overline{x}_j\right), i \in [1, I], j \in [1, J], k = 1 \tag{1}$$

In this context, $x_{i,j}^{k}$ represents the *j*th value of the *i*th solution in the *k*th cycle, *i* indicates the total solution count in the current pack, and *j* signifies the variable count corresponding to the dimensions of the optimization problem. Additionally, Ø(*L,U*) denotes the function that generates a uniformly distributed random number within the range [*L*, *U*], where *L* and *U* are the lower and upper limits of the variables used in the optimization, respectively.

2) Team Communication Operator

Every staff member has the opportunity to gain new perspectives through knowledge exchange with higher-ranking individuals, including the supervisors' and directors' boards. As specified in (2), the communication process is segmented into three parts: *A* signifies the intellectual capacity of the chairperson, *B* represents the collective knowledge held by the directors' board, and *C* denotes the combined intelligence of the supervisors' board. The board randomly selects the chairperson of directors to mimic a revolving mechanism. Additionally, the values of *B* and *C* are computed using identical positional information provided to all members of the supervisors' and directors' boards.

$$u_{i,j}^{k+1} = x_{i,j}^{k} + A_{i,j}^{k} + B_{i,j}^{k} + C_{i,j}^{k}, i \in [1, I], j \in [1, J], k \in [1, K] \tag{2}$$

$$A_{i,j}^{k} = \log\left(1/\varnothing(0,1)\right).\left(gbest_{m,j}^{k} - x_{i,j}^{k}\right) \tag{3}$$

$$B_{i,j}^{k} = \alpha.\varnothing(0,1).\left[\frac{1}{M}\sum_{m=1}^{M} gbest_{m,j}^{k} - x_{i,j}^{k}\right] \tag{4}$$

$$C_{i,j}^{k} = \beta.\varnothing(0,1).\left[\frac{1}{I}\sum_{i=1}^{I} pbest_{i,j}^{k} - x_{i,j}^{k}\right] \tag{5}$$

In this scenario, $u_{i,j}^{k+1}$ denotes the *j*th value within the *i*th group solution during the (*k+1*)th cycle. The *j*th value of the *i*th personal best-known solution at the *k*th cycle is represented as $pbest_{i,j}^{k}$. Similarly, $gbest_{m,j}^{k}$ indicates the *j*th value within the global best-known solution of the *m*th instance, spanning from the initial phase to the *k*th cycle. The value of *m* is randomly chosen from the set {*1, 2, ..., M*}. Knowledge assimilated from the chairman is denoted as $A_{i,j}^{k}$. The learning factors *α* and *β* adjust the influence of $B_{i,j}^{k}$ and $C_{i,j}^{k}$, respectively. $B_{i,j}^{k}$ corresponds to the average knowledge derived from the *M* best-known solutions achieved so far across a broad spectrum, while $C_{i,j}^{k}$ relates to the personal best-known solutions of *I* instances. The coefficients regarding computation (*M*, *β*, and *α*) are initially assigned the values 3, 0.15, and 0.1, respectively, as specified in the original paper introducing the CSA algorithm [35].

3) Reflective Learning Operator

In addition to gleaning insights from the top-performing contestant solutions, the team can acquire fresh insights by pooling its expertise in the opposite direction, as illustrated by the equations below.

$$v_{i,j}^{k+1} = \begin{cases} r_{i,j}^{k+1} \; if \left(u_{i,j}^{k+1} \geq c_j\right) \\ p_{i,j}^{k+1} \; if \left(u_{i,j}^{k+1} < c_j\right) \end{cases}, i \in [1, I], j \in [1, J], k \in [1, K] \tag{6}$$

$$r_{i,j}^{k+1} = \begin{cases} \varnothing\left(\overline{x}_j + \underline{x}_j - u_{i,j}^{k+1}, c_j\right) if \left(\left|u_{i,j}^{k+1} - c_j\right| < \varnothing(0,1).\left|\overline{x}_j - \underline{x}_j\right|\right) \\ \varnothing\left(\underline{x}_j, \overline{x}_j + \underline{x}_j - u_{i,j}^{k+1}\right) \quad otherwise \end{cases} \tag{7}$$

$$p_{i,j}^{k+1} = \begin{cases} \varnothing\left(c_j, \overline{x}_j + \underline{x}_j - u_{i,j}^{k+1}\right) if \left(\left|u_{i,j}^{k+1} - c_j\right| < \varnothing(0,1).\left|\overline{x}_j - \underline{x}_j\right|\right) \\ \varnothing\left(\overline{x}_j + \underline{x}_j - u_{i,j}^{k+1}, \overline{x}_j\right) \quad otherwise \end{cases} \tag{8}$$

$$c_j = \left(\overline{x}_j + \underline{x}_j\right).0.5 \tag{9}$$

where $v_{i,j}^{k+1}$ represents the *j*th value of the *i*th solution at the (*k+1*) th cycle.

4) Internal Competition Operator

The team builds a more potent competitive edge over time by holding onto its top performers. This is achieved through the application of (10).

$$x_{i,j}^{k+1} = \begin{cases} u_{i,j}^{k+1} if \left(F\left(\boldsymbol{u}_i^{k+1}\right) \leq F\left(\boldsymbol{v}_i^{k+1}\right)\right) \\ v_{i,j}^{k+1} \; if \left(F\left(\boldsymbol{u}_i^{k+1}\right) > F\left(\boldsymbol{v}_i^{k+1}\right)\right) \end{cases}, i \in [1, I], j \in [1, J], k \in [1, K] \tag{10}$$

In this expression, *F*(*x*) denotes the fitness value of the solution ***x***. The total number of variables within solution *x* must be adjusted according to (11) to conform to the feasible zone.

$$x_j = max\left\{min\left\{\overline{x}_j, x_j\right\}, \underline{x}_j\right\} \tag{11}$$

The pseudocode of the CSA is given in Algorithm 1.

B. Opposition-Based Learning
Opposition-based learning is a recognized technique renowned for augmenting the exploration capabilities of metaheuristic algorithms [37]. The foundation of OBL lies in converging toward the optimal solution by simultaneously exploring the current position x and its opposite position $\bar{x}$.

Consider x as a real number within the [L, U] range. The opposite position $\bar{x}$ is defined for a one-dimensional space as given in (12).

$$\bar{x} = U + L - x \tag{12}$$

In an n-dimensional space, where each component X_i resides within the range [L_i, U_i], and i takes on values from 1 to n, the opposite position $\bar{x}$ is defined as given in (13).

$$\bar{x}_i = U_i + L_i - x_i \tag{13}$$

Following the generation or recent update of all x positions, the corresponding opposite positions $\bar{x}$ are computed. Subsequently, x and the $\bar{x}$ positions' fitness is evaluated, and the superior positions are retained. Finally, with each iteration, the approach converges progressively closer to the optimal solution.

C. Pattern Search Algorithm
Pattern search (PS) techniques represent a class of direct search algorithms that leverage historical data to identify effective patterns for search point selection. These identified patterns are subsequently utilized to predict promising search points in subsequent iterations, thereby facilitating an efficient exploration of the solution space. Pattern search algorithm exhibits characteristics analogous to various direct search methods, such as the Simplex algorithm [38].

In this context, Torczon [39] introduced the multidirectional search (MDS) algorithm in 1989, a derivative of the PS approach specifically designed to address unconstrained minimization problems. The MDS algorithm demonstrates particular efficacy in identifying optimal solutions through a dual strategy: retaining the most promising vertex from the preceding iteration while simultaneously conducting line searches in multiple directions. This approach enables the accumulation of exploratory data, effectively converging toward the global minimum.

The efficiency of the MDS algorithm is largely governed by three key parameters: ρ, μ, and θ. These parameters control the step lengths relative to the original simplex edges. In this case, ρ, μ, and θ are set to 1, 2, and 0.5, respectively, as was chosen in [40]. Additionally, the initial step size requisite for constructing the initial simplex is established at 0.05, while a critical tolerance value of 10^{-5} is implemented as the algorithm's termination criterion by the guidelines provided in [40].

The operational framework of the PS algorithm is delineated in Algorithm 2, which provides a comprehensive pseudocode representation of the procedure.

D. The Proposed Improved Version
While previous studies [41, 42] have demonstrated the superiority of the CSA over several traditional evolutionary algorithms, recent research [43] has identified certain limitations, indicating potential areas for enhancement. A notable drawback of CSA is the gradual reduction in population diversity over successive iterations, which may lead to premature convergence in global search operations [41]. To address this limitation, the integration of an OBL mechanism into the CSA framework has been proposed. In the ICSA (Improved Cooperation Search Algorithm) presented in this study, the OBL mechanism facilitates exploration in opposing directions within the global search space. This enhancement significantly increases the probability of identifying superior local search regions.

Furthermore, the incorporation of a PS method augments the algorithm's exploitation capabilities. This dual enhancement strategy aims to strike a balance between exploration and exploitation, potentially leading to more robust and efficient optimization performance.

The operational framework of the proposed ICSA, including these enhancements, is delineated in Algorithm 3, which provides a comprehensive pseudocode representation of the procedure.

III. PROBLEM DEFINITION

A. Infinite Impulse Response Filter-Based System Identification
Fig. 1 shows the block diagram of the system identification process using the IIR filter. Eq. (14) governs the input–output relationship of an IIR filter.

$$y(k) + \sum_{i=1}^{M} b_i y(k-i) = \sum_{i=0}^{L} a_i x(k-i), \quad M \geq L \tag{14}$$

where $x(k)$ and $y(k)$ are the filter's input and output, respectively. M ($\geq L$) is the filter order. The filter's input-to-output transfer function can be written in general form as given in (15).

$$H(z) = \frac{A(z)}{B(z)} = \frac{\sum_{i=0}^{L} a_i z^{-i}}{1 + \sum_{i=1}^{M} b_i z^{-i}} \tag{15}$$

Hence, the design of the model to identify an unknown plant of $P(z)$ can be considered a minimization problem of a cost function J(w), as stated in (16).

$$\underset{w \in W}{\arg\min} \, \boldsymbol{J}(\boldsymbol{w}) \quad w = [a_0 \quad a_1 \quad \cdots \quad a_L \quad b_1 \quad b_2 \quad \cdots \quad b_M]^T \tag{16}$$

where $\boldsymbol{w}$ is the filter coefficient vector with a dimension of $D = M + L + 1$ and W is the coefficient search space. The goal is to find the optimal coefficients $\boldsymbol{w}$, which minimize the cost function $J(\mathbf{w})$. For practical reasons, the cost function is usually expressed as the time-averaged

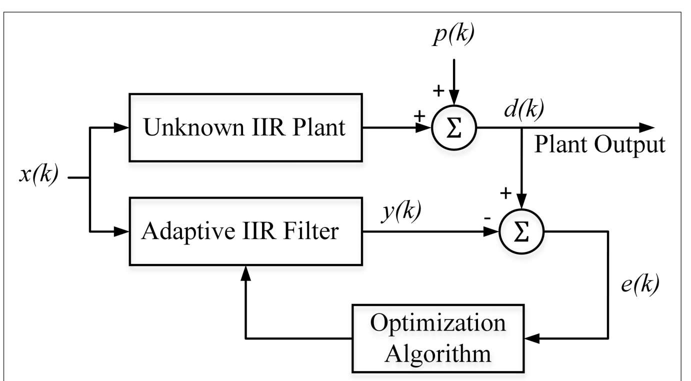

Fig. 1. Block diagram of system identification process using IIR filter.

squared error given in (17). Additionally, $p(k)$ is the perturbation, which is not taken into account in this particular example.

$$MSE = J(w) = E\left[e^2(k)\right] \cong \frac{1}{N}\sum_{k=1}^{N}\left(d(k)-y(k)\right)^2 = \frac{1}{N}\sum_{k=1}^{N}e^2(k) \quad (17)$$

where $E[.]$ is the statistical expectation operator, also called the ensemble operator. $d(k)$ and $y(k)$ are the desired and actual responses of the filter, respectively. $e(k) = d(k)-y(k)$ is the output error function, and N is the number of samples used for the calculation of the cost function, which approximates the ensemble operation. Note that the cost function of MSE given in (17) can also be expressed in decibel form as $MSEdB = 10log_{10}(MSE)$ for better comparison and interpretation of results.

During the adaptive process, the stability of the IIR filter must always be maintained. This can be handled either by limiting the parameter space [5] or by choosing an alternative filter structure, such as a lattice structure instead of using a direct form structure [5, 6], or by calculating the model system's poles to check whether they are located inside the unit circle [7]. In this study, the parameter space limitation method is chosen to assure the modeled system's stability, which reduces the calculation burden of the optimizer significantly. This is because unstable solutions will be automatically discarded by the optimization algorithm due to having larger objective function values. This way, search agents will be forced toward stable solutions without calculating the modeled system's poles or the parameters of a different filter structure during system identification.

B. Proposed ICSA Approach for IIR System Identification

In this subsection, based on the input–output data of an unknown plant, the plant will be represented either by its matched- or reduced-order model by minimizing the difference between their outputs. Fig. 2 illustrates the IIR system identification process using the proposed ICSA algorithm.

Here, the input data are processed by both adaptive IIR filter-based systems, namely the estimated model and the actual plant, and the proposed algorithm tries to find the optimal parameters of the estimated model by minimizing the difference between both outputs. The input data used in this study is white noise uniformly distributed in the range of (–0.5, 0.5) with a length of N = 200 and is illustrated in Fig. 3. Note that the input data are also provided in the Appendix section for those readers who would like to duplicate the obtained results. All simulation experiments are conducted with a maximum iteration number of 500, a population size of 100, and a maximum run number of 30. The simulations are performed with MATLAB software installed on a PC with an Intel i5-12600 3.30 GHz processor and 16 GB RAM.

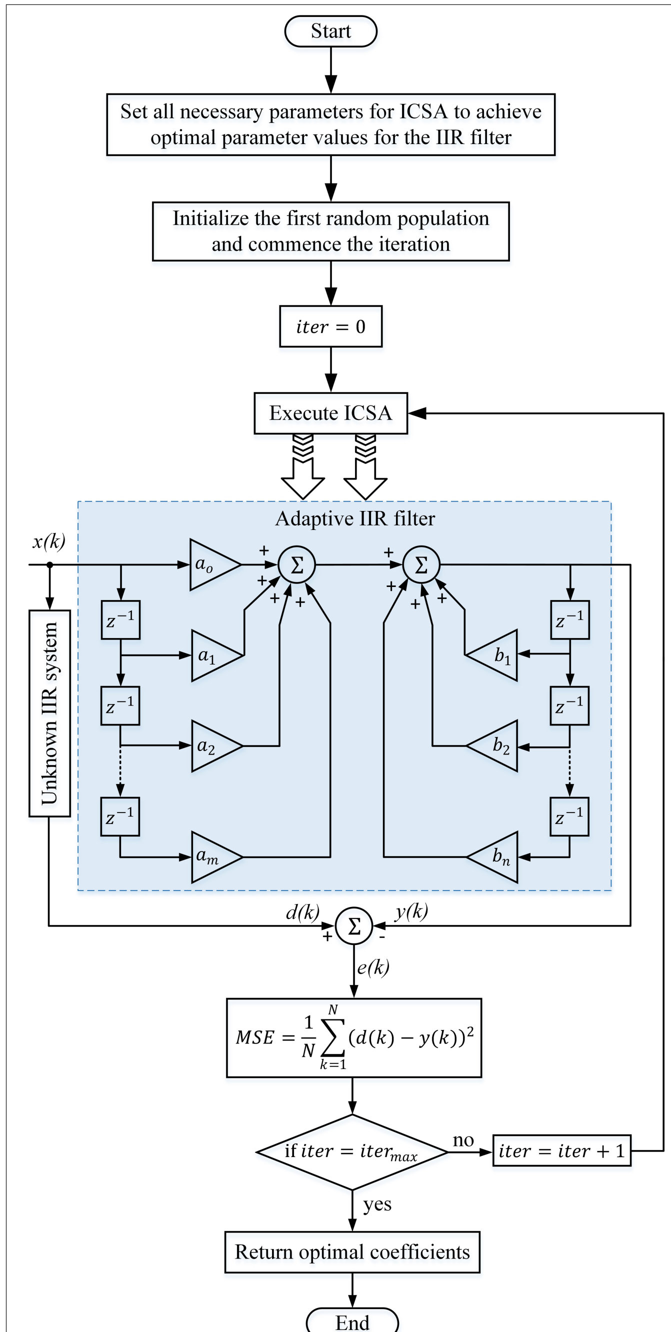

Fig. 2. IIR system identification process using the proposed ICSA algorithm.

IV. SIMULATION RESULTS OF BENCHMARK IIR SYSTEMS

The benchmark examples utilized in this paper are second-, third-, fourth-, and fifth-order systems, which will be evaluated using both CSA and its improved version ICSA. The results obtained by both algorithms will be compared in detail with other results from the literature to assess their performance. Note that the additive noise will not be used for a fair comparison with the literature in all subsequent examples. Please be advised that the formulation of coefficients in the denominator of the plants' transfer functions in the IARO [13], AHA [44], and ADE-LS [14] studies differ from that in the proposed method. As a result, the plus or minus signs of the denominator coefficients for the corresponding studies in Tables 1, 3, 5, and 7 were adjusted accordingly.

A. Example 1—Second-Order Plant

Transfer functions of the second-order plant and its matched- and reduced-order models are given as (18, 19, and 20).

$$H_{P1}(z) = \frac{0.05 - 0.4z^{-1}}{1 - 1.1314z^{-1} + 0.25z^{-2}} \quad (18)$$

$$H_{M1}(z) = \frac{a_0 + a_1 z^{-1}}{1 + b_1 z^{-1} + b_2 z^{-2}} \quad (19)$$

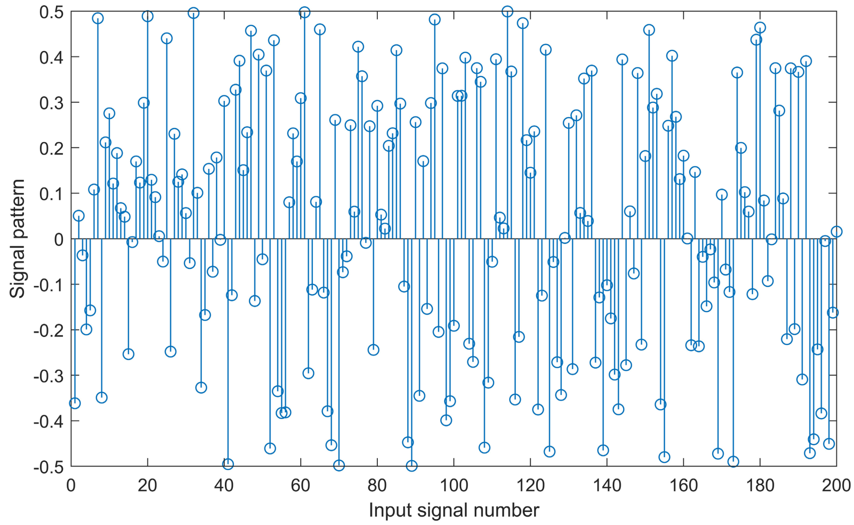

Fig. 3. Input data used for IIR system identification.

$$H_{R1}(z) = \frac{a_0'}{1 + b_1' z^{-1}} \tag{20}$$

The coefficients of matched- and reduced-order IIR models obtained by CSA and ICSA are given in Table 1. The scatter plots of MSE values versus number of runs are shown in Fig. 4(a) and 4(b), while convergence curves of best runs are given in Fig. 5(a) and 5(b).

In the case of the matched-order model of the second-order system, the MSE values for ICSA, which are depicted in the scatter plot in Fig. 4(a), are much lower than the original CSAs. This shows that the ICSA algorithm can optimize the system coefficients with greater efficiency, resulting in enhanced performance. In the case of the reduced-order model, most data points acquired through ICSA are lower compared to those obtained with CSA, as seen in Fig. 4(b). Examining the convergence plot given in Fig. 5(a), one can see the faster convergence of the ICSA against CSA also with much lower MSE values. For the reduced-order model, very close MSE values are recorded as a convergence plot for the ICSA and CSA given in Fig. 5(b). Additionally, because of the reduction in filter order, algorithms become trapped in local optimal solutions while conducting the search process. Hence, the premature convergence for both algorithms in Fig. 5(b).

In the analysis of the second-order system IIR filters, various metrics, including standard deviation, mean, worst, and best, are assessed. Reviewing Table 2 shows that the ICSA consistently surpasses CSA in yielding superior results throughout all metrics for the matched-order model. For the reduced order, ICSA outperforms CSA in worst and standard deviation metrics, while CSA has a lower best value, and the mean values are exactly the same.

B. Example 2—Third-Order Plant

The transfer functions of the third-order plant and its matched and reduced-order models are given in (21, 22, and 23).

$$H_{P2}(z) = \frac{-0.2 - 0.4z^{-1} + 0.5z^{-2}}{1 - 0.6z^{-1} + 0.25z^{-2} - 0.2z^{-3}} \tag{21}$$

TABLE 1. SECOND-ORDER SYSTEM'S MODEL COEFFICIENTS

Model Type	Coefficients	CSA	ICSA	IARO [13]	AHA [44]	ADE-LS[14]
Matched-order	a_0	0.050606728799885	0.05	0.05	0.05	0.05
	a_1	−0.402197481915466	−0.4	−0.4	−0.4	−0.4
	b_1	−1.127038715264740	−1.1314	−1.1314	−1.1314	−1.1314
	b_2	0.246094644851396	0.25	0.25	0.25	0.25
	MSE	3.73514E-07	**0**	**0**	**0**	**0**
Reduced-order	a_0'	−0.313641027643965	−0.313381211666222	−0.218395277719291	−0.3156	−0.297
	b_1'	−0.906688872531020	−0.906716701813246	−0.923418356533178	−0.9082	−0.9065
	MSE	**1.70199E-02**	1.70200E-02	1.99497E-02	1.70336e-02	1.71509E-02

CSA, Cooperation Search Algorithm; ICSA Improved Cooperation Search Algorithm; IARO, improved artificial rabbits optimization; AHA, artificial hummingbird algorithm; ADELS, average differential evolution with local search. Bold values mean the better result, in this particular example it means the lower value.

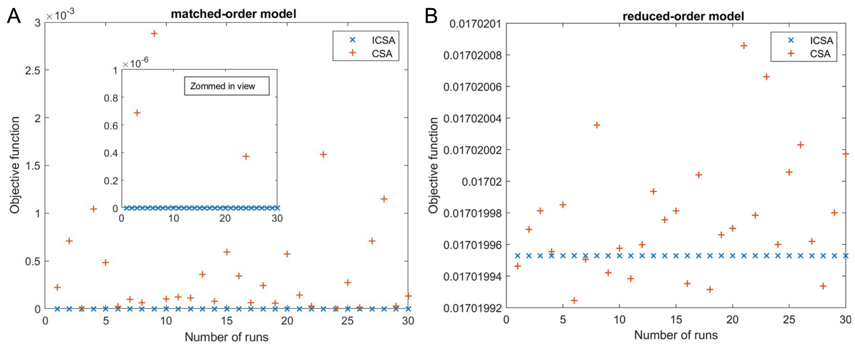

Fig. 4. Scatter plots of algorithms for matched-order and reduced-order models of the second-order plant.

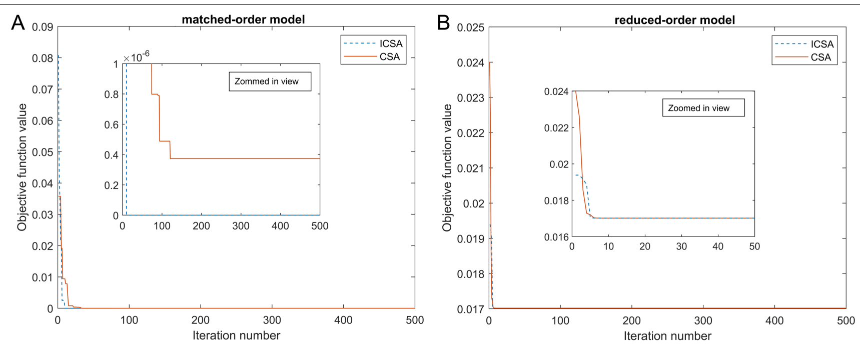

Fig. 5. Convergence curves of algorithms for matched-order and reduced-order models of the second-order plant.

$$H_{M2}(z)=\frac{a_0+a_1z^{-1}+a_2z^{-2}}{1+b_1z^{-1}+b_2z^{-2}+b_3z^{-3}} \tag{22}$$

$$H_{R2}(z)=\frac{a_0'+a_1'z^{-1}}{1+b_1'z^{-1}+b_2'z^{-2}} \tag{23}$$

The coefficients of matched and reduced-order IIR models obtained by CSA and ICSA are given in Table 3. The scatter plots of MSE values versus number of runs are given in Fig. 6(a) and 6(b), while convergence curves of best runs are given in Fig. 7(a) and 7(b).

TABLE 2. STATISTICAL COMPARISONS OF THE COOPERATION SEARCH ALGORITHM AND IMPROVED COOPERATION SEARCH ALGORITHM FOR THE SECOND-ORDER SYSTEM

Model Type	Metric	CSA	ICSA
Matched-order	Best	3.73514E-07	**0**
	Worst	2.88144E-03	**1.14196E-32**
	Mean	4.08634E-04	**5.21131E-33**
	Std	5.98878E-04	**3.10492E-33**
Reduced-order	Best	**1.70199E-02**	1.70200E-02
	Worst	1.70201E-02	**1.70200E-02**
	Mean	**1.70200E-02**	**1.70200E-02**
	Std	3.81077E-08	**1.12507E-12**

CSA, Cooperation Search Algorithm; ICSA, Improved Cooperation Search Algorithm. Bold values mean the better result, in this particular example it means the lower value.

For the matched-order model of the third-order system, the scatter plot in Fig. 6(a) illustrates 27 orders of magnitude lower MSE values for ICSA compared to the original CSA. In the case of a reduced-order system, values remain nearly similar to each other, as depicted in Fig. 6(b). Fig. 7(a) displays the convergence plot, revealing the accelerated convergence of ICSA over CSA with considerably lower MSE values. A similar convergence pattern is observed in Fig. 7(b); again, both algorithms experience premature convergence due to a reduction in filter order, leading them to get stuck in local optimal solutions during the search process.

Analyzing the third-order system in Table 4 reveals that ICSA outperforms CSA for matched and reduced-order models across all metrics except for the best value in the reduced-order model. The difference between the best values is only 0.0085%. Like the second-order system, the ICSA algorithm demonstrates superior efficiency in optimizing system coefficients, thereby leading to improved performance.

C. Example 3—Fourth-Order Plant

Transfer functions of the fourth-order plant and its matched and reduced-order models are given in (24, 25, and 26).

$$H_{P3}(z)=\frac{1-0.9z^{-1}+0.81z^{-2}-0.729z^{-3}}{1+0.04z^{-1}+0.2775z^{-2}-0.2101z^{-3}+0.14z^{-4}} \tag{24}$$

$$H_{M3}(z)=\frac{a_0+a_1z^{-1}+a_2z^{-2}+a_3z^{-3}}{1+b_1z^{-1}+b_2z^{-2}+b_3z^{-3}+b_4z^{-4}} \tag{25}$$

TABLE 3. THIRD-ORDER SYSTEM'S MODEL COEFFICIENTS

Model Type	Coefficients	CSA	ICSA	IARO [13]	AHA [44]	ADE-LS[14]
Matched-order	a_0	−0.200386817110689	−0.2	−0.199999999999999	−0.2	−0.2
	a_1	−0.401700466049329	−0.4	−0.4	−0.4	−0.4
	a_2	0.501906592226980	0.5	0.499999999999999	0.5	0.5
	b_1	−0.601561722125977	−0.600000000000001	−0.599999999999999	−0.6	−0.6
	b_2	0.246877427439000	0.25	0.250000000000001	0.25	0.25
	b_3	−0.203019236521218	−0.2	−0.199999999999999	−0.2	−0.2
	MSE	1.24417E-06	3.24441E-33	2.10167E-31	**0**	**0**
Reduced-order	a_0'	−0.202491709522824	−0.203057284352129	−0.212213933861540	−0.2173	−0.2463
	a_1'	−0.566836483411288	−0.566829374374005	−0.593635989853768	−0.5764	−0.5829
	b_1'	0.166048680026948	0.165388560659273	0.150804672088005	0.1609	0.1565
	b_2'	0.398586630635224	0.398595308600334	0.363071095485534	0.3780	0.3495
	MSE	**1.29913E-03**	1.29924E-03	1.42999E-03	1.33998E-03	1.55554E-03

CSA, Cooperation Search Algorithm; ICSA, Improved Cooperation Search Algorithm; IARO, improved artificial rabbits optimization; AHA, artificial hummingbird algorithm; ADELS, average differential evolution with local search. Bold values mean the better result, in this particular example it means the lower value.

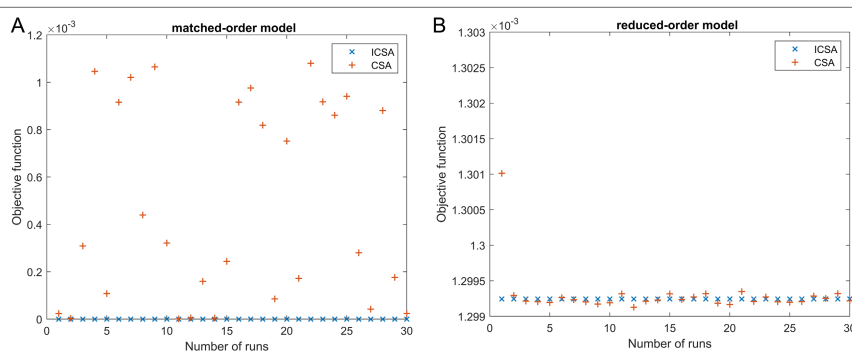

Fig. 6. Scatter plots of algorithms for matched-order and reduced-order models of the third-order plant.

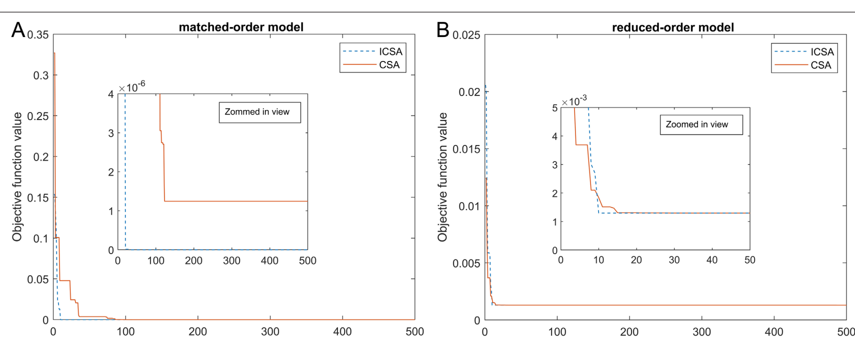

Fig. 7. Convergence curves of algorithms for matched-order and reduced-order models of the third-order plant.

TABLE 4. STATISTICAL COMPARISONS OF THE COOPERATION SEARCH ALGORITHM AND IMPROVED COOPERATION SEARCH ALGORITHM FOR THE THIRD-ORDER SYSTEM.

Model Type	Metric	CSA	ICSA
Matched-order	Best	1.24417E-06	**3.24441E-33**
	Worst	1.08018E-03	**4.654E-29**
	Mean	4.86334E-04	**2.81326E-30**
	Std	4.11923E-04	**9.70101E-30**
Reduced-order	Best	**1.29913E-03**	1.29924E-03
	Worst	1.30101E-03	**1.29924E-03**
	Mean	1.29930E-03	**1.29924E-03**
	Std	3.23206E-07	**3.35617E-13**

CSA, Cooperation Search Algorithm; ICSA, Improved Cooperation Search Algorithm. Bold values mean the better result, in this particular example it means the lower value.

$$H_{R3}(z) = \frac{a_0' + a_1' z^{-1} + a_2' z^{-2}}{1 + b_1' z^{-1} + b_2' z^{-2} + b_3' z^{-3}} \quad (26)$$

The coefficients of matched and reduced-order IIR models obtained by CSA and ICSA are given in Table 5. The scatter plots of MSE values versus number of runs are shown in Fig. 8(a) and 8(b), while convergence curves of best runs are given in Fig. 9(a) and 9(b).

In this section, the performance evaluation of the ICSA is done for the fourth-order system. The results portrayed in Figs. 8 and 9, along with Tables 5 and 6, show the superiority of the ICSA compared to CSA. Fig. 8(a) and 8(b) showcase scatter plots obtained from 30 runs regarding the fourth-order system, taking into account both matched- and reduced-order IIR filters. Fig. 8(a) and Table 5's matched-order section indicate that the ICSA returned 18 orders of magnitude lower MSE values than CSA. Similarly, Fig. 8(b) highlights that most of the data points produced by ICSA came in lower than the ones acquired with CSA, underscoring the algorithm's enhanced performance. Moreover, Fig. 9(a) illustrates the convergence behavior for the matched-order model of the fourth-order system. Similar to prior cases, ICSA converges much faster and achieves lower objective function values than CSA, indicating its efficacy for minimizing errors and converging toward better solutions. In the reduced-order model of the fourth-order system, ICSA converges faster than CSA and also has lower MSE values, as depicted in Fig. 9(b).

Table 7 reports statistical values for compared algorithms. Here, it becomes evident that the ICSA outperforms CSA in achieving the lowest best values for both matched- and reduced-order and lower mean values for reduced-order models. It should also be noted that CSA produces lower worst, mean, and standard deviation values for matched-order models, and lower worst and standard deviation values for the reduced-order model of the fourth-order system.

TABLE 5. FOURTH-ORDER SYSTEM'S MODEL COEFFICIENTS

Model Type	Coefficients	CSA	ICSA	IARO [13]	AHA [44]	ADE-LS[14]
Matched-order	a_0	0.971199200866865	0.999999999997536	0.999999901046974	1	1
	a_1	−0.925355436183355	−0.900000000175921	−0.899999446607367	−0.9	−0.9
	a_2	0.900158825921694	0.810000000043018	0.809999381423445	0.81	0.81
	a_3	−0.747481373935235	−0.729000000065149	−0.728999769621451	−0.7290	−0.729
	b_1	−0.070978731377729	0.039999999816822	0.040000592685006	0.04	0.04
	b_2	0.209398714034827	0.277499999872700	0.277500038362770	0.2775	0.2775
	b_3	−0.242054004589077	−0.210100000070009	−0.210100173789422	−0.2101	−0.2101
	b_4	0.152456230349440	0.140000000016099	0.139999722985085	0.14	0.14
	MSE	1.18228E-03	7.48299E-22	1.27628E-14	**0**	**0**
Reduced-order	a_0'	0.987397020943236	0.979315691174832	0.974795108953559	1.0048	1.0129
	a_1'	0.032307519423511	0.113969631247592	0.052616545573838	0.0442	0.0817
	a_2'	0.654202397062296	0.590632444308354	0.663473896344331	0.6080	0.6571
	b_1'	0.908558012429699	1.032082105086330	0.921607029275574	0.9289	0.9509
	b_2'	0.736872837418550	0.839347974784953	0.747757460347637	0.7289	0.7679
	b_3'	0.094978667095542	0.151226263626034	0.098218859095828	0.0871	0.1069
	MSE	7.54069E-03	**7.11818E-03**	7.53734E-03	7.46118E-03	7.41056E-03

CSA, Cooperation Search Algorithm; ICSA, Improved Cooperation Search Algorithm; IARO, improved artificial rabbits optimization; AHA, artificial hummingbird algorithm; ADELS, average differential evolution with local search. Bold values mean the better result, in this particular example it means the lower value.

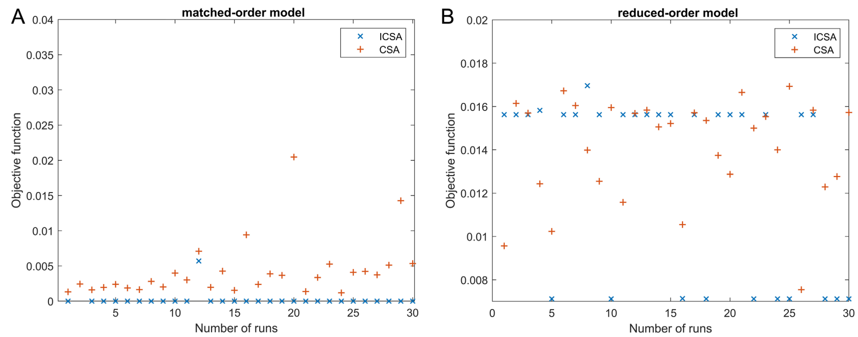

Fig. 8. Scatter plots of algorithms for matched-order and reduced-order models of the fourth-order plant.

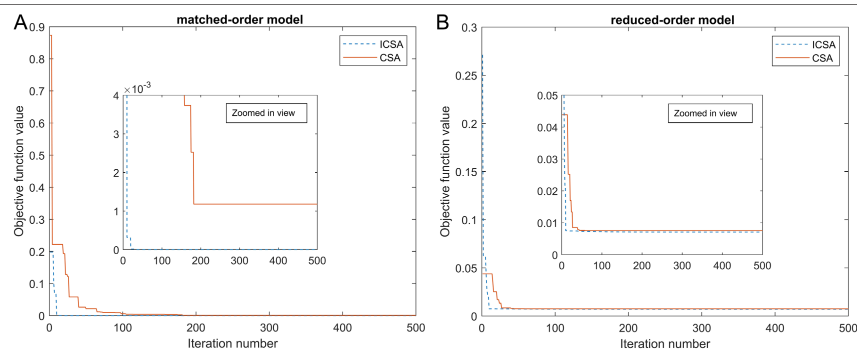

Fig. 9. Convergence curves of algorithms for matched-order and reduced-order models of the fourth-order plant.

D. Example 4—Fifth-Order Plant

Transfer functions of the fifth-order plant and its matched- and reduced-order models are given in (27, 28, and 29).

$$H_{P4}(z)=\frac{0.1084+0.5419z^{-1}+1.0837z^{-2}+1.0837z^{-3}+0.5419z^{-4}+0.1084z^{-5}}{1+0.9853z^{-1}+0.9738z^{-2}+0.3864z^{-3}+0.1112z^{-4}+0.01134z^{-5}} \quad (27)$$

$$H_{M4}(z)=\frac{a_0+a_1z^{-1}+a_2z^{-2}+a_3z^{-3}+a_4z^{-4}+a_5z^{-5}}{1+b_1z^{-1}+b_2z^{-2}+b_3z^{-3}+b_4z^{-4}+b_5z^{-5}} \quad (28)$$

TABLE 6. STATISTICAL COMPARISONS OF THE COOPERATION SEARCH ALGORITHM AND IMPROVED COOPERATION SEARCH ALGORITHM FOR THE FOURTH-ORDER SYSTEM

Model Type	Metric	CSA	ICSA
Matched-order	Best	1.18228E-03	**7.48299E-22**
	Worst	**2.04607E-02**	1.489s02E+02
	Mean	**4.25539E-03**	4.96358E+00
	Std	**4.02016E-03**	2.67287E+01
Reduced-order	Best	7.54069E-03	**7.11818E-03**
	Worst	**1.69281E-02**	1.69576E-02
	Mean	1.41052E-02	**1.28398E-02**
	Std	**2.34596E-03**	4.05152E-03

CSA, Cooperation Search Algorithm; ICSA, Improved Cooperation Search Algorithm. Bold values mean the better result, in this particular example it means the lower value.

$$H_{R4}(z)=\frac{a_0'+a_1'z^{-1}+a_2'z^{-2}+a_3'z^{-3}+a_4'z^{-4}}{1+b_1'z^{-1}+b_2'z^{-2}+b_3'z^{-3}+b_4'z^{-4}} \quad (29)$$

The coefficients of matched- and reduced-order IIR models obtained by CSA and ICSA are given in Table 7. The scatter plots of MSE values versus number of runs are given in Fig. 10(a) and 10(b), while convergence curves of best runs are given in Fig. 11(a) and 11(b).

In this section, the ICSA and CSA performance evaluations are conducted for the fifth-order system. Similar to prior sections, the outcomes given in Figs. 10 and 11, along with Tables 7 and 8, demonstrate the superiority of ICSA over CSA. Fig. 10(a) and 10B exhibit scatter plots derived from 30 runs for the fifth-order system for both matched-order and reduced-order models. Fig. 10(b) and Table 5 show that ICSA yields MSE values much lower than CSA. Similarly, Fig. 10(b) highlights that most data points produced by ICSA are significantly lower than the ones obtained by CSA, emphasizing the algorithm's enhanced performance. Furthermore, Fig. 11(a) illustrates convergence behavior for the matched-order model of the fifth-order system. Analogous to previous cases, ICSA converges much faster and achieves lower MSE values compared to CSA, showcasing its efficacy for minimizing errors and converging toward better solutions. In the reduced-order model of the fifth-order system, once again, ICSA exhibits faster convergence than CSA, along with lower MSE values, as depicted in Fig. 11(b).

Table 8 presents statistical values for the compared algorithms. It becomes evident that ICSA outperforms CSA in achieving the lowest best values for matched and reduced-order scenarios and lower values for all metrics in the reduced-order model. Additionally, it should be noted that CSA produces lower worst, mean, and standard

TABLE 7. FIFTH-ORDER SYSTEM'S MODEL COEFFICIENTS

Model Type	Coefficients	CSA	ICSA	IARO [13]	AHA [44]	ADE-LS[14]
Matched-order	a_0	0.116860344899451	0.108400031283855	0.108415440623010	0.1084	0.1084
	a_1	0.447275586714338	0.541878903194725	0.445050812699318	0.4492	0.5419
	a_2	0.661069422017368	1.083603682858840	0.634505033342557	0.6515	1.0837
	a_3	0.188472581365701	1.083531676634670	0.283668284692613	0.3109	1.0838
	a_4	−0.369575200750678	0.541765769741106	−0.113062384689373	−0.0959	0.5420
	a_5	−0.260343486851618	0.108358374075899	−0.103891170657143	−0.1006	0.1084
	b_1	0.261304999310042	0.985105546505000	0.091963933310944	0.1287	0.9854
	b_2	−0.051272907383393	0.973691874994718	0.417953338036308	0.4269	0.9738
	b_3	−0.188045714652736	0.386266680778307	−0.231718561869757	−0.2098	0.3865
	b_4	−0.267793791741098	0.111182430938613	0.000226928316145	−0.0016	0.1112
	b_5	0.047239489891187	0.011290766160077	−0.023273128348011	−0.0215	0.0113
	MSE	9.64938E-05	**1.16588E-12**	1.02125E-05	1.00544E-05	1.94307E-09
Reduced-order	a'_0	0.088201924500194	0.108541409266959	0.107788331761506	0.1089	0.1087
	a'_1	0.487539379647886	0.497319694894943	0.497356787857328	0.4543	0.4982
	a'_2	0.690417815328724	0.873237743003499	0.874769314421812	0.6848	0.8805
	a'_3	0.422708349130072	0.701222228054601	0.704424827667655	0.4180	0.7107
	a'_4	0.021342775749398	0.219856174035467	0.222506867289702	0.05	0.2259
	b'_1	0.261272186899093	0.573220064192672	0.577526454538850	0.1647	0.5880
	b'_2	0.553165151992960	0.686453685943388	0.688559929527913	0.5948	0.6893
	b'_3	−0.015907647135098	0.099127831455708	0.101214412003194	−0.0974	0.1061
	b'_4	0.061549498376859	0.044605392818530	0.044934419547747	0.0645	0.0438
	MSE	4.76099E-04	1.97738E-05	**1.97044E-05**	4.31824E-05	2.00885E-05

CSA, Cooperation Search Algorithm; ICSA, Improved Cooperation Search Algorithm; IARO, Improved artificial rabbits optimization; AHA, artificial hummingbird algorithm; ADELS, average differential evolution with local search. Bold values mean the better result, in this particular example it means the lower value.

deviation values for the matched-order model of the fifth-order system.

E. Non-Parametric Statistical Test

Here, the outcomes of the non-parametric Wilcoxon signed-rank test are presented. It is utilized to determine the statistical significance of variations in performance among the proposed ICSA and CSA for matched- and reduced-order models of second-, third-, fourth-, and fifth-order systems. Table 9 shows the results for the Wilcoxon signed-rank test, which indicate that the proposed ICSA performs better than the CSA in the majority of models. The resulting *p*-values are considerably smaller than 0.05 for most models, which is the determined significance level, indicating significant performance differences. In five of the eight cases, ICSA excels as the preferred method, emphasizing its ability to optimize system parameters and attain lower objective function values. These statistical results additionally confirm the effectiveness of ICSA in generating solutions with improved performance and precision across a range of IIR system identification tasks.

V. CONCLUSION

This study investigates the application of the ICSA for designing optimal IIR filter systems within an adaptive system identification framework. The ICSA, which incorporates a pattern search algorithm and an OBL method, is employed to enhance exploratory capabilities and exploitation efficiency. Utilizing IIR filter systems from second to fifth order, the research employs the mean squared error (MSE) objective function to optimize filter coefficients for both matched-order and reduced-order models. Comprehensive performance evaluations,

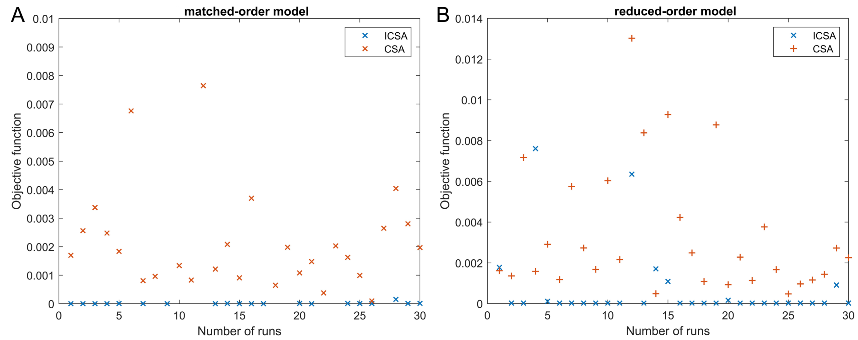

Fig. 10. Scatter plots of algorithms for matched- and reduced-order models of the fifth-order plant.

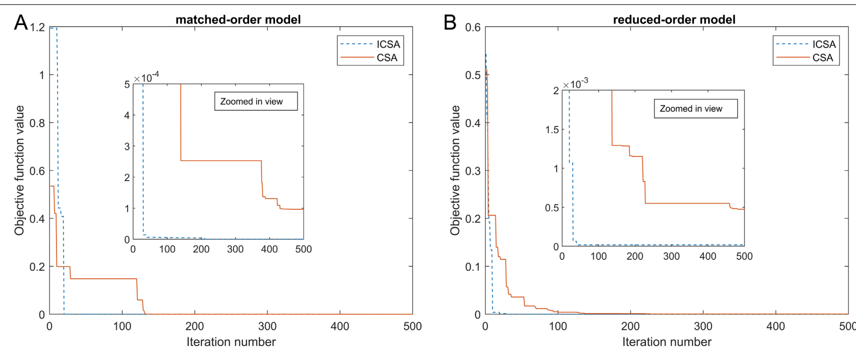

Fig. 11. Convergence curves of algorithms for matched- and reduced-order models of the fifth-order plant.

including statistical analysis, convergence response, scatter plot analysis, and non-parametric tests, are conducted across diverse IIR plants, benchmarking against established methodologies such as IARO [13], AHA [44], and ADE-LS [14]. Results demonstrate the ICSA's superior performance, achieving the lowest MSE values and exhibiting enhanced accuracy in coefficient identification across various IIR system orders. The Wilcoxon signed-rank test provides additional statistical validation of ICSA's improved performance. These findings underscore the ICSA's efficacy in generating efficient IIR systems and suggest its potential in related fields such as signal compression and integrated circuit design optimization. Future research directions include exploring ICSA's application to nonlinear and time-varying systems, integrating it with advanced signal processing techniques for improved performance in noise-rich environments, and investigating its potential in machine learning, robotics, and network optimization. Additionally, scaling ICSA for large-scale system identification problems using parallel computing techniques could further

TABLE 8. STATISTICAL COMPARISONS OF THE COOPERATION SEARCH ALGORITHM AND IMPROVED COOPERATION SEARCH ALGORITHM FOR THE FIFTH-ORDER SYSTEM

Model Type	Metric	CSA	ICSA
Matched-order	Best	9.64938E-05	**1.16588E-12**
	Worst	**1.74212E-02**	7.45348E+05
	Mean	**3.04631E-03**	3.95997E+04
	Std	**3.79108E-03**	1.51832E+05
Reduced-order	Best	4.76099E-04	**1.97738E-05**
	Worst	1.30243E-02	**7.60745E-03**
	Mean	3.35611E-03	**6.71589E-04**
	Std	3.07882E-03	**1.75872E-03**

CSA, Cooperation Search Algorithm; ICSA, Improved Cooperation Search Algorithm. Bold values mean the better result, in this particular example it means the lower value.

TABLE 9. NON-PARAMETRIC WILCOXON SIGNED-RANK TEST FOR THE IMPROVED COOPERATION SEARCH ALGORITHM AND COOPERATION SEARCH ALGORITHM

System	Model	*P*	Winner
Second-order system	Matched-order	1.7344E-06	+
	Reduced-order	2.2551E-03	+
Third-order system	Matched-order	1.7344E-06	+
	Reduced-order	6.5833E-01	=
Fourth-order system	Matched-order	3.1123E-05	+
	Reduced-order	1.7138E-01	=
Fifth-order system	Matched-order	6.4352E-01	=
	Reduced-order	4.8603E-05	+

CSA, Cooperation Search Algorithm; ICSA, Improved Cooperation Search Algorithm.

expand its capabilities in handling complex, high-dimensional systems, potentially leading to significant advancements in signal processing, control systems, and optimization across various domains.

Availability of Data and Materials: No new data were created or analyzed in this study. Data sharing does not apply to this article.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – B.H.; Design – B.H., C.E.; Supervision – B.H.; Resources – B.H., C.E.; Materials – B.H., C.E.; Data Collection and/or Processing – B.H., C.E.; Analysis and/or Interpretation – B.H., C.E.; Literature Search – B.H., C.E.; Writing – B.H., C.E.; Critical Review – B.H.

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ALGORITHM 1. CSA'S PSEUDO CODE.

Start

Specify the starting variables and objective function

Initialize a diverse population of solutions within the feasible search space.

Subsequently, evaluate the fitness of each individual solution.

t = 0

Specify maximum iteration number

while t < maximum iteration **do**

for every solution within the population **do**

Execute team communication operator using Eqs. (3-5)

Determine group solution $u_{i,j}$

Update the $u_{i,j}^{k+1}$ position

Execute the reflective learning operator.

if $\frac{\left|u_{i,j}^{k+1} - c_j\right|}{\left|\bar{x}_j - \underline{x}_j\right|} < \varnothing(0,1)$ **then**

Calculate $r_{i,j}^{k+1}$ and $p_{i,j}^{k+1}$ according to Eq. (7) and (8).

end if

if $u_{i,j}^{k+1} \geq c_j$ **then**

Calculate $v_{i,j}^{k+1}$ according to Eq. (6)

end if

Apply boundary check

Execute the internal competition operator.

if $F\left(\boldsymbol{u}_i^{k+1}\right) \leq F\left(\boldsymbol{v}_i^{k+1}\right)$ **then**

Calculate $x_{i,j}^{k+1}$ according to Eq. (10)

end if

end for

Update the individual best-known solutions based on the initial population.

Update the globally best-known solutions

Advance iteration counter.

if t >= max_iteration **then**

Export the best solution.

end if

end while

CSA: Cooperation search algorithm.

ALGORITHM 2. PSEUDOCODE OF THE PS ALGORITHM.

Specify the values for expansion factor (ρ), contraction factor (θ), and reflection factor (μ).

Generate the initial simplex (S_0)

$iter = 0$

while $iter < iter_{max}$ & distance > tol **do**

Determine the fitness values for every vertex within the simplex.

Select the optimal vertex, denoted as the one v_{i}^k which has the one the lowest fitness value

Perform the reflection stage and find r_i^k

if $f\left(r_i^k\right) < f\left(v_i^k\right)$ **then**

Perform the expansion stage and find e_i^k

if $f\left(e_i^k\right) < f\left(r_i^k\right)$ **then**

Replace v_i^k with e_i^k

else

Replace v_i^k with r_i^k

end if

else

Perform the contraction stage and find c_i^k

if $f\left(c_i^k\right) < f\left(v_i^k\right)$ **then**

Replace v_i^k with c_i^k

end if

end if

Advance the iteration.

end while

Export the best solution.

PS: Pattern search.

ALGORITHM 3. PSEUDOCODE FOR THE PROPOSED ICSA.

Start (population size, maximum iteration number, upper and lower limits for the parameters)

Produce various possible solutions and evaluate their efficacy for the intended results.

while $t<t_{max}$ **do**

Execute CSA algorithm

Update the current population (x)

Compute the inverse of the revised population ($\bar{x}$)

Choose the optimal solutions from x and $\bar{x}$ to constitute the subsequent updated population

Choose the optimal solution from the revised population.

if mod(iteration, 10) = 0 **then**

Perform a local search with PS

end if

Advance the iteration. counter

end while

Return the best solution.

ICSA: Improved Cooperation Search Algorithm.

TABLE A1. APPENDIX A1. INPUT DATA ($N = 200$)

1–20	21–40	41–60	61–80	81–100	101–120	121–140	141–160	161–180	181–200
−0.36155291	0.12948333	−0.495473038	0.497490616	0.052827491	0.313813679	0.235925847	−0.175051911	0.000448802	0.08395619
0.05041453	0.091306102	−0.124111067	−0.295588057	0.022179881	0.314185791	−0.375344273	−0.298494258	−0.234044729	−0.092977744
−0.03658402	0.005538616	0.327323403	−0.111749841	0.204132814	0.397865494	−0.124919134	−0.374913046	0.14662467	−0.001431883
−0.19928643	−0.050265829	0.391132914	0.080969105	0.231736857	−0.230645508	0.415432423	0.393934496	−0.236363397	0.374765145
−0.15745604	0.440374235	0.150589431	0.460119331	0.414211289	−0.270604061	−0.467810868	−0.277873696	−0.039924678	0.281522609
0.10800484	−0.24804068	0.23397025	−0.118276856	0.296914838	0.374843984	−0.05114723	0.060077637	−0.14840654	0.088416022
0.48442858	0.23049747	0.457075983	−0.379174861	−0.105057316	0.344775673	−0.271380052	−0.076354478	−0.023448899	−0.220686014
−0.34910717	0.125062297	−0.136745844	−0.453742336	−0.447398317	−0.45910115	−0.343386261	0.364109485	−0.096118664	0.37439728
0.21163937	0.141327958	0.404657629	0.261043732	−0.499122053	−0.316242801	0.001685878	−0.232596071	−0.472372778	−0.198586209
0.27550176	0.056352065	−0.045223734	−0.49821629	0.256171256	−0.050745085	0.25448323	0.181657759	0.096859248	0.3665842
0.12121417	−0.053678547	0.369438518	−0.073614456	−0.345243606	0.39445871	−0.286528561	0.4588198	−0.067812148	−0.30928202
0.18814971	0.496006096	−0.460863749	−0.03865067	0.170594259	0.046353505	0.271155647	0.288220908	−0.117018643	0.390337351
0.06714753	0.10089265	0.436098259	0.249366409	−0.154122991	0.022605305	0.056604198	0.318381941	−0.489899469	−0.471191552
0.04823951	−0.327189324	−0.335137595	0.059390037	0.298139534	0.499327676	0.351999866	−0.364211532	0.365186688	−0.440746485
−0.25355387	−0.16756238	−0.383069119	0.422024347	0.481708848	0.367426763	0.038940178	−0.47991922	0.199625639	−0.243067327
−0.0073562	0.153576981	−0.381633964	0.356996449	−0.204697358	-0.353321094	0.369343471	0.248301204	0.102340654	−0.383873551
0.16982315	−0.072503002	0.080099191	−0.009105468	0.374331033	−0.21563199	−0.272253028	0.402113716	0.05960202	−0.005097663
0.12336565	0.178502394	0.231564808	0.247215455	−0.399012963	0.473747003	−0.128956089	0.267884842	−0.121788543	−0.450711682
0.29875932	−0.002456432	0.169717361	−0.244234928	−0.356966615	0.216584194	−0.465009727	0.130951665	0.437343124	−0.162344979
0.48889785	0.302717134	0.308849432	0.291967762	−0.191272772	0.145044332	−0.102138679	0.182433138	0.46409939	0.015548417