System Identification of Small Scale Helicopter using Invasive Weed Optimization on Flight Data

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Abstract: This paper presents the System Identification through dynamic modelling of scale model Helicopter UAV using Invasive Weed Optimization (IWO) algorithm. The Helicopter used is in this experiment is a 1.2 meter main rotor diameter Align 550 flybarless helicopter. A flybar is used commonly on model scale helicopters and in this experiment a flybarless helicopter is used which is increasing in popularity for its mechanical simplicity and fast response. The identification is done using actual flight data for hovering condition and a complete dynamic model is obtained. A comparison of the results of IWO and GA shows the accuracy of the identified model by IWO over the more commonly used GA.

Keywords: **Helicopter UAV, System Identification, Evolutionary algorithms in control and identification**

1. INTRODUCTION

Model-scale Helicopters are aerial robots that are popular for their vertical take-off and land capabilities and their dexterity in cruise flight. This makes it a highly-sought after platform for unmanned aerial vehicles (UAVs). However, helicopters are mechanically complex and their dynamic behaviour is highly nonlinear. Implementing mathematical model through first principles of helicopter have only been partially successful in understanding the full capabilities of helicopter UAVs (H-UAVs) as much as it has been used by its full-sized counterpart. This complexity arises due to its high sensitivity towards control inputs, external perturbations and a high degree of inter-axis coupling. These behaviours make autonomous flight of helicopters still far from reality. From control system point of view, Helicopters are multi input-multi output (MIMO) systems. Metaheuristic algorithms as of now have been most successful in identifying a model that is practically close enough to the degree of accuracy required for such highly nonlinear and unstable platforms to be autonomous. We have chosen genetic algorithm (GA) and invasive weed optimization (IWO) algorithm to identify the state-space parameters for an H-UAV.

Genetic Algorithm is a nature-inspired metaheuristic method, introduced by John Holland in 1970, commonly adopted to solve many optimization problems. This falls under a larger class of algorithms which supplies satisfactorily good solutions especially with incomplete or imperfect information or limited computation capacity. In this method, a population of solutions, called Phenotypes or Individuals, of an optimization problem is evolved towards better solutions by mimicking the natural selection process in a genetic level which involves crossovers and mutations. There are two variants of the genetic algorithm based on the encoding of the chromosome: Binary-Coded GA and Real-Coded GA. Binary-coded GA was employed in to solve the present problem as it is more nature-identical than the latter. System identification using genetic algorithm has been extensively dealt by K.Kristinsson et.al.

Invasive Weed Optimization (IWO) algorithm was first proposed by Mehrabian and Lucas in 2006, which was inspired by the vigorous and invasive growth habits of weeds which posed a threat to cultivated plants. The highly adaptive, robust and random nature of the weed’s colonizing behaviour is used in this algorithm which makes it a powerful optimization tool.

2. HELICOPTER UAV DESCRIPTION

2.1 Align TREX 550 Flybarless Helicopter

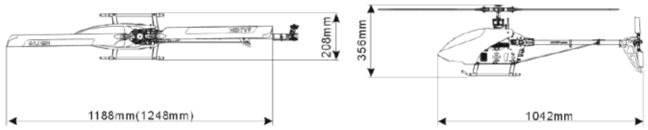


Fig. 1. TREX 550 physical characteristics

The Align TREX 550 helicopter used is a 550 size helicopter capable of 3D flight and is mainly used in hobby and sports flying. It does not use a traditional flybar as used by the majority of the scale-model helicopters available commercially. Flybars provide a negative feedback to the lateral and longitudinal motion of the aircraft due to the Coriolis force. The TREX 550 uses an electronic flybar that makes use of a micro electro-mechanical system (MEMS) gyroscope, so that the motion feedback can be tuned according to requirements, either to maximize agility while sport flying or maximize stability for beginners.

Fig. 2. TREX 550 used for collecting flight data

2.2 H-UAV Instrumentation

Indian Institute of Science's TREX 550 H-UAV is equipped with state-of-the-art sensor equipment that produce high quality flight-data. The core of the on-board systems is a Pixhawk flight controller board. The Pixhawk houses a number of sensors that have been proven to provide good quality data apt for system identification. It contains a 3-axis gyroscope (which gives rates *p*, *q*, *r)*, an accelerometer (which gives airframe accelerations a_x, a_y, a_z) and a magnetometer. Apart from this, a GPS module is also connected to the Pixhawk. A separate 3-axis gyro is installed to serve as an electronic flybar. The data is logged onto a micro-SD card mounted on the Pixhawk board at the rate of 100 Hz.

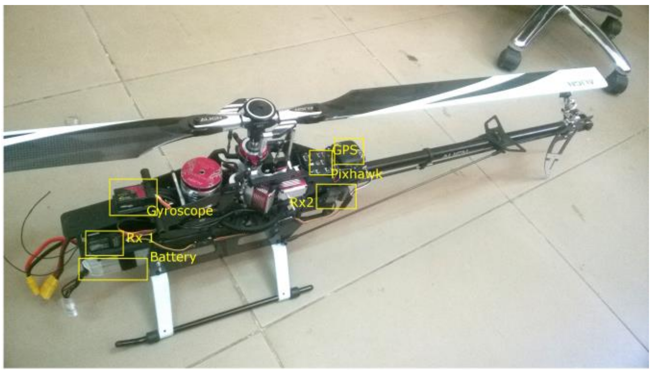


Fig. 3. TREX 550 instrumentation

3. FLIGHT TEST PROCEDURE

In order to excite the full range of responses from the H-UAV, the pilot is required to provide specific inputs. As the system identification is in the time-domain, a doublet input manages excite all the motions and states. The inputs were given by the pilot for both lateral and longitudinal directions keeping the pedal input for directional corrections. The both the tests were conducted in the hover condition with a fixed collective and motor rpm.

As suggested in a book by M.B Tischler et.al., to get a good instrumentation (sample rate and bandwidth) must be carefully selected so that its dynamic response has little effect on the identified overall dynamic response. The characteristics of the sensors and filters are known so that their effects can be incorporated in the analysis. To obtain good quality data, flight tests were conducted during periods of minimum ambient wind and turbulence. Steady winds of less than 2.57 m/s (5 knots) are desirable when the helicopter is in hover because measured response distortion resulting from recording equipment, sensor and filter dynamics, and atmospheric disturbances all degrade the precision and accuracy with which the real vehicle dynamics can be identified.

4. STATE-SPACE MODEL

The state-space model of an H-UAV has been adopted from the paper on system identification of small-scale helicopter by M.Bernard et.al. A few differences between the Yamaha R-50 helicopter used by them and the TREX 550 used in this paper are:

- The R-50 has a flybar whereas the TREX 550 is flybarless.
- The R-50 incorporates flapping of blades for uniform lift distribution whereas TREX 550 uses changes in blade pitch to achieve the same.

The parameters *c* and *d* in the state matrix correspond to stabilizer bar feedback in the longitudinal and lateral axes respectively. For the TREX 550, the flybar is an electronic element whose feedback is provided by the gyroscope. The parameters *a* and *b* are the flapping angles of the blade in the R-50 but for the TREX, the blade pitch angle provides for *a* and *b* by linear interpolation of the radio inputs.

$$
\begin{bmatrix} \dot{u} \\ \dot{v} \\ \dot{p} \\ \dot{q} \\ \dot{\phi} \\ \dot{\theta} \\ \tau_f \dot{a} \\ \tau_f \dot{b} \\ \dot{w} \\ \dot{r} \\ \dot{r}_{fb} \\ \tau_s \dot{c} \\ \tau_s \dot{d} \end{bmatrix}
=
\begin{bmatrix}
X_u & 0 & 0 & 0 & 0 & -g & X_a & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & Y_v & 0 & 0 & g & 0 & 0 & Y_b & 0 & 0 & 0 & 0 & 0 \\
L_u & L_v & 0 & 0 & 0 & 0 & 0 & L_b & L_w & 0 & 0 & 0 & 0 \\
M_u & M_v & 0 & 0 & 0 & 0 & M_a & 0 & M_w & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & -\tau_f & 0 & 0 & -1 & A_b & 0 & 0 & 0 & A_c & 0 \\
0 & 0 & -\tau_f & 0 & 0 & 0 & B_a & -1 & 0 & 0 & 0 & 0 & B_d \\
0 & 0 & 0 & 0 & 0 & 0 & Z_a & Z_b & Z_w & Z_r & 0 & 0 & 0 \\
0 & N_v & N_p & 0 & 0 & 0 & 0 & 0 & N_w & N_r & N_{rfb} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & K_r & K_{rfb} & 0 & 0 \\
0 & 0 & 0 & -\tau_s & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 \\
0 & 0 & -\tau_s & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1
\end{bmatrix}
\begin{bmatrix} u \\ v \\ p \\ q \\ \phi \\ \theta \\ a \\ b \\ w \\ r \\ r_{fb} \\ c \\ d \end{bmatrix}
+
\begin{bmatrix}
0 & 0 & 0 & 0 \\
0 & 0 & Y_{ped} & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & M_{col} \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
A_{lat} & A_{lon} & 0 & 0 \\
B_{lat} & B_{lon} & 0 & 0 \\
0 & 0 & 0 & Z_{col} \\
0 & 0 & N_{ped} & N_{col} \\
0 & 0 & 0 & 0 \\
0 & C_{lon} & 0 & 0 \\
D_{lat} & 0 & 0 & 0
\end{bmatrix}
\begin{bmatrix} \delta_{lat} \\ \delta_{lon} \\ \delta_{ped} \\ \delta_{col} \end{bmatrix}
$$

Table 1. State-Space Equation

5. METAHEURISTICS ON FLIGHT DATA

Metaheuristic techniques like genetic algorithm (GA) and particle swarm optimization (PSO) have been widely used in the field of system identification due to their powerful optimization technique. Invasive Weed Optimization (IWO) is a fairly recent entrant into the family of nature-inspired techniques. IWO is compared with GA due to their similar natural selection based model of optimization. The following sections discuss how each of the methods were employed to identify the state-space parameters of the H-UAV model.

5.1 Genetic Algorithm (GA)

Step 1: *Initialization*: The initial set of candidate solutions are randomly initialized where each individual contains 40 values corresponding to each parameter of the state-space model. With each parameter being provided a specific set of upper and lower bounds.

Step 2: *Assigning the Fitness/Cost to Each Individuals*: The Cost function is defined by a combination of two methods: the Least squares method and the Population Pearson correlation coefficient.

The method of least squares minimizes the sum of the squared residuals, where the residual is the absolute difference between the actual output and the estimated output.

$$S = \sum_{i=1}^{n} r_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (1)$$

$$r_i = y_i - \hat{y}_i$$

Where r_i is the residual, y_i is the actual data and $\hat{y}_i$ is the estimated data.

The Population Pearson correlation coefficient of two sets of data is a measure of their frequency correlation or rather their “shape fitness”. Consider data sets A and B have N scalar observations each, then the Pearson correlation coefficient is defined as in (2).

$$\rho(A,B) = \frac{1}{N-1} \sum_{i=1}^{N} \left(\frac{A_i - \mu_A}{\sigma_A} \right) \left(\frac{B_i - \mu_B}{\sigma_B} \right) \qquad (2)$$

Where σ_A and σ_B are standard deviations of sets A and B respectively and μ_A and μ_B are the means of A and B respectively.

And the total Cost is expressed as in (3)

$$Z = \frac{S}{\rho^2} \qquad (3)$$

With this as a basis, probabilities are assigned to each of the individuals in the population by the method shown in (4).

$$P_i = 1 - \frac{Zi}{\sum_{j=1}^{N} Z_j} \qquad (4)$$

Step 3: *Selection of Mate*: Weights are assigned to each member which are proportional to the probability that was assigned to them. Two members of the population are chosen by weighted random sampling which means that the lower the cost, higher the probability of getting chosen.

Step 4: *Crossover*: Both the chosen individuals are converted into their binary equivalents after adding offsets to eradicate the negative and non-integer terms. The point of crossover (or *Chiasma*) is chosen randomly within the binary digit matrix of the individuals. Every binary digit from the chiasma to the end is swapped between the chosen individuals. This is done so that the characteristics of the parent is inherited by the children. The children are put through the cost function and if any or both of the children have a lower value of Z than the highest Z in the current population, then they are inducted into the population replacing the worst individual(the one with the highest cost) in the population. This process is iterated till the best solution is achieved.

Step 5: *Mutation*: After a few generations, the gene pool becomes saturated and to give the population a chance in improvement, a mutation is induced after every 5 generations. Mutation is a method where a randomly selected binary digit in one of the parent is flipped from either 0 to 1 or 1 to 0.

5.2 Invasive Weed Optimization (IWO)

Step 1: *Initialization*: A finite number of seeds are deposited randomly over a search space. Cost/Fitness of each seed is determined by running it through a cost function. The cost function being used is the same as that used in the genetic algorithm (GA) for the sake of comparison.

Step 2: *Reproduction*: Every seed grows into a flowering plant which in turn deposits its own seeds. But the number of seeds each flowering plant can deposit linearly varies from the minimum possible seeds to the maximum possible seeds based on its fitness value. In other words, the plant with a higher fitness score can deposit the maximum number of seeds.

Step 3: *Spatial Dispersal*: The spawned seeds are distributed randomly over the search space by normally distributed random number with zero mean and varying variance. The variance varies the following way

$$\sigma_{iter} = \frac{(iter_{max} - iter)^n}{iter_{max}} \left(\sigma_{initial} - \sigma_{final} \right) + \sigma_{final}$$

Where $iter_{max}$ is the maximum number of iterations and σ_{iter} is the standard deviation of the current iteration and n is the nonlinear modulation index.

This ensures that the probability of dropping a seed in a distant area decreases nonlinearly at each iteration which groups fitter plants and eliminates weak ones.

Step 4: *Competitive Exclusion*: Initially all the seeds are allowed to grow unchecked till it reaches the population limit. Once the population limit is reached, a function to eliminate plants with poor fitness gets called. This function ranks all the seeds in the population with their parents' ranks and eliminates weeds with lower fitness and allows newer seeds to fill the population. This way plants with low fitness scores are allowed to survive if their offspring gives a high fitness score.

5.3 Results

Each flight data output is compared to its estimated value and the fit is calculated and tabulated as shown in Table 2.

Table 2. Performance Comparison

	GA	IWO
u	0.7732	0.8517
v	0.7235	0.8209
p	0.7791	0.85
q	0.7641	0.7685
r	0.66	0.6711
θ	0.7768	0.7860
ϕ	0.8318	0.9005

6. CONCLUSIONS

The state-space model for the H-UAV was successfully identified using IWO and it has provided a more accurate model than the one given by the traditional GA. This shows that IWO is a powerful tool in system identification.

REFERENCES

A.R Mehrabian and C.Lucas (2006) A Novel Numerical Optimization Algorithm Inspired from Weed Colonization, *Ecological Informatics 1*, Pg 355-366.

B.Mettler, M.B. Tischler, T.Kanade (1999). System Identification of Small-Size Unmanned Helicopter Dynamics, *Proceedings of American Helicopter Society 55th Forum*, American Helicopter Society, Montreal,Canada.

M.B.Tischler, J.W.Fletcher,V.L.Diekmann, R.A Williams and R.W.Cason (1987). *Demonstration of Frequency Sweep Testing Technique Using a Bell 214-ST Helicopter*, Pg 5, NASA and US Army Aviation Systems Command, California, USA.

K.Kristinsson and G.A. Dumont (1992) System Identification and Controls using Genetic Algorithm, *IEEE Transactions on Systems, Man and Cybernetics*,Vol.22,No.5,Pg 1033-1046.

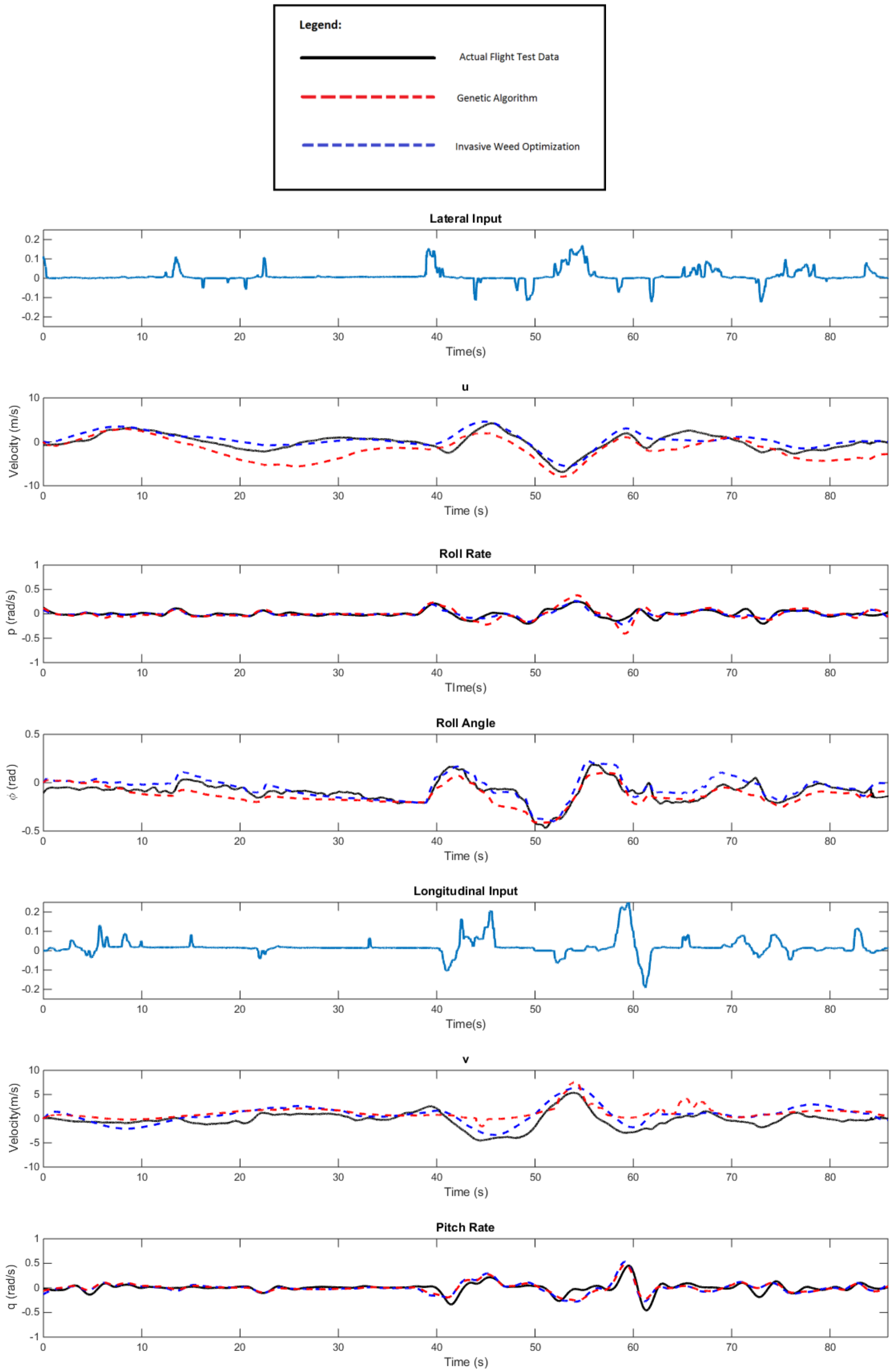
Appendix A. IDENTIFIED PARAMETERS

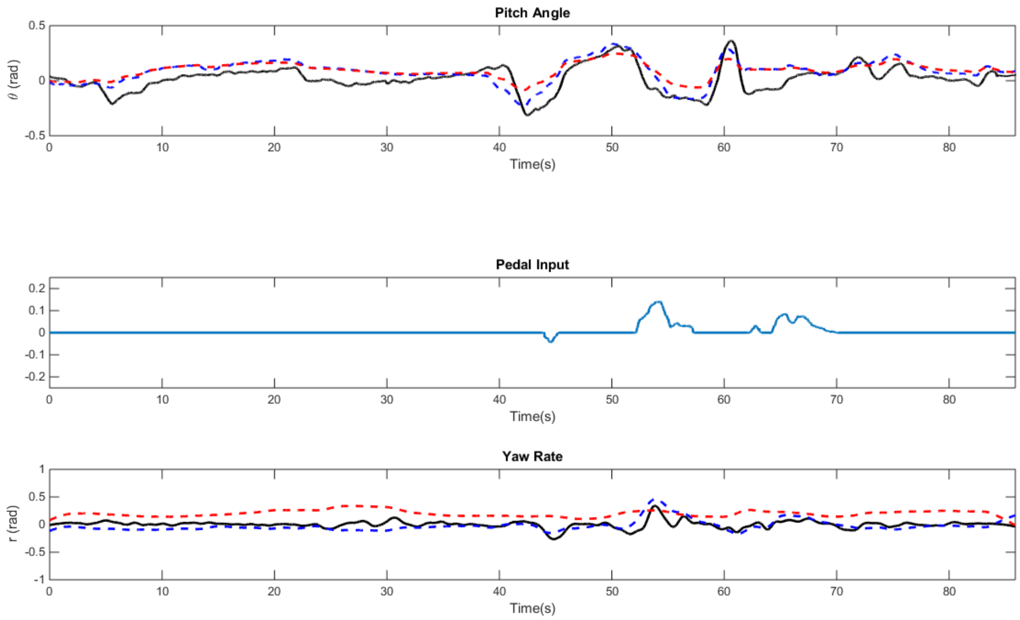
Appendix B. TIME-DOMAIN PLOTS

APPENDIX A: IDENTIFIED PARAMETERS

Parameters	Values
Xu	1.0845
Xa	-29.8529
Yv	-1.3166
Yb	34.9489
Lu	3.7164
Lv	2.3703
Lb	166.6251
Lw	5.4805
Mu	-1.4641
Mv	4.1149
Ma	85.0845
Mw	1.31985
T_f	12.0950
Ab	-2.5187
Ba	-0.2134
Ac	0.0724
Bd	-1.5359
Za	-6.6556
Zb	-137.6766
Zw	-18.9351
Zr	3.0638
Nv	0.8455
Np	-11.5782
Nw	1.8573
Nr	-5.5928
Nrfb	-30.2645
Kr	5.9745
Krfb	-7.9522
T_s	-2.4283
Yped	1.6964
Mcol	-0.7090
Alat	-3.6724
Alon	4.7059
Blat	7.3277
Blon	-2.7503
Zcol	-41.2789
Nped	36.5245
Ncol	-0.063
Clon	-2.3719
Dlat	0.6487

APPENDIX B: TIME- DOMAIN PLOTS




Pitch Angle
θ (rad)
Time(s)
Pedal Input
Time(s)
Yaw Rate
r (rad)
Time(s)