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Quadrotor Black-Box System Identification using Metaheuristics

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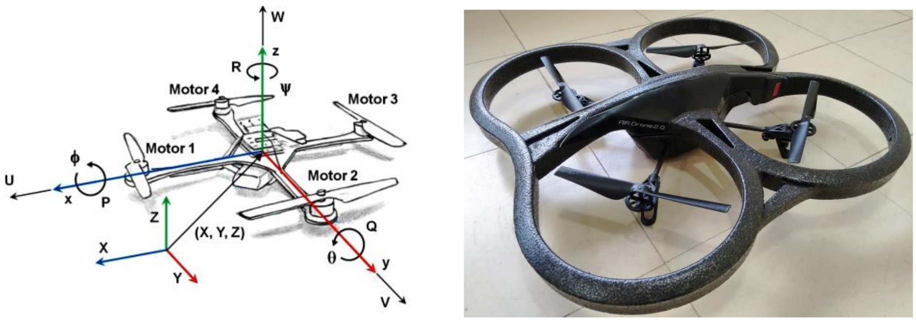
Abstract: The complexity of nonlinear and multivariable dynamic systems, such as Unmanned Aerial Vehicle (UAV), have been aim of several researches, mainly directed to identification model and controller design, because the drones have several applications in trade, industry, military, etc. However, the low error and high precision in identification of nonlinear multivariable systems is a great challenge for traditional techniques. Therefore, this paper has the objective to present the applicability of metaheuristics in quadrotor systems identification, further a comparative study of three metaheuristics, Particle Swarm Optimization (PSO), Adaptive Particle Swarm Optimization (APSO) and Cuckoo Search (CS), in black-box system identification from real data of an unmanned quadrotor model AR.Drone 2.0, where was used four uncoupled NARX structs, and the performance of each metaheuristic is evaluated according to mean squared error (MSE), precision and average processing time (APT) after 30 simulations in parameter estimation using Matlab software. The results show that PSO had better performance in precision and APT, and CS reached minor MSE.

Keywords: Parameter Estimation, Drone, PSO, APSO, Cuckoo Search.

INTRODUCTION

Quadrotor drones are UAV symmetric rotary wings structures, where each one of four extremity has helices controlled by electric motor-drive rotors, which provide flight propulsion. Furthermore, other components as Electronic Speed Controllers (ESC's), battery, control board and IMU (Inertial Measurement Unit) are essentials (Chovancová *et al*, 2014). Figure 1a illustrates the quadrotor state variables Roll (ϕ), Pitch (θ), Yaw (ψ) and Altitude (Z) (Valavanis and Vachtsenavos, 2018). Figure 1b shows the AR.Drone 2.0 (Parrot®) used for black-box system identification in this paper.



a) b)

Figure 1 – Structures of UAV quadrotor: a) Ideal model; b) AR.Drone 2.0.

In last years, the UAV have been largely used in applications as traffic surveillance, rescue missions, environment monitoring, agricultural spraying (Stanculeanu and Borangiu, 2011).

For control and stabilize the quadrotor is necessary some steps, and one of most important is the system identification, because it is so difficult to develop a control system for a quadrotor without its accurate dynamic model. Morris, Chen and Kind (2018) used a real time integral-based system identification technique for determining specific dynamics of UAV quadrotor. In Yang et al (2014) a Genetic Algorithm (GA) was applied to mechanic coefficients estimation of a quadrotor, using error minimization of the state signals. Stanculeanu and Borangiu (2011) used Prediction Error Method for black-box system identification of a quadrotor in closed-loop with its controller. In Chovancová et al (2014) was approached the mathematical modelling and parameter identification of quadrotor, where practical instrumental methods were used for thrust and rotor drag parameter estimation.

Therefore, the aim of this study is to apply and evaluate the performance of PSO, APSO and Cuckoo Search algorithms in uncoupled MIMO (multiple-input multiple-output) system identification of an UAV drone, using four nonlinear autoregressive exogenous (NARX) structures to each state variable, which are the Euler's angle and altitude. The PSO and Cuckoo Search were chosen because they reached good performance in terms of MSE in nonlinear system identification and they are among the most commonly used metaheuristics (Alfi, 2011; Souza et al, 2014), and APSO was applied because it reached good performance in average processing time in linear system identification (Oliveira, 2018).

Metaheuristics

The metaheuristics are optimization algorithms of stochastic search, which can coordinate procedures of local search with global high-level strategy, which create a process that can escape from local minimum and perform a robust search on solution space of a problem with complex solution (Glover and Kochenberger, 2003). These algorithms were created to solve complex problems where analytical solution is unknow or difficult to implement, including the identification of systems with complex dynamics. Below are described three metaheuristic algorithms used in this paper.

Particle Swarm Optimization (PSO)

The PSO algorithm was firstly described on Eberhart and Kennedy's work in 1995, which approach an algorithm inspired in flock of birds behavior. This algorithm consists basically in a group of N particles, swarm, where each position $\vec{x}_i(t)$ of the i-th particle in the t-th iteration is a vector that represents a possible solution of a problem, which are limited by X_{min} and X_{max}; $\vec{v}_i(t)$ represents de velocity of the particle, which are limited by V_{min} and V_{max}; $\vec{p}_i(t)$ is the best position already reached by each particle, and $\vec{G}(t)$ is the best position of the swarm in actual iteration. Equations (1) and (2) show how the position and the velocity of a particle are updated in PSO.

$$\vec{V}_i(t+1) = w\vec{V}_i(t) + c_1 R_1(t)(\vec{P}_i(t) - \vec{x}_i(t)) + c_2 R_2(t)(\vec{G}(t) - \vec{x}_i(t)) \tag{1}$$

$$\vec{x}_i(t+1) = \vec{x}_i(t) + \vec{V}_i(t+1) \tag{2}$$

The coefficient w is the inertial factor, R_1 and R_2 are random numbers initialized between 0 and 1 in each iteration, and c_1 and c_2 are the acceleration coefficients of the particles.

The main purpose of PSO, and others metaheuristics, is to seek for an optimal solution that can minimize or maximize an objective function J (fitness or cost function). The Algorithm maintains in the memory of each particle the best position that was visited in the past, and uses it to keep the best position in the swarm. After the update of velocities and positions, the $\vec{p}_i(t)$ is also updated and the best particle of the swarm is updated too.

After these processes, the best particle is evaluated in order to check if the stop criterion was reached, if it was reached, the algorithm stops and the optimal solution of the problem is the parameters of vector $\vec{G}(t)$, however, if the criterion was not reached, algorithm continues to update the positions and velocities until the criterion is reached.

Adaptive Particle Swarm Optimization (APSO)

The first proposal of adaptive PSO occurred on works of Zhan et al (2009). This algorithm has some structures that guarantee the adaptability of the swarm, and consequently, the scape from local optimal. The difference between this algorithm and PSO is that before the update of positions and velocities, the APSO has its adaptive mechanism, which consist in the classification of evolutionary state of the swarm in the t-th iteration using the evolutionary factor f, Eq. (3), where d_g is the mean distance between the best particle with the other ones each, $d_{\min}$ and $d_{\max}$ are the minimum and the maximum mean distance among the particles.

$$f = \frac{d_g - d_{\min}}{d_{\max} - d_{\min}} \tag{3}$$

The evolutionary state is classified using a group of fuzzy membership. Figure 2 shows the four evolutionary states.

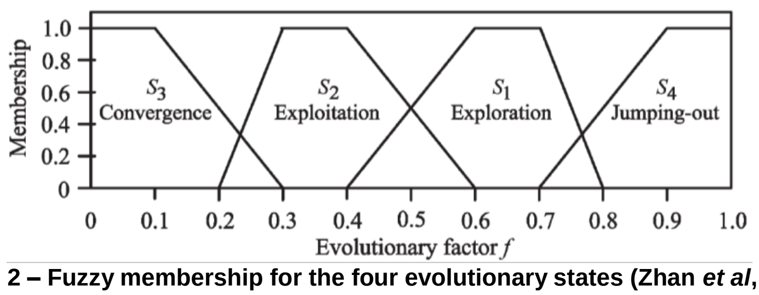


Figure 2 – Fuzzy membership for the four evolutionary states (Zhan *et al*, 2009).

Table 1 shows the modification of acceleration coefficients according to each evolutionary state, where these can be increased or decreased, where this change is applied with a random uniform variable between 0,05 and 0,10, and this value is multiplied by 0,5 in cases of slightly increase and decrease. However, when the swarm is classified in convergence, a Gaussian perturbation is applied on best particle in order to evaluate other regions for better results (elitist learning).

Table 1 – Adaptive update of acceleration coefficients.

Evolutionary State	c_1	c_2
Exploration	Increase	Decrease
Exploitation	Slightly Increase	Slightly Decrease
Convergence	Slightly Decrease	Slightly Increase
Jumping Out	Decrease	Increase

After the update of acceleration coefficients, the inertial factor is updated in function of evolutionary factor, according to Eq. (4). After these adaptive mechanisms, the APSO follows the same steps as described in PSO.

$$w(f) = \frac{1}{1+1,5e^{-2,6f}} \tag{4}$$

Figure 3 illustrates the flowchart of APSO algorithm, where the blue blocks represents the beginning and the end of this algorithm, the red blocks represents the adaptive mechanism of this metaheuristic described before, and the black blocks are the common steps between PSO and APSO.

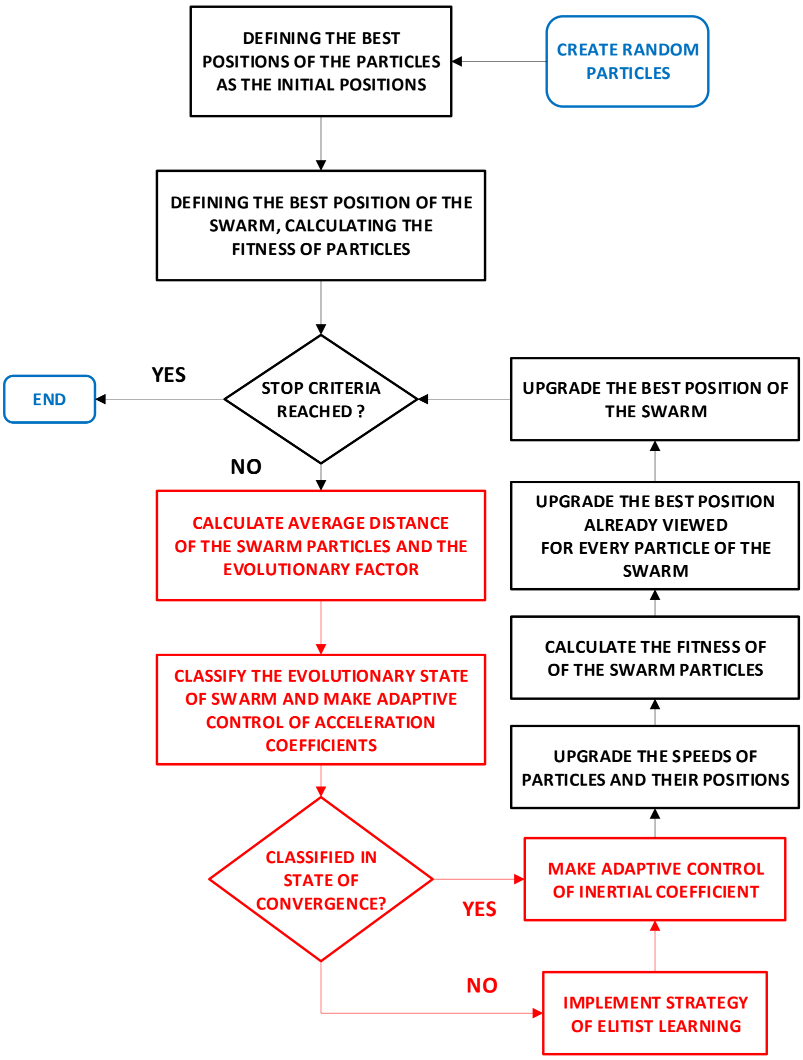


Figure 3 – Flowchart of APSO algorithm.

Cuckoo Search (CS)

Cuckoo Search algorithm was proposed by Yang and Deb (2009). This is a bio-inspired algorithm based in cuckoo's behavior of brood parasitism and their co-evolution with host bird species, where the cuckoo lays their eggs in communal nests.

Each egg, $\vec{n}_i(t)$, represents a vector of possible solution in multidimensional search space. The main steps of CS are: firstly, an initial population of eggs is generated and each cuckoo put one egg at a time and dump it in randomly chosen nest. The next step a nest is chosen randomly and a Lévy Flight is applied in egg's genetic in order to generate a new cuckoo's egg, also another egg is chosen randomly for compare the fitness between these two eggs, and the best one replaces the egg with changed genetic.

After this evaluation, a fraction P_a of worse nests are abandoned and new ones are built, keeping the best solutions, where the eggs with high quality will carry over next generation. After this step, the algorithm runs other iteration, repeating previous steps until reaches some of the stop criteria.

The generation of new solution in CS based on Lévy flight is showed in Eq. (5) and (6), where $\alpha > 0$ is the step size which should be related to scales of the problem of interest. And $\beta \in]1,3]$ is a constant of Lévy distribution.

$$\vec{n}_i(t+1) = \vec{n}_i(t) + \alpha \oplus \text{Lévy}(\beta) \tag{5}$$

$$\text{Lévy} \sim u_L = t^{-\beta} \tag{6}$$

Figure 4 illustrates the flowchart of CS algorithm, where the blue blocks represents the beginning and the end of this algorithm, and the black blocks are the standard steps of this metaheuristic.

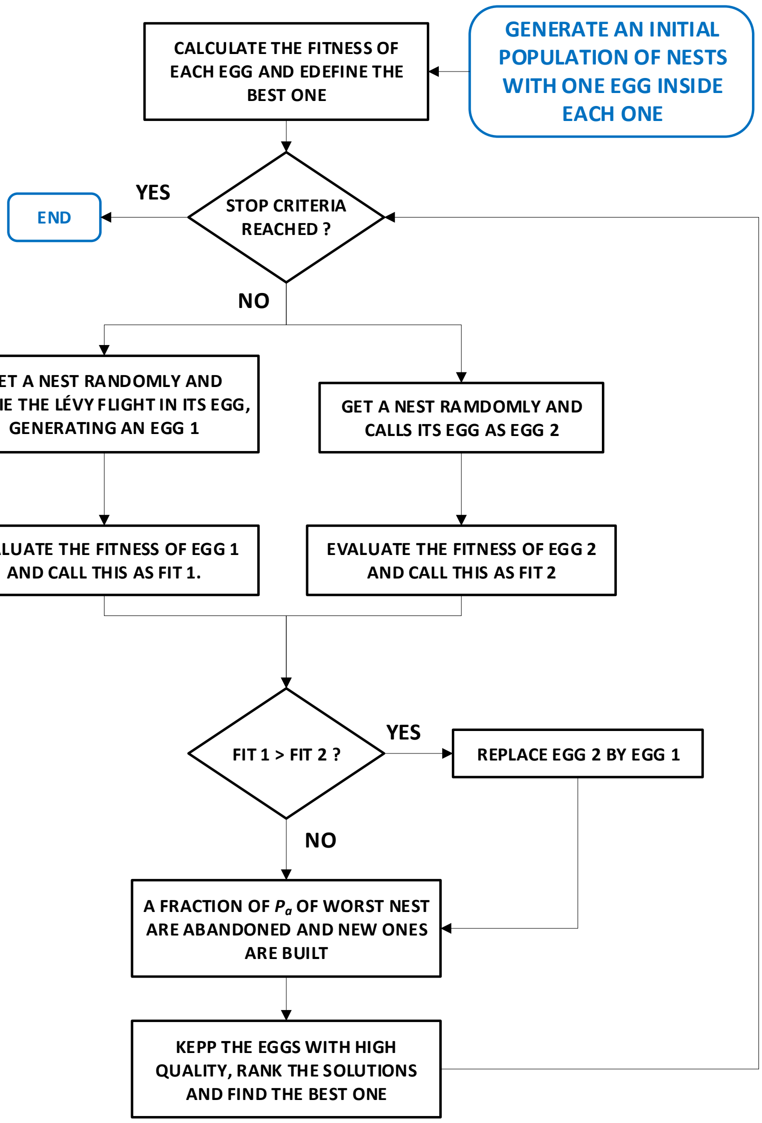


Figure 4 – Flowchart of Cuckoo Search algorithm.

Quadrotor system identification

The methodology of system identification used in quadrotor consists in four uncoupled NARX polynomial models, where each polynomial is related with an input signal of internal drone control, $u_{c(\phi,\theta,\psi,Z)}(k)$, and with an output signal $y_{(\phi,\theta,\psi,Z)}(k)$. The input signals are the ailerons, elevator, yaw rate command and vertical speed command sent from SDK in Matlab software to AR.Drone 2.0 via WI-FI communication. The output signals used for the process of identification are measured by inertial navigator sensors (gyroscope, accelerometer, magnetometer and altitude ultrasound sensor), and are sent from AR.Drone 2.0 to SDK (Sanabria and Mosterman, 2014).

Figure 5 shows the identification process in closed-loop drone dynamic with its controllers. Equation (7) is the generic polynomial NARX model chosen to represent each system state variable in this work.

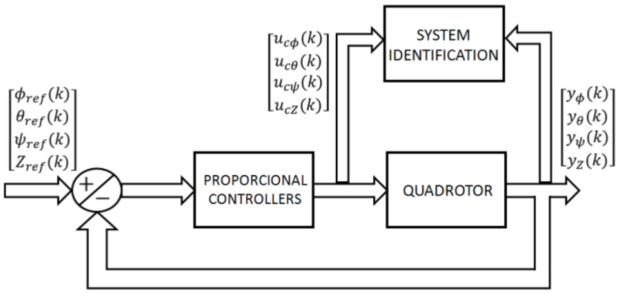


Figure 5 – Block diagram of quadrotor system identification.

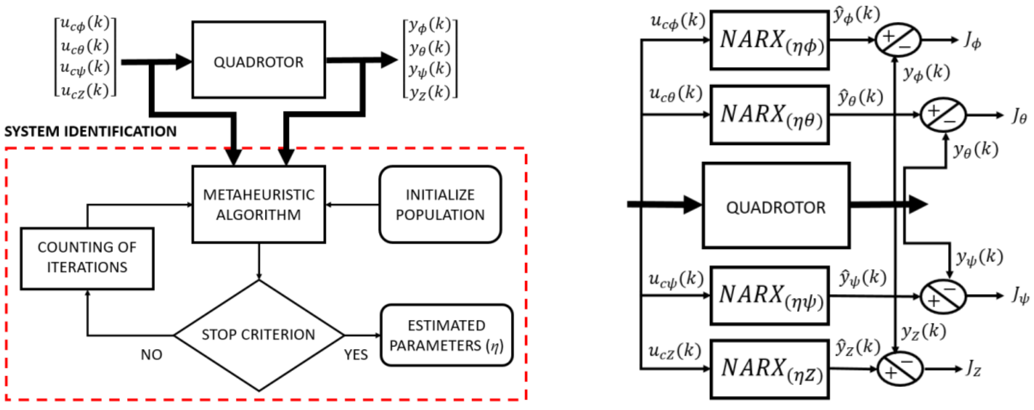
$$\hat{y}_h(k) = \eta_{0h} + \eta_{1h}\hat{y}_h(k-1) + \eta_{2h}\hat{y}_h(k-2) + \eta_{3h}u_{ch}(k-1) + \eta_{4h}u_{ch}(k-2) + \eta_{5h}\hat{y}_h^2(k-1) + \eta_{6h}\hat{y}_h^2(k-2)$$
$$+ \eta_{7h}u_{ch}^2(k-1) + \eta_{8h}\hat{y}_h(k-1)u_{ch}(k-1) + \eta_{9h}\hat{y}_h(k-2)u_{ch}(k-2) \quad (7)$$

The index h represents the states ϕ, θ, ψ or Z. The coefficients η are the parameters of NARX equation of each state, and $\hat{y}_h$ is the estimated output signal. In total, the four equations have 36 parameters that must be estimated by metaheuristics. Each agent (particle ($\vec{x}_i(t)$) or egg ($\vec{n}_i(t)$)) of metaheuristics is a vector containing the estimated parameters of NARX equation, and the best agent has the optimal parameters that minimize the cost function, Eq. (8), where S_k is the output length vector.

$$J_h = \frac{1}{S_k}\sum_{k=1}^{S_k}(y_h(k) - \hat{y}_h(k))^2 \quad (8)$$

The application of metaheuristics in system identification consists in minimize the error between y_h and $\hat{y}_h$, and for this paper, it is made separately with the four output signals in order to obtain the uncoupled estimated systems.

Figure 6a illustrates a flowchart of identification process using metaheuristics, and the Fig. 6b shows a generic diagram of how the cost function is calculated in function error, where $NARX_{(\eta h)}$ is the uncoupled nonlinear model of each closed-loop system related with each state variable with parameters estimated by metaheuristics.



a) b)

Figure 6 – Structures of quadrotor system identification with metaheuristic: a) General structure; b) Cost functions.

Metrics of metaheuristics performance evaluation

The evaluation metrics are tools for performance evaluation of each algorithm, and they have the importance in indicate if an algorithm is “good” in relation to other ones in a given criterion (Oliveira et al, 2018). The metrics used in this work are the mean square error (MSE), precision and average processing time (APT) (Oliveira, 2018).

The MSE is calculated according to Eq. (9), where J_{hm} is the minor value of cost function reached by each metaheuristic in each m-th simulation, in total of N_s simulations for each state variable.

$$\text{MSE} = \frac{\sum_{m=1}^{N_s} J_{hm}}{N_s} \tag{9}$$

The precision, Eq. (10), is a statistical measure that indicates how near or dispersed are the measures among them. This metric is calculated for each state variable using the inverse of the mean among the standard deviations of each parameter estimated by the best agent of metaheuristic in each simulation, where σ_l is the standard deviation of l-th parameter, and N_p is the number of parameters estimated for each NARX equation.

$$\text{Precision} = \frac{N_p}{\sum_{l=1}^{N_p} \sigma_l} \tag{10}$$

The APT, Eq. (11), is the mean of processing time, PT, in each simulation of each metaheuristic in system identification for each estate variable, where each metaheuristic is simulated N_s times. The PT starts to count when each algorithm initializes its agents, and it ends when the algorithm reaches some one of its stop criteria.

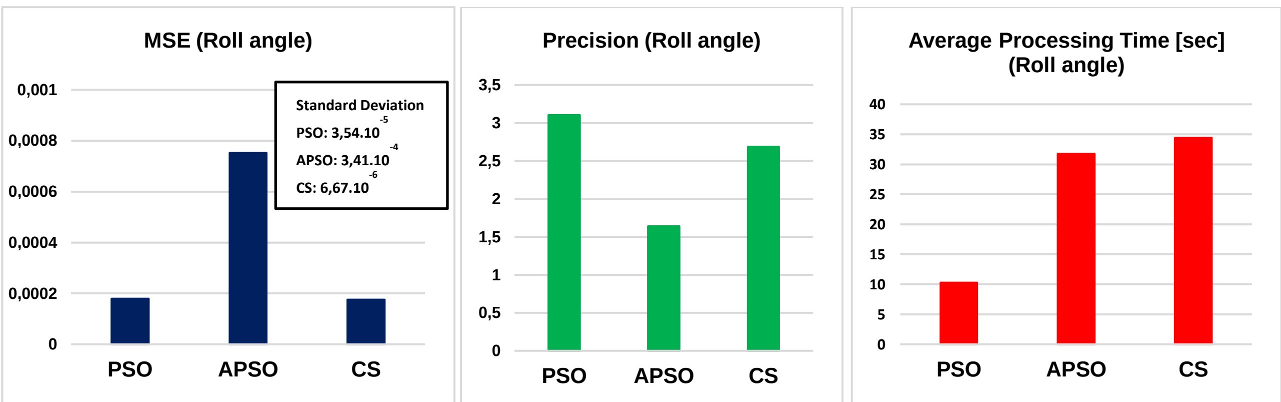
$$\text{APT} = \frac{\sum_{m=1}^{N_s} PT_m}{N_s} \tag{11}$$

RESULTS

The results of quadrotor black-box system identification using the algorithms PSO, APSO and CS were simulated 30 times in order to estimate the ten parameters (dimension of the agents) of each NARX equation of each state variable, and it was established the number of iterations and the maximum MSE as the stop criterions, where this last one was set as $1{,}0.10^{-5}$. The input and output signals used were obtained from real tests in an AR.Drone 2.0 navigation, using a sample time of 0,065 sec. Table 2 shows the parameters values of each metaheuristic, and the Fig. 7 shows the results of MSE, precision and APT reached by metaheuristics in the identification of the four state variable.

Table 2 – Parameters of metaheuristics used in quadrotor system identification.

Metaheuristic	Population Size	Number of Iterations	w	$c_{1,2}$	X_{min}	X_{max}	V_{min}	V_{max}	P_a
PSO	20	700	0,8	2,0	-2	2	-0,01	0,01	-
APSO	60	800	0,9	2,0	-2	2	-0,01	0,01	-
CS	20	200	-	-	-2	-2	-	-	0,25



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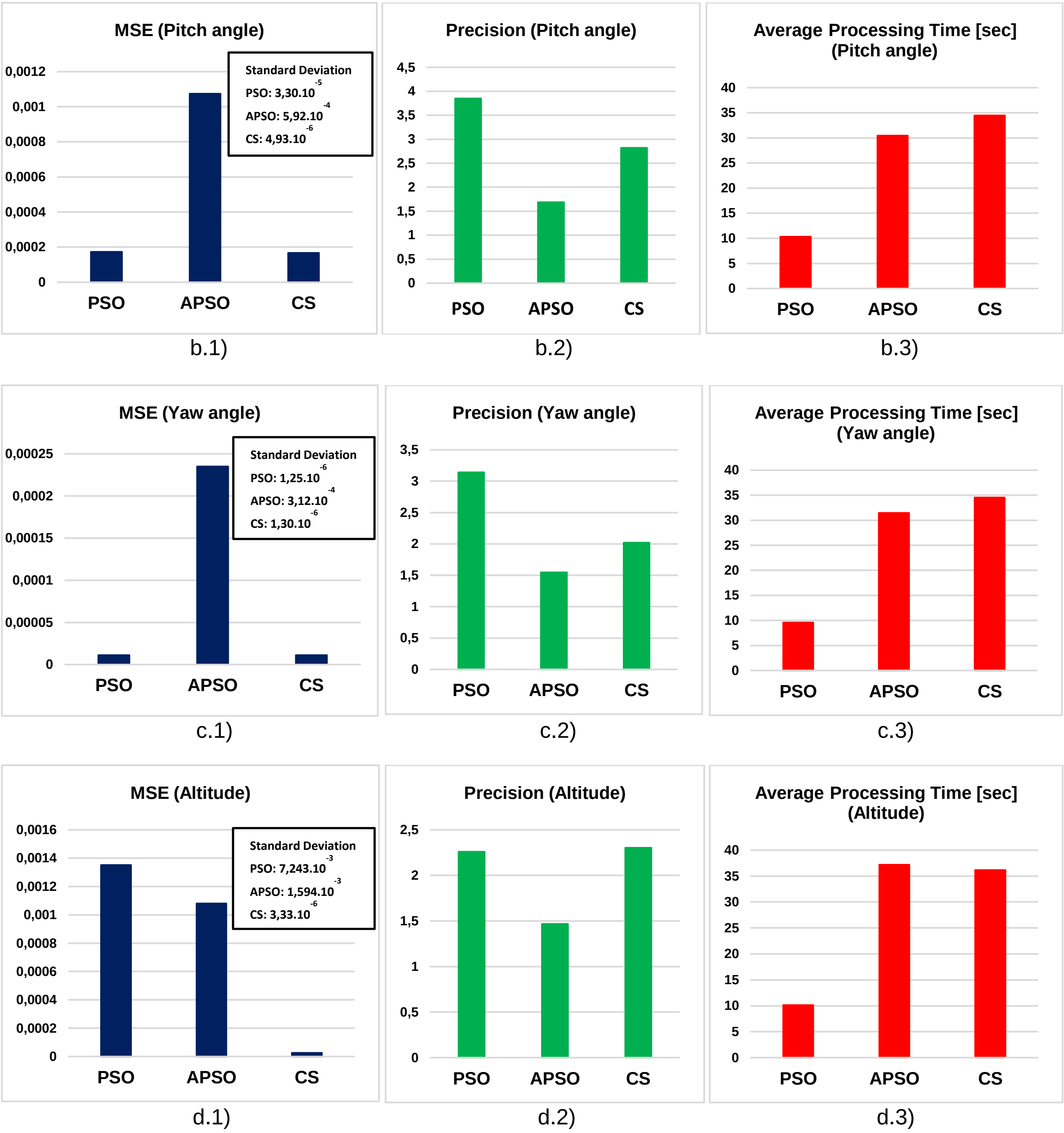

Figure 7 – Results of MSE, precision and APT of metaheuristics in quadrotor system identification: a) Roll angle; b) Pitch angle; c) Yaw angle; d) Altitude.

Table 3 shows the results of MSE(30, 4), Precision(30, 4) and average processing time (APT(30, 4)), which represent the mean of each performance metric among the four state variables in thirty simulations, where the term (30, 4) represents 30 simulations and 4 states variables respectively.

Table 3 – Mean results of performance evaluation of metaheuristics in quadrotor system identification.

Performance Metric	PSO	APSO	CS
MSE(30, 4)	$2{,}0836 \times 10^{-4}$	$7{,}6073 \times 10^{-4}$	$9{,}4834 \times 10^{-5}$
Precision(30, 4)	3,09	1,58	2,46
APT(30, 4) [sec]	10,08	32,71	34,89

According to the results in Fig. 7 and the Table 3, the CS algorithm reached the minor MSE and MSE(30, 4), further the second best Precision(30, 4), what makes it more efficient in quadrotor system identification, although the minor APT(30, 4) was reached by PSO. Figure 8 shows the estimated state variable outputs estimated by CS, which had the minor MSE(30, 4). Table 4 shows the ten mean parameters of NARX model estimated by CS for roll angle, pitch angle, yaw angle and altitude respectively.

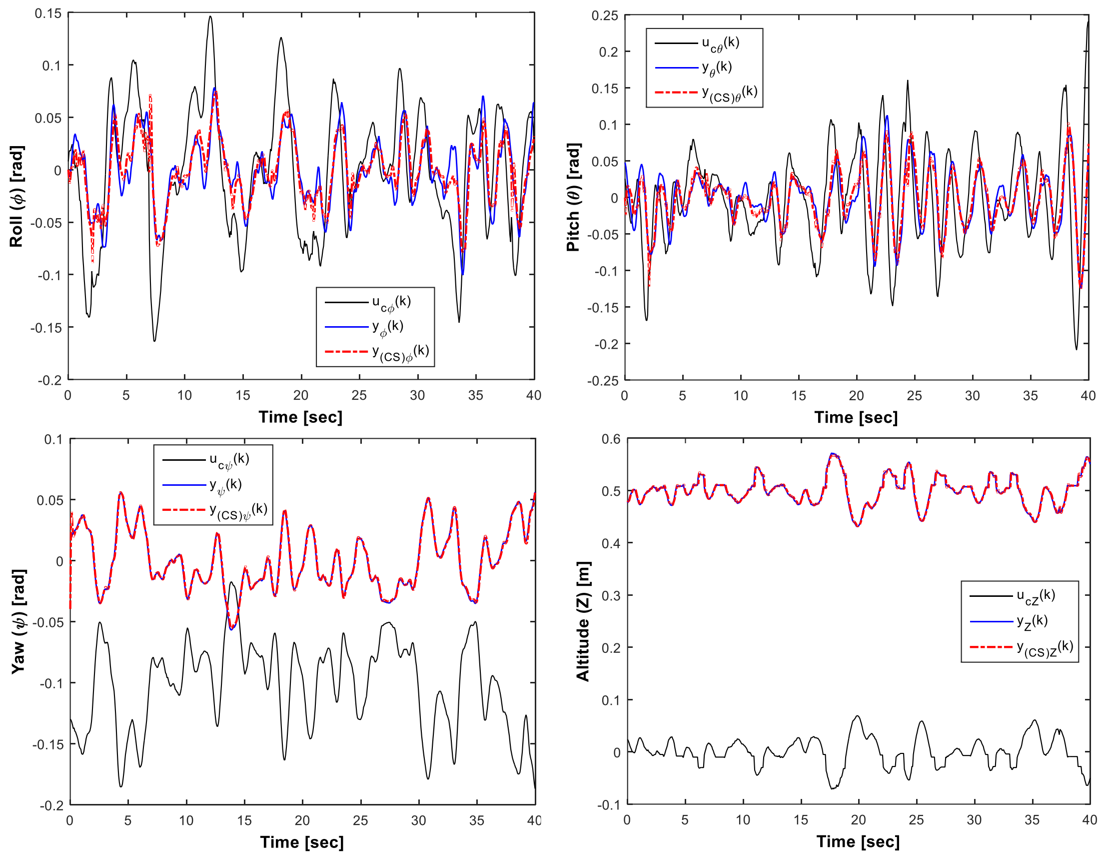

Figure 8 – Original input and output signals, and CS estimated output signals of four state variables.

Table 4 – Mean parameters of NARX model estimated by CS algorithm for each quadrotor state variable.

Parameter	Roll (ϕ)	Pitch (θ)	Yaw (ψ)	Altitude (Z)
η_0	-3,20x10^{-6}	-0,0002	-0,0396	0,4773
η_1	0,6046	0,4135	0,5970	0,2862
η_2	-0,1594	0,0472	-0,2596	0,2558
η_3	-1,1231	-0,9547	-0,6129	-0,9630
η_4	1,3334	1,2015	0,3051	-0,0968
η_5	0,0004	0,3345	-0,4252	-0,4613
η_6	-0,1972	-0,1959	-0,3648	-0,5303
η_7	-0,1038	0,1519	0,7541	-0,1137
η_8	0,5257	-0,2519	0,4436	-0,5372
η_9	-0,3177	-0,1088	0,0491	-0,1620

CONCLUSION

This work approached the basic concepts of UAV quadrotor dynamics and also about the metaheuristics PSO, APSO and CS. Also, it was explained how to apply metaheuristics in uncoupled black-box quadrotor system identification, using four NARX structures for each state variable. The results show that metaheuristics can be used to do uncoupled black-box system identification of a quadrotor. Furthermore, the results also show that the PSO had better performance in precision and TAP, however the minor MSE was reached by CS. All the metaheuristics used showed acceptable results and can be a novel method to system identification.

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