Birotor Coaxial Model Estimation using Different Influence Function of Cultural Algorithm

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Abstract. This work investigates the estimation of a coaxial birotor UAV's model parameters by utilizing four influence function of Cultural Algorithm (CA). The CA is regarded as a strong algorithm that can adapt to a variety of problems. In this case, we are utilizing Situational and Normative knowledge sources, evaluating the efficacy of the proposed techniques is believed to depend on applying these tactics to uncover the coaxial birotor's autonomous complicated and nonlinear dynamics. The coaxial birotor model's parameters are retrieved using intelligent CA-(NS), CA-(SD), CA-(SD+NS), and CA-(ND+NS) techniques after the birotor dynamic modeling is defined using the Newton-Euler formalism. Ultimately, simulation results demonstrate the superior efficiency of CA-(SD+NS) in birotor identification parameter optimization.

1 Introduction

Unmanned aerial vehicles, or UAVs, have become increasingly popular in recent decades for use in both military and civilian contexts [1].

The development of miniature Unmanned Aerial Vehicles (UAVs) has been made feasible in recent years by advancements in computer and electrical technology. Among the UAVs are some extremely sophisticated devices, such as helicopters. Their adaptability and dexterity to perform a wide range of activities accounts for their complexity. There are several sorts of configurations that may be used, such as a standard Helicopter configuration, tandem rotor configuration, single main rotor and a tail rotor configuration, coaxial rotor configuration, and so on [2][3][4][5]. Our primary goal is to create a dynamic model of a coaxial birotor and estimated its parameters in order to design a nonlinear control that will enable an autonomous flight.

Coaxial helicopter is a dual main rotor helicopter structure with two concentric shafts and two contrarotating rotors of similar size and weight, using the Newton-Euler or Euler-Lagrange formalisms [4], birotor coaxial modeling is considered a delicate endeavor for both techniques, and the resulting model is highly nonlinear, completely coupled, under-actuated, dynamically unstable, and exhibiting complicated behavior. In this work, we define the birotor dynamics using the most used Newton-Euler formalism. Consequently, our objective is to explore a successful model parameter estimation technique that does not require complicated model structures to produce correct modeling outcomes.

An approximate mathematical model of the birotor may be constructed using systems identification, considering the aircraft as a black-box operation and depending only on input-output data. As a result, an ideal estimate of the model's parameter values is required. modeling the highly nonlinear birotor system's unstable divergent behavior is challenging. The least-squares method is a basic technique that's often used for parameter estimation [6], it has proven effective in determining the parameters of both dynamic and static systems. This approach proved to be the best for parametric identification, several researchers use least square technique to estimate various systems [7].

When compared to the previously discussed classical and statistical method, meta-heuristic techniques (MA) may successfully tackle complicated optimization issues[8]. Different types of meta-heuristic approaches, such as EAs, SI algorithms can be distinguished according to where they got their inspiration. Evolutionary algorithms, or EAs, are grounded in the Darwinian theory of evolution, which postulates that natural processes like reproduction, selection, and survival of the fittest enhance biological species' capacity for survival. For instance, the EAs category includes GAs, DEs, and BBO. Swarm intelligence or SIs, imitates the collaborative intellect observed in natural groups or swarms of various species like birds, ants, and fish. Methods like PSO, ABC algorithm, and ACO exemplify swarm intelligence, drawing inspiration from the swarming behaviors observed in bird flocks and ant colonies. In [9], for instance, a comparison of new meta-heuristic approaches for the identification and control of various systems reveals that Cultural Algorithm (CA) performs better in terms of exploration and exploitation than Ant Colony Optimization (ACO), Invasive Weed

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Optimization (IWO), and Black Hole Algorithm (BHA). Similarly, in [7], a quadrotor dynamics identification using the cooperative Particle Swarm Optimization-Cuckoo Search (PSO-CS) was carried out and compared to Particle Swarm Optimization (PSO), Cuckoo Search (CS), the results show the potency of the PSO method and the hybrid PSO-CS in identifying the quadrotor's ideal outputs.

In this study, we propose a comparison analysis that uses the Cultural Algorithm (CA) technique, which incorporates four impact functions, to precisely determine the dynamics of a birotor under certain operating circumstances. Four second-order subsystems with the same structures make up the model used to estimate variations in roll (ϕ), pitch (θ), yaw (ψ) angles, and altitude (z) through flight. To efficiently describe the outputs of the birotor, the coefficients of these subsystems are determined using CA. A comparative investigation between several impact functions demonstrates the efficacy of the proposed intelligent CA techniques for birotor identification.

This is how the paper is organized. The Newton-Euler formalism is used in Section 2 to generate the birotor's motion equations. The identification strategy using the recommended intelligent CA technique with four influence functions is explained in Section 3. Section 4 displays the simulation findings. The final part 5 contains our conclusions.

2 Birotor Coaxial Dynamic Modelling

Figure 1 shows the frames of the birotor. The product of the UAV's body-fixed frame (O_B) and its inertial frame (O_E) yields the transformation matrix $R_{\phi\theta\psi}$, where ϕ, θ, and ψ stand for the roll, pitch, and yaw angles, respectively. Equation (10) provides the connections between the yaw, pitch, and roll angles in both frames through the matrix $R_{\phi\theta\psi}$.

The fundamental principle of dynamics, whether in rotation or in translation, results in:

$$\begin{cases} m\ddot{\xi} = R^{-1}_{\phi\theta\psi}(F_g + F_{thi} + F_{ths}) + F_p + F_{dhs} + F_{dhi} + F_{dc} \\ J\dot{\Omega} = Q_z + \frac{L_D}{2}\begin{pmatrix} F_{dhsy} + F_{dhiy} + F_{dcy} + F_{ty} \\ F_{dhsx} + F_{dhix} + F_{dcx} + F_{tx} \\ 0 \end{pmatrix} \end{cases} \tag{1}$$

The cosine and sine functions are represented by the symbols C and S in the matrix, respectively. Comparably, the angular velocities recorded in body frames, $\Omega = [p, q, r]$, and the Euler angles rates in inertial frame, $\eta = [\phi, \theta, \psi]$, are transformed as (2):

$$\Omega = W_\eta \dot{\eta} \tag{2}$$

with

$$W_\eta = \begin{pmatrix} 1 & 0 & -\sin(\theta) \\ 0 & \cos(\phi) & \sin(\phi)\cos(\theta) \\ 0 & -\sin(\phi) & \cos(\phi)\cos(\theta) \end{pmatrix} \tag{3}$$

W_η may be roughly compared to the identity matrix I, since the roll and pitch angles are minimal. To address

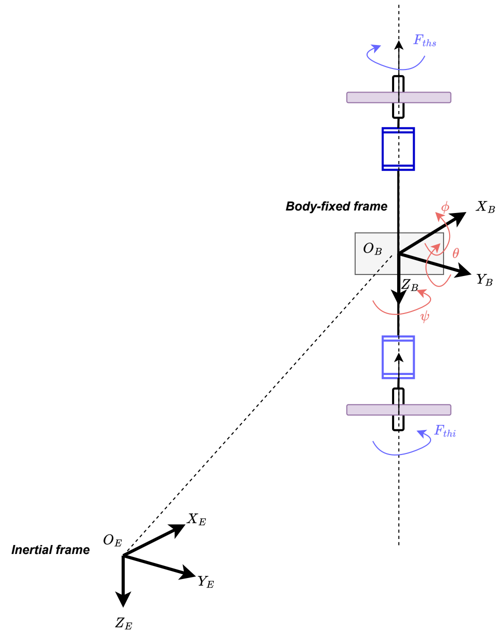

Figure 1. Birotor Coaxial Configuration

this, we have:

$$\Omega = \dot{\eta} = [\dot{\phi}, \dot{\theta}, \dot{\psi}] \tag{4}$$

J represents the system's inertia:

$$J = \begin{pmatrix} I_x & 0 & 0 \\ 0 & I_y & 0 \\ 0 & 0 & I_z \end{pmatrix} \tag{5}$$

F_g total weight of the mobile applied to the center of mass:

$$F_g = R_{\phi\theta\psi}\begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} mg \tag{6}$$

F_{ths} is lifts of the upper main propellers:

$$F_{ths} = R_{\phi\theta\psi}\begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} b_s\Omega^2_{hs} \tag{7}$$

F_{thi} is lifts of the lower main propellers:

$$F_{thi} = R_{\phi\theta\psi}\begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} b_i\Omega^2_{hi} \tag{8}$$

with $b_s = b_i = \frac{1}{2}\rho S C_T$ Where $C_T = 0.115$ is the thrust coefficient of the propeller, S is the surface (disc) formed by the rotation of the propellers, Ω_{hs} and Ω_{hi} are the angular velocities of the propellers in rad/s.

F_{pl} is the force generated by the two servomotors:

$$F_{pl} = \begin{pmatrix} F_{plx} \\ F_{ply} \\ 0 \end{pmatrix} \tag{9}$$

with

$$R_{\phi\theta\psi} = \begin{pmatrix} C(\psi)C(\theta) & C(\psi)S(\theta)S(\phi) - S(\psi)C(\phi) & C(\psi)S(\theta)C(\phi) + S(\psi)S(\phi) \\ S(\psi)C(\theta) & S(\psi)S(\theta)S(\phi) + C(\psi)C(\theta) & S(\psi)S(\theta)C(\phi) - C(\psi)S(\phi) \\ -S(\theta) & C(\theta)S(\phi) & C(\theta)C(\phi) \end{pmatrix} \tag{10}$$

$$F_{plx} = \frac{1}{2}\rho S C_{yx} R^2 (\Omega_{hi} + \Omega_{hs})^2 \tag{11}$$

$$F_{ply} = \frac{1}{2}\rho S C_{yy} R^2 (\Omega_{hi} + \Omega_{hs})^2 \tag{12}$$

C_{yx} , C_{yy} represents, first lateral lift coefficient which is worth $0.1(1+\alpha)$ and second lateral lift coefficient which is worth $0.1(1+\beta)$, respectively.

F_{dhs}, F_{dhi} and F_{dc} drag due to the translation of the system in x, y space (on the two main propellers and the body):

$$F_{dhs} = \begin{pmatrix} F_{dhsx} \\ F_{dhsy} \\ 0 \end{pmatrix} = -C_s \begin{pmatrix} \dot{x}^2 \\ \dot{y}^2 \\ 0 \end{pmatrix} \tag{13}$$

$$F_{dhi} = \begin{pmatrix} F_{dhix} \\ F_{dhiy} \\ 0 \end{pmatrix} = -C_i \begin{pmatrix} \dot{x}^2 \\ \dot{y}^2 \\ 0 \end{pmatrix} \tag{14}$$

$$F_{dc} = \begin{pmatrix} F_{dcx} \\ F_{dcy} \\ 0 \end{pmatrix} = \begin{pmatrix} -C_{cx}\dot{x}^2 \\ -C_{cy}\dot{y}^2 \\ 0 \end{pmatrix} \tag{15}$$

Q_z is the result of the counter torque due to air friction on the main propellers:

$$Q_z = \begin{pmatrix} 0 \\ 0 \\ Q_{hs} - Q_{hi} \end{pmatrix} \tag{16}$$

$$Q_{hs} = d_{hs}\Omega_{hs}^2 \;\; ; \;\; Q_{hi} = d_{hi}\Omega_{hi}^2 \tag{17}$$

with $d_{hs} = d_{hi} = 3.10^{-6}\mathrm{N\,m\,s^2}$ are air friction coefficients on the two propellers, upper and lower.

The birotor's dynamic model may thus be represented by the following equations, which are listed in (1):

$$\ddot{x} = \frac{1}{m}[\frac{1}{2}\rho S C_{yx} 0.1(1+\alpha)R^2(\Omega_{hi}^2 + \Omega_{hs}^2) - (C_s + C_i + C_{cx})\dot{x}^2] \tag{18}$$

$$\ddot{y} = \frac{1}{m}[\frac{1}{2}\rho S C_{yy} 0.1(1+\beta)R^2(\Omega_{hi}^2 + \Omega_{hs}^2) - (C_s + C_i + C_{cy})\dot{y}^2] \tag{19}$$

$$\ddot{z} = \frac{1}{m}[-mg + (b_s + b_i)(\Omega_{hi}^2 + \Omega_{hs}^2)] \tag{20}$$

$$\ddot{\phi} = \frac{L_d}{2I_x}[b_s(\cos(\phi)\sin(\theta)\sin(\psi) - \sin(\phi)\cos(\psi))(\Omega_{hi}^2 + \Omega_{hs}^2) - (C_s + C_i + C_{cy})\dot{y}^2] \tag{21}$$

$$\ddot{\theta} = \frac{L_d}{2I_y}[b_s(\cos(\phi)\sin(\theta)\cos(\psi) + \sin(\phi)\sin(\psi))(\Omega_{hi}^2 + \Omega_{hs}^2) - (C_s + C_i + C_{cx})\dot{x}^2] \tag{22}$$

$$\ddot{\psi} = \frac{L_d}{2I_z}[d_{hs}(\Omega_{hs}^2 - \Omega_{hi}^2)] \tag{23}$$

First, using the birotor's state equations (18)-(23), one must define the entry points of the simulation system Figure 2 in relation to the motors' rotational speeds, inclinations, and coefficients of drag and lift (24).

$$\begin{cases} C_1 = \frac{1}{2}\rho S\, 0.1(1+\alpha)R^2(\Omega_{hi}^2 + \Omega_{hs}^2) \\ C_2 = \frac{1}{2}\rho S\, 0.1(1+\beta)R^2(\Omega_{hi}^2 + \Omega_{hs}^2) \\ U_1 = (b_s + b_i)(\Omega_{hi}^2 + \Omega_{hs}^2) \\ U_2 = d_{hs}(\Omega_{hs}^2 - \Omega_{hi}^2) \end{cases} \tag{24}$$

3 Identification of Birotor Using Cultural Algorithm (CA)

3.1 Identification Strategy

Equations (18)–(23), which describe the birotor coaxial dynamical model, are simulated to get unstable responses. For $C1$, $C2$, $U1$, and $U2$, a unit step reference signal is used. Second-order systems may be used to mimic the divergent type of instability for the four flight variables. Moreover, the flight parameters of the birotor may be split, yielding four subsystems of order two with the same form, $G_{mi}(p)$, where $i = \{\phi, \theta, \psi, z\}$.

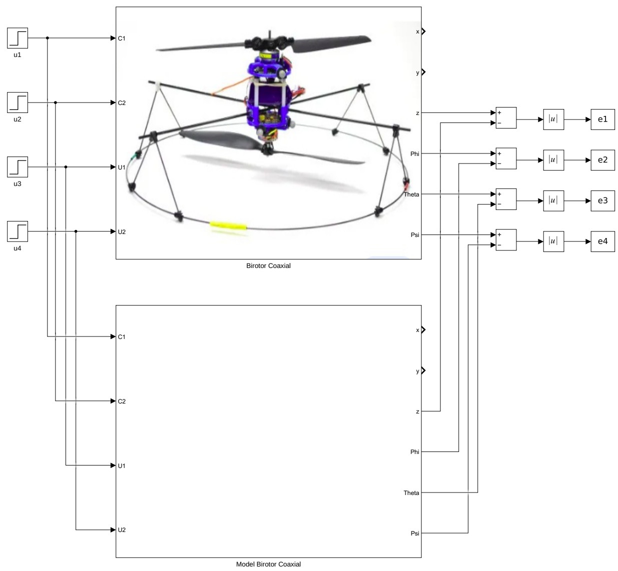

Figure 2. Birotor identification scheme.

$$G_{mi}(p) = \frac{k{\omega_n}^2}{p^2 + 2\xi\omega_n p + {\omega_n}^2} \tag{25}$$

It becomes possible to establish the issue as an optimization problem by repairing the system model. Comparing the time-dependent reactions of the system and the model using only input and output data is the fundamental principle behind parameter estimation[10]. With respect to Figure 2, u_i and e_i represent the excitation inputs and identification errors, respectively, that describe the behavioral differences between the birotor system and model, with $i = \{\phi, \theta, \psi, z\}$. Then, suitable techniques such as CA with different influence function are applied to best estimate the model parameters of the birotor (k, ω_n, ξ).

Table 1. The parameters of the birotor.

Parameter (unit)	Value
m (kg)	0.6
g (m/s^2)	9.806
L_d (m)	0.17
C_T	0.115
C_s, C_i	0.07
d_{hs}, d_{hi} (N m s^2)	3×10^{-6}
I_x (kg m^2)	5.12×10^{-4}
I_y (kg m^2)	5.3×10^{-4}
I_z (kg m^2)	8.16×10^{-4}

To minimize the disparity between the actual output and the expected output (ϕ, θ, ψ, z), the parameters (k, ω_n, ξ) are computed using Cultural Algorithm (CA). Consequently, the fitness or adaptation function (26) employed in this application accommodates for the quadratical error between the birotor's outputs and the recognized model (25).

$$f = \sum_{i=1}^{N} (y_j(i) - \hat{y}_j(i))^2 \quad ; \quad j = \{\phi, \theta, \psi, z\} \tag{26}$$

3.2 Cultural Algorithm Principle

Cultural Algorithm (CA): Robert Reynolds first proposed the idea of cultural algorithms in 1994 [11]. These algorithms are special because they use the belief space knowledge mechanism, which is a subset of evolutionary computation.

Equation (27) provides a formal definition of the belief space.

$$B^t = [S^t, N^t] \tag{27}$$

With the number of repetitions is indicated by t, situational knowledge is represented by S^t, normative knowledge by N^t, and belief space by B^t. The initial two knowledge sources (Normative and Situational) that are applied to our situation are well discussed.

- Situational Knowledge

  The situational knowledge source, denoted by S^t, contains the finest data from every population space era. The situational knowledge component (27) is updated as follow (28):

$$S^{t+1} = \begin{cases} X_l^t & if\ f(X_l^t) < f(S^t) \\ S^t & otherwise \end{cases} , l = 1, 2, \ldots, n_{accepte} \tag{28}$$

  where $n_{accepte}$ is the number of approved elite individuals required to update the belief space, and X_l^t is the lth accepted person at iteration t.

- Normative Knowledge

  Equation (29) may be used to express the collection of data in normative knowledge that corresponds to each problem dimension:

$$N^t = \begin{bmatrix} I_1^t & I_2^t & \cdots & I_n^t \\ L_1^t & L_2^t & \cdots & L_n^t \\ U_1^t & U_2^t & \cdots & U_n^t \end{bmatrix} \tag{29}$$

  $I_j^t = \left[x_{min,j}^t, x_{max,j}^t\right]$ at each iteration t, denotes the belief boundary of the jth dimension of the issue. The values of the fitness function for the lower and upper normative limits are L_j^t and U_j^t, respectively, where N^t signifies the normative knowledge source. $x_{min,j}^t$ and $x_{max,j}^t$ indicate the bottom and upper normative bounds of the problem's, respectively.

  When updating the normative knowledge source, CA is mindful to prevent belief intervals from becoming too narrow. The normative knowledge source's following components are updated using equations (30)-(33):

$$x_{min,j}^{t+1} = \begin{cases} x_{i,j}^t & if\ x_{l,j}^t \leq x_{min,j}^t\ or\ f(X_l^t) < L_j^t \\ x_{min,j}^t & otherwise \end{cases} \tag{30}$$

$$x_{max,j}^{t+1} = \begin{cases} x_{i,j}^t & if\ x_{l,j}^t \geq x_{max,j}^t\ or\ f(X_l^t) < U_j^t \\ x_{max,j}^t & otherwise \end{cases} \tag{31}$$

$$L_j^{t+1} = \begin{cases} f(X_l^t) & if\ x_{l,j}^t \leq x_{min,j}^t\ or\ f(X_l^t) < L_j^t \\ L_j^t & otherwise \end{cases} \tag{32}$$

$$U_j^{t+1} = \begin{cases} f(X_l^t) & if\ x_{l,j}^t \geq x_{max,j}^t\ or\ f(X_l^t) < U_j^t \\ U_j^t & otherwise \end{cases} \tag{33}$$

  Within the provided equations (30)(31)(32)(33), X_l^t represents the lth accepted individual at iteration t with $l = 1, 2, \ldots, n_{accepte}$, and $x_{l,j}^t$ indicates its jth variable.

The primary difficulty in creating influence functions when several information sources are utilised is figuring out how much each one affects the population space. Based on situational and normative information sources, Reynolds and Chung [12] developed the following four influence functions:

- The first influence function for CA-(NS) determines the step size during the search process by using just the normative knowledge source (34):

$$x_{i,j}^{t+1} = x_{i,j}^t + size(I_j^t) N_{i,j}(0, 1) \quad j = 1, 2, \ldots, n \tag{34}$$

  where $N_{i,j}(0, 1)$ is the random number generated by a normal distribution with a mean value of 0 and a standard deviation of 1. The jth element of the ith individual at iteration $t + 1$ is denoted by $x_{i,j}^{t+1}$. The size of the normative interval for the jth variable is indicated by $size(I_j^t) = x_{max,j}^t - x_{min,j}^t$.

- The second influence function for CA-(SD) chooses the direction of the search based on the situational knowledge (35):

$$x_{i,j}^{t+1} = \begin{cases} x_{i,j}^t + |\sigma_{i,j}^t N_{i,j}(0,1)| & if\ x_{i,j}^t < s_j^t \\ x_{i,j}^t - |\sigma_{i,j}^t N_{i,j}(0,1)| & if\ x_{i,j}^t > s_j^t \\ x_{i,j}^t + \sigma_{i,j}^t N_{i,j}(0,1) & otherwise \end{cases} \quad (35)$$

  where s_j^t is the jth element of the situational information at iteration t, and $\sigma_{i,j}^t$ is the procedure parameter of the jth variable of the ith individual.

- The third influence function for CA-(SD+NS) determines the direction of the search using situational knowledge, and the normative knowledge component determines the step size, which is expressed as follows (36):

$$x_{i,j}^{t+1} = \begin{cases} x_{i,j}^t + |\alpha size(I_j^t) N_{i,j}(0,1)| & if\ x_{i,j}^t < s_j^t \\ x_{i,j}^t - |\alpha size(I_j^t) N_{i,j}(0,1)| & if\ x_{i,j}^t > s_j^t \\ x_{i,j}^t + \alpha size(I_j^t) N_{i,j}(0,1) & otherwise \end{cases} \quad (36)$$

  with the constant value $\alpha > 0$.

- The fourth influence function for CA-(ND+NS) establishes the following search direction and step size, with reference to the normative knowledge source (37):

$$x_{i,j}^{t+1} = \begin{cases} x_{i,j}^t + |size(I_j^t) N_{i,j}(0,1)| & if\ x_{i,j}^t < x_{min,j}^t \\ x_{i,j}^t - |size(I_j^t) N_{i,j}(0,1)| & if\ x_{i,j}^t > x_{max,j}^t \\ x_{i,j}^t + \beta size(I_j^t) N_{i,j}(0,1) & otherwise \end{cases} \quad (37)$$

  with the constant value $\beta > 0$.

4 Simulation and Results

Equation (25) provides a model of the birotor system, which is constructed in 100 simulation seconds and is made up of four identically structured subsystems, denoted by $G_{mi}(p)$. The parameters of these subsystems (k, ω_n, ξ) that were calculated using CA with four influence functions are summarized in Table 3.

The birotor system's responses and the models made using CA-(NS), CA-(SD), CA-(SD+NS), and CA-(ND+NS) are displayed in Figure 4-Figure 7.

In order to ensure fairness in the comparison, in Table 2 we maintain the same numbers of population (500), maximum number of iteration (100) and same objective function (26), Figure 3 shows the flowchart of CA. As can be seen in Figure 4-Figure 7, The responses of the model with modified parameters using CA-(SD+NS) and CA-(SD) are quite similar to the responses of the birotor compared to CA-(NS) and CA-(ND-NS). This is because of direction of the search using situational knowledge and step size of normative knowledge in order to determine solutions that are as close as possible to the birotor system's responses (roll, pitch, yaw, and altitude z).

Even though it can be somewhat challenging to discover unstable responses, these data, which cover 100 seconds, demonstrate the reliability of the selected model (25) in recognizing the divergent responses of the birotor as well as the effectiveness of CA in finding the optimal solution.

Table 2. The adaptation of the CA parameters for identification

Parameters	Symbol	Value
The problem's dimensions	$n = (n_\xi, n_{\omega_n}, n_k)$	3
Quantity of population	N	500
Maximum iteration	t	100
Alpha	α	0.2
Beta	β	0.2
Acceptance ratio	p_{accept}	0.35

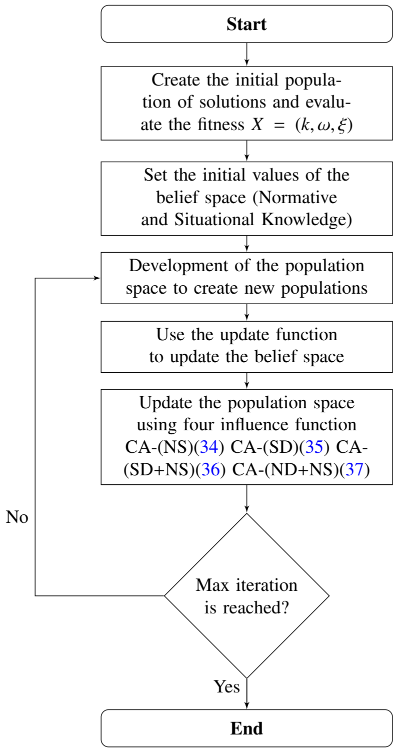

Figure 3. Flow chart of Cultural Algorithm (CA)

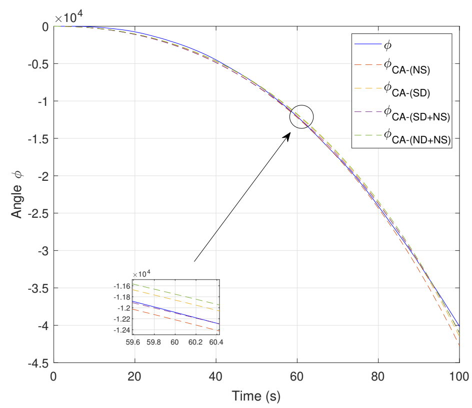

Figure 4. Angle ϕ of the coaxial birotor and the models $G_{m\phi}(p)$ obtained using CA

Table 3. Model parameters obtained using CA technique

Methods	Parameters	$G_{m\phi}(p)$	$G_{m\theta}(p)$	$G_{m\psi}(p)$	$G_{mz}(p)$
CA-(NS) model	k	−90499	−72498	$6.2982e+07$	$-4.0093e+06$
	ξ	−1.0889	−1.0248	−1.6314	−1.5654
	ω_n	0.0073458	0.0077885	0.0012215	0.0013312
CA-(SD) model	k	−69558	−94724	$5.1792e+07$	$-4.9783e+06$
	ξ	−1.0012	−1.0043	−1.0266	−1.0082
	ω_n	0.0082272	0.0070584	0.0013618	0.0012376
CA-(SD+NS) model	k	−99063	$-1e+05$	$6.9997e+07$	$-6.799e+06$
	ξ	−1	−1	−1	−1.0006
	ω_n	0.0071248	0.0068982	0.0011802	0.0010648
CA-(ND+NS) model	k	−89621	−77776	$6.144e+07$	$-7.7806e+06$
	ξ	−1.1011	−1.1573	−1.5129	−1.1403
	ω_n	0.007242	0.0073913	0.0012247	0.00098901

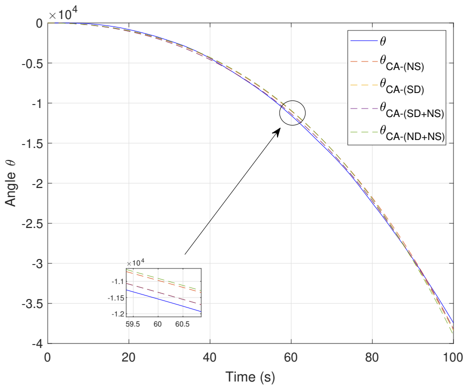

Figure 5. Angle θ of the coaxial birotor and the models $G_{m\theta}(p)$ obtained using CA

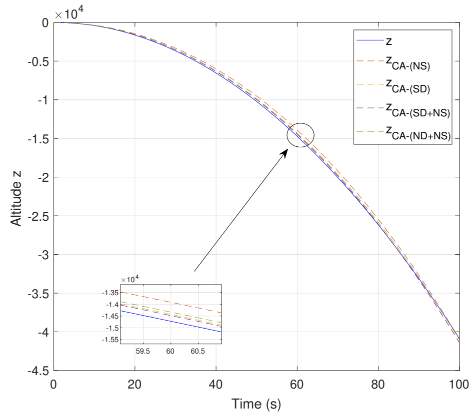

Figure 7. Altitude z of the coaxial birotor and the models $G_{mz}(p)$ obtained using CA

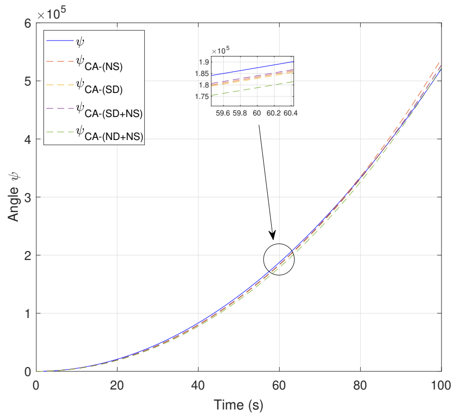

Figure 6. Angle ψ of the coaxial birotor and the models $G_{m\psi}(p)$ obtained using CA

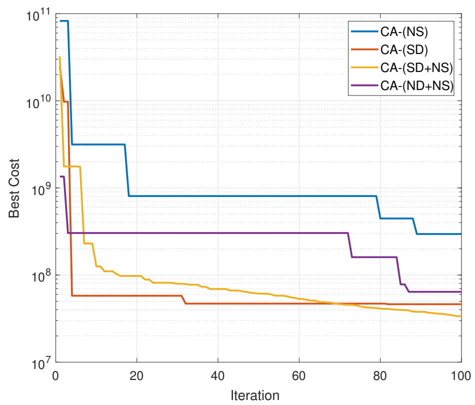

Figure 8. Convergence of the CA with different influence function to the best value for Altitude (z)

Figure 8 shows the convergence rate of the employed approaches. As shown, CA-(SD+NS) had the fastest rate of convergence and could reach values very close to the ideal value. The statistical results in Table 4 illustrate an example of the error of altitude z between the system output and the model output, proving that IAE, ISE, ITAE, and ITSE are all reduced than CA-(NS), CA-(SD) and CA-(ND+NS) when CA-(SD+NS) constructs the model.

5 Conclusion

This study used the Cultural Algorithm (CA) with differents functions to determine how a coaxial birotor UAV's

Table 4. Statistical analysis of the altitude (z) error using CA models

Methods	IAE	ISE	ITAE	ITSE
CA-(NS) model	46141	$2.9574e+07$	$2.7616e+06$	$1.846e+09$
CA-(SD) model	18015	$4.6103e+06$	$1.0849e+06$	$3.0242e+08$
CA-(SD+NS) model	15225	$3.3572e+06$	$9.282e+05$	$2.2679e+08$
CA-(ND+NS) model	21373	$6.4159e+06$	$1.2389e+06$	$3.8458e+08$

rotational movements (ϕ, θ, ψ) and translational motions along the z-axis varied. Simulation results demonstrated the effectiveness of the CA approach with various impact functions in optimally identifying the birotor's outputs (ϕ, θ, ψ, z). The optimal outcome is achieved by applying information to determine the direction (using situational component) and step size (using normative component), in other cases, regulating simply the direction yields the best results.

These accomplishments are the consequence of good model structure selection to detect unstable responses from the birotor system and good adjustement of the CA parameters.

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