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ADAPTIVE MODEL PREDICTIVE CONTROL OF THE UNMANNED ROTORCRAFT USING RECURSIVE LEAST SQUARES PARAMETER ESTIMATION

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Abstract

The main purpose of the presented paper is to evaluate the performance of an automatic flight control system for an unmanned helicopter, utilizing Model Predictive Control (MPC) enhanced with Recursive Least Squares (RLS) model parameter estimation. The proposed control system integrates a Stability Augmentation System (SAS) in the inner loop and an MPC-based system in the outer loop, which iteratively solves a constrained optimization problem through quadratic programming. By employing RLS for model parameter estimation, the proposed system adapts to changing environmental conditions and takes into account nonlinearities in rotorcraft dynamics. Simulation tests are conducted using the unmanned helicopter mathematical model built in the Flightlab environment, fully integrated with the Matlab/Simulink platform. Moreover, this paper presents a general methodology for synthesizing an MPC-based controller for unmanned rotorcraft. Simulation tests compare the performance of MPC with and without RLS parameter estimation during a level change maneuver, increasing forward flight velocity and changing yaw angle. The results provide insights into the limitations of the proposed algorithms and suggest potential upgrades for the automatic flight control system. The test results can guide the tuning of MPC algorithms for future unmanned helicopter control systems. Additionally, the research highlights the impact of model disturbances within the MPC-based control loop on helicopter dynamics. This paper introduces an integrated control system and discusses the potential advantages of using RLS parameter estimation algorithms in predictive control systems.

Keywords: Model Predictive Control; Quadratic Programming; Recursive Least Squares; Flightlab; Helicopter Dynamics

1. Introduction

Unmanned Aerial Vehicles (UAVs) have earned significant attention in recent years due to their versatile applications in areas such as remote sensing, transportation, search and rescue, and more. Among UAVs, unmanned helicopters stand out for their ability to hover, perform vertical take-offs and landings, and maneuver in confined spaces. However, the complexity of helicopter dynamics and varying environmental conditions present substantial challenges in developing reliable and efficient automatic flight control systems.

Model Predictive Control (MPC) is an advanced method for designing control systems, prevalent in various branches of engineering due to its strong mathematical foundations. The ability to set constraints on control signals during the design process and control plants characterized by Multiple Input Multiple Output (MIMO) systems has made MPC widely used in control engineering. A successful application of an MPC controller for a tilt-rotor VTOL aircraft is presented in reference [1].

In addition to Model Predictive Control, a wide variety of methods for designing automatic flight control systems for unmanned rotorcraft is present in the literature. An overview of these methods is presented below.

Reference [2] describes a methodology for designing a flight control system for unmanned rotorcraft using an improved PID tuning method based on pole placement and Linear Quadratic Regulator principles. Another popular framework based on robust control foundations is presented in reference [3], which describes the design process of H_∞ static output-feedback control for an unmanned rotorcraft. A deeper insight into designing a robust flight controller for an unmanned helicopter is provided in reference [4], which proposes the design of a centralized controller via μ-synthesis and compares its efficiency with a variant of the H_∞ controller.

Reference [5] presents a solution for synthesizing a helicopter flight control system based on a Linear Quadratic Regulator, demonstrating the efficiency of a Kalman filter-based LQG control algorithm utilizing limited state measurements applied to gain information referring to SW-4 helicopter dynamics. Another LQR-based rotorcraft flight control system is detailed in reference [6], where the algorithm is used to control a helicopter during landing on a moving confined platform.

Flight control systems for helicopters are often designed to handle nonlinear rotorcraft dynamics, performing well for agile and small UAVs with non-classical configurations. Reference [7] presents attitude control using the Incremental Nonlinear Dynamic Inversion method. Another prevalent solution in nonlinear flight control, based on strong mathematical foundations, is presented in reference [8], which studies the design of a hovering controller for a quad tiltrotor aircraft using Lyapunov design. Reference [11] details a Takagi-Sugeno fuzzy controller used to regulate the attitude angles of an autonomous helicopter. Additionally, reference [12] describes the successful application of reinforcement learning to autonomous helicopter flight. A method closely related to the topic of this paper is presented in reference [10], where nonlinear MPC is applied to control a propeller-tilting hybrid unmanned air vehicle.

Another family of flight control systems puts strong focus on changing environmental conditions or possible failures in the aerial vehicle structure. This branch of control engineering, which provides solutions for designing systems which constantly adapt to changing conditions is known as adaptive control. An example of usage of this framework, applied to UAV altitude control is presented in reference [9], where a Model Reference Adaptive Controller utilizing an Updated MIT-Rule is used.

Several methods for using an adaptive Model Predictive Control framework to control autonomous rotorcraft are known. Despite the advantages of applying MPC methodology to flight control systems, its strong reliance on the mathematical model of the plant's dynamics makes it sensitive to subtle differences in the implemented dynamical system. To address these challenges, one solution is combining an MPC controller with a Dynamic Mirror Descent online learning algorithm for model parameter estimation, as described in reference [16]. A popular method of online system identification used in adaptive control is the Recursive Least Squares (RLS) algorithm, which enhances Model Predictive Control of a quadrotor as proposed in reference [14]. Another variant of combining RLS with MPC, applied to controlling a permanent magnet synchronous motor, is detailed in reference [18]. Online parameter identification working with Model Predictive Control can also be achieved via Adaline Neural Network methods, as presented in reference [13].

Based on the presented literature review, this paper proposes enhancing a Dynamic Matrix Control (DMC) MPC-based control system with Recursive Least Squares (RLS) real-time model parameter estimation. By integrating a Stability Augmentation System (SAS) in the inner control loop and an MPC-based system in the outer loop, the proposed approach aims to improve the adaptability and robustness of the flight control system. The RLS algorithm is expected to constantly update the model parameters, enabling the MPC to effectively account for nonlinearities and changing environmental conditions. While this paper employs the standard RLS algorithm, reference [15] presents several modifications that could mitigate numerical instability or enhance the algorithm's ability to handle measured data that may not provide sufficient information about the real plant's dynamics.

2. Helicopter Model

The mathematical model presented in this paper describes the dynamics of the ARCHER helicopter (shown in Figure 1), which was developed in 2018 at the Warsaw University of Technology. This small-scale rotorcraft is designed to be easily reconfigurable, allowing for the attachment of various additional components such as propellers, wings, and stabilizers. The base configuration consists of a fuselage, propulsion unit, main rotor, and tail rotor.

In the tested configuration, the ARCHER helicopter operates without any additional actuators, relying solely on the main rotor and tail rotor for control. Both rotors are rigid, meaning there is no blade flapping. Each rotor is driven by its own electric motor.

The helicopter's dynamics are modeled using FLIGHTLAB, a well-known software used both in industry and academia to simulate rotorcraft behavior. FLIGHTLAB facilitates the modeling of multi-body dynamics, structural vibrations, nonlinear unsteady aerodynamics, and control systems. Its modular architecture also supports integration with external software such as CFD tools and Matlab/Simulink.

Figure 1 – The ARCHER helicopter [23]

The main rotor is modeled using the blade element method, which calculates aerodynamic loads as nonlinear functions of dynamic pressure, angle of attack, and Mach number. To accurately compute drag, lift, and pitching moments on each blade, the software uses predefined data stored in lookup tables. These aerodynamic coefficients are validated against flight test data from conventional helicopter configurations. The main rotor has two rigid, rectangular, untwisted blades, with induced velocity computed using the Peters-He six-state model. The rotor rotates in a clockwise direction.

The tail rotor is modeled using disc theory, which ensures computational efficiency for flight control system calculations.

The fuselage is treated as a rigid structure with six degrees of freedom (DOF). Aerodynamic loads on the fuselage are determined using lookup tables that map forces and moment coefficients to the angle of attack and sideslip angle. The model does not account for interference effects between the main rotor, tail rotor, and fuselage.

Additionally, the model includes sensor positions and a landing gear system, with nonlinear strut and tire models representing the skids. Ground friction between the skids and the surface is also taken into account. The propulsion system is idealized, assumed to provide sufficient power under all flight conditions.

The helicopter's numerical model also incorporates environmental factors. Atmospheric conditions are modeled using the 1959 ARDS atmospheric model, which is based on hydrostatic equations and the ideal gas law. Turbulence is not considered.

The nonlinear model includes 26 state variables:

- Helicopter fuselage: inertial position (3), velocities in the body frame of reference (3), integrals of velocities in the body frame of reference (3), roll, pitch, and yaw angles (3), body roll, pitch, and yaw rates (3), integrals of body roll, pitch, and yaw rates (3).
- Main rotor: induced velocity (6) – uniform, 0th harmonic, 1st harmonics (sine and cosine), 2nd harmonics (sine and cosine).
- Tail rotor: induced flow state (1), coning angle (1).

Performing helicopter flight control using MPC algorithm was obtained using linearized state space dynamics model created using FLIGHTLAB software. State vector in linear dynamics model contains information about:

- X - X axis position in inertial coordinate system [ft]
- Y - Y axis position in inertial coordinate system [ft]
- Z - Z axis position in inertial coordinate system [ft]
- Φ - roll angle of the helicopter [rad]
- Θ - pitch angle of the helicopter [rad]
- Ψ - yaw angle of the helicopter [rad]
- V_x - X axis velocity in body-fixed coordinate system [ft/s]
- V_y - Y axis velocity in body-fixed coordinate system [ft/s]
- V_z - Z axis velocity in body-fixed coordinate system [ft/s]
- P - angular velocity of helicopter with respect to X axis in body-fixed coordinate system [rad/s]
- Q - angular velocity of helicopter with respect to Y axis in body-fixed coordinate system [rad/s]
- R - angular velocity of helicopter with respect to Z axis in body-fixed coordinate system [rad/s]

The nonlinear helicopter dynamics were linearized around an equilibrium point corresponding to hovering at an altitude of 11 feet above the ground. The initial conditions are as follows:

$$\boldsymbol{x_0} = \begin{bmatrix} X_0 \\ Y_0 \\ Z_0 \\ \Phi_0 \\ \Theta_0 \\ \Psi_0 \\ Vx_0 \\ Vy_0 \\ Vz_0 \\ P_0 \\ Q_0 \\ R_0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ -11.27 \\ 0.0698 \\ -0.0087 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{1}$$

Presented initial conditions were obtained from trim analysis, which resulted with calculation of pitch and roll angle sufficient to preserve equilibrium for the described helicopter.

3. Control methodology

The control system described in this paper is divided into two loops: an inner loop and an outer loop, as illustrated in Figure 2.
The inner loop consists of a stability augmentation system designed using the root locus method. This system helps dampen the helicopter's responses and improves the stability of the plant. The inner loop of the automatic flight control system relies on measurements of the helicopter's angular velocities $[P, Q, R]$.
The outer loop processes both control action measurements $[x_a, x_b, x_c, x_p]$ and a 12-element state vector, which includes:

- $[X, Y, Z]$: Position of the rotorcraft in the inertial Cartesian coordinate system
- $[\Phi, \Theta, \Psi]$: Attitude (roll, pitch, yaw angles) of the rotorcraft
- $[V_x, V_y, V_z]$: Linear velocities in the body-fixed Cartesian coordinate system
- $[P, Q, R]$: Angular velocities of the rotorcraft

The system stores measurements in a moving window of N samples and uses this data to estimate model parameters through the Recursive Least Squares (RLS) algorithm. To avoid unexpected behavior during steady-state flight [15], the model used by the proposed system is a linear combination of the initial linear dynamics and the estimated model.
The continuously updated model is then used in the next stage, where the Dynamic Matrix Control (DMC) framework is used to formulate a quadratic programming problem. This problem minimizes a cost function over a chosen prediction horizon.
Finally, the system applies quadratic programming principles to minimize the cost function based on both measurements and user inputs. The result of these computations is a control signal necessary to execute the predefined mission.

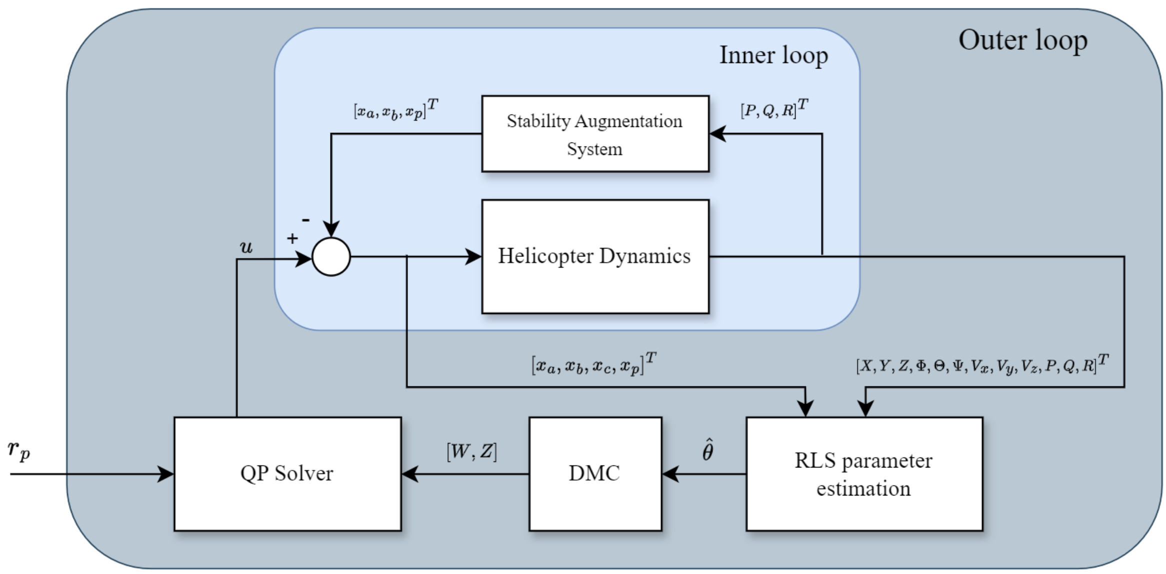

Figure 2 – Automatic Flight Control System scheme

3.1 Model Predictive Control principles

Model Predictive Control is build on minimization of quadratic cost function, which is mathematically described by formulas 2 and 3:

$$u = \underset{u}{argmin}\, J(x(0), u) \tag{2}$$

$$J(x(0), u) = \sum_{i=1}^{N} ||x(i) - r_p(i)||_Q + ||u(i)||_R, \qquad x(i) \in \mathbb{X}^n, u(i) \in \mathbb{U}^m \tag{3}$$

where:

- $x(i)$ refers to current state of the dynamical system at the timestep i
- $r_p(t)$ describes the reference track for the tracking problem at the timestep i
- $u(i)$ refers to control action at the timestep i
- Q and R are semi-positive definite matrices storing control weights

Suppose that our plant can be described as a linear-time invariant (LTI) system in form:

$$\dot{x} = \boldsymbol{A}x + \boldsymbol{B}u$$
$$y = \boldsymbol{C}x$$

where $\boldsymbol{A} \in \mathbb{R}^{m\times m}$, $\boldsymbol{B} \in \mathbb{R}^{m\times n}$ and $\boldsymbol{C} \in \mathbb{R}^{p\times m}$ Considering a discretized form of a linear dynamical system with a full state measurement:

$$\Delta x(k+1) = \boldsymbol{\Phi}\Delta x(k) + \boldsymbol{\Gamma}\Delta u(k) \tag{4}$$

$$y(k) = \boldsymbol{C}x(k) \tag{5}$$

where:

$$\boldsymbol{\Phi} = e^{\boldsymbol{A}\Delta t} \qquad \boldsymbol{\Gamma} = \int_0^{\Delta t} e^{\boldsymbol{A}\eta}\boldsymbol{B}d\eta \tag{6}$$

By extrapolating current system dynamics on future time, we can evaluate future states of the plant over prediction horizon using recursive formula [20]:

$$\begin{aligned}
x(k+1|k) &= \boldsymbol{\Phi}x(k) + \boldsymbol{\Gamma}\Delta u(k) \\
x(k+2|k) &= \boldsymbol{\Phi}x(k+1|k) + \boldsymbol{\Gamma}\Delta u(k+1) = \boldsymbol{\Phi}^2 x(k) + \boldsymbol{\Phi}\boldsymbol{\Gamma}\Delta u(k) + \boldsymbol{\Gamma}\Delta u(k+1) \\
&\vdots \\
x(k+N|k) &= \boldsymbol{\Phi}^N x(k) + \sum_{i=0}^{N-1} \boldsymbol{\Phi}^i \boldsymbol{\Gamma}\Delta u(k+N-1-i)
\end{aligned}$$

The given set of equations can be written in a matrix form as:

$$\begin{bmatrix} x(k+1|k) \\ x(k+2|k) \\ \vdots \\ x(k+N|k) \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Phi} \\ \boldsymbol{\Phi}^2 \\ \vdots \\ \boldsymbol{\Phi}^N \end{bmatrix} x(k) + \begin{bmatrix} \boldsymbol{\Gamma} & 0 & \cdots & 0 \\ \boldsymbol{\Phi}\boldsymbol{\Gamma} & \boldsymbol{\Gamma} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{\Phi}^{N-1}\boldsymbol{\Gamma} & \boldsymbol{\Phi}^{N-2}\boldsymbol{\Gamma} & \cdots & \boldsymbol{\Gamma} \end{bmatrix} \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+N-1) \end{bmatrix} = \boldsymbol{W}x(k) + \boldsymbol{Z}\Delta\boldsymbol{U}$$

Applying these results to formula 3 for previously defined cost function, we achieve equation:

$$J(\Delta\boldsymbol{U}) = \frac{1}{2}(\boldsymbol{r_p} - \boldsymbol{X})^T \boldsymbol{Q}(\boldsymbol{r_p} - \boldsymbol{X}) + \frac{1}{2}\Delta\boldsymbol{U}^T \boldsymbol{R}\boldsymbol{U} \tag{7}$$

After algebraic transformations, resulting cost function can be transformed to quadratic objective function in form:

$$J(\Delta\boldsymbol{U}) = \frac{1}{2}\Delta\boldsymbol{U}^T \boldsymbol{H}\Delta\boldsymbol{U} + \boldsymbol{f}^T\Delta\boldsymbol{U} \tag{8}$$

where:

$$\boldsymbol{H} = \boldsymbol{Z}^T\boldsymbol{Q}\boldsymbol{Z} + \boldsymbol{R}, \quad \boldsymbol{f} = [\boldsymbol{W}x(k) - \boldsymbol{r_p}]^T \boldsymbol{Q}^T \boldsymbol{Z} \tag{9}$$

Transforming initial problem to the form presented in the equation 8 enables us to solve this problem with quadratic programming optimization techniques and with adding constraints to calculated control vector. Final form of optimization task is denoted below:

$$\min_{\Delta\boldsymbol{U}} \frac{1}{2}\Delta\boldsymbol{U}^T \boldsymbol{H}\Delta\boldsymbol{U} + \boldsymbol{f}^T\Delta\boldsymbol{U} \quad , \quad a \leq \Delta\boldsymbol{U} \leq b \tag{10}$$

3.2 Recursive Least Squares algorithm

Recursive Least Squares algorithm is a popular and powerful tool widely used in order to perform online system identification. Assuming, that:

$$\hat{\theta}\phi = Y \tag{11}$$

where:

- $\hat{\theta} = [\boldsymbol{\Phi}, \boldsymbol{\Gamma}]$ is a matrix with dynamics model parameters
- ϕ is a regressor storing state and control variables measurements from previous timesteps
- $\boldsymbol{Y}$ is matrix storing previous state data, concatenated with current timestep state vector

Knowing initial covariance matrix and assuming value of forgetting factor, algorithm can be summarized with equations enlisted below [18]:

$$\boldsymbol{K}(t) = \boldsymbol{P}(t)\boldsymbol{\phi}(t)\left[\mathbb{I}\cdot\lambda + \boldsymbol{\phi}(t)^T\boldsymbol{P}(t)\boldsymbol{\phi}(t)\right]^{-1} \tag{12}$$

$$\hat{\boldsymbol{\theta}}(t+1|t) = \boldsymbol{\theta}(t) + \left[\boldsymbol{Y}(t)^T - \boldsymbol{\theta}(t)\cdot\boldsymbol{\phi}(t)\right]\boldsymbol{K}(t)^T \tag{13}$$

$$\boldsymbol{P}(t+1|t) = \frac{1}{\lambda}\cdot\left[\boldsymbol{P}(t) - \boldsymbol{K}(t)\boldsymbol{\phi}(t)^T\boldsymbol{P}(t)\right] \tag{14}$$

where $\boldsymbol{P}(t)$ is a covariance matrix, λ is a forgetting factor and $\boldsymbol{K}(t)$ is a gain matrix. Iterative utilizing of the model parameter estimation algorithm enables user to identify helicopter's dynamics online and to continuously adapt to environmental changes.
Assuming using previous N data samples for model parameter estimation, we know that $P \in \mathbb{R}^{(m+n)\times(m+n)}$, $\phi \in \mathbb{R}^{(m+n)\times N}$, $Y \in \mathbb{R}^{(m)\times N}$ and $\theta \in \mathbb{R}^{(m)\times(m+n)}$.
Recognizing the RLS model parameter estimation algorithm's limitations in steady-state flight due to insufficient helicopter dynamics information, the system proposed in this paper combines a mathematical model derived from the FLIGHTLAB model's linearization with an online estimated model from RLS. These models are mixed using weighted average with proportions determined through heuristic reasoning.

4. Test cases

In the conducted research, several test cases were performed to evaluate the performance and stability of the proposed flight control system. Another objective of the simulations was to compare the performance of the MPC algorithm with and without the RLS online model parameter estimation. The simulation scenarios are divided as follows:

- Case 1: The helicopter performs a level change maneuver, increasing its altitude to 15 feet above ground level.
- Case 2: The helicopter maintains its initial altitude while increasing its forward flight velocity from 0 to 5 feet per second.
- Case 3: The helicopter changes its yaw angle (Ψ) from 0 to 90 degrees while holding its position in space.

Each scenario assumes ideal measurements and neglects time delays in the control system. The following parameters of RLS algorithm were used in all cases:

- $\lambda = 0.99$
- $\boldsymbol{P}(0) = \mathbb{I}\cdot 10^6$
- $N = 100$ samples

The initial conditions for all simulations correspond to the equilibrium point conditions during a hover at an altitude of 11 ft above sea level, around which the mathematical model used by the FLIGHTLAB software was linearized. Initial state vector is presented in equation 1.

In Case 1 (shown in Figure 3), the ARCHER rotorcraft successfully achieved the target altitude of 15 feet above ground level, with minimal overshoot and a settling time of approximately 4 seconds. In this case, an initial linear model of helicopter dynamics was combined with an estimated one in a proportion of 20% and 80%, respectively. Notably, the MPC controller without the RLS algorithm introduced a slight shift in the X and Y axes along with the altitude change. By contrast, the use of the RLS algorithm allowed the helicopter to operate with much higher precision, reducing the horizontal shifts to within ±0.1 feet.
Another notable difference is a slight disturbance in altitude when using the RLS algorithm between the first and third seconds of the simulation. This perturbation is caused by the transition to the RLS algorithm after storing N measurements of state variables, which are necessary for the online model parameter estimation.

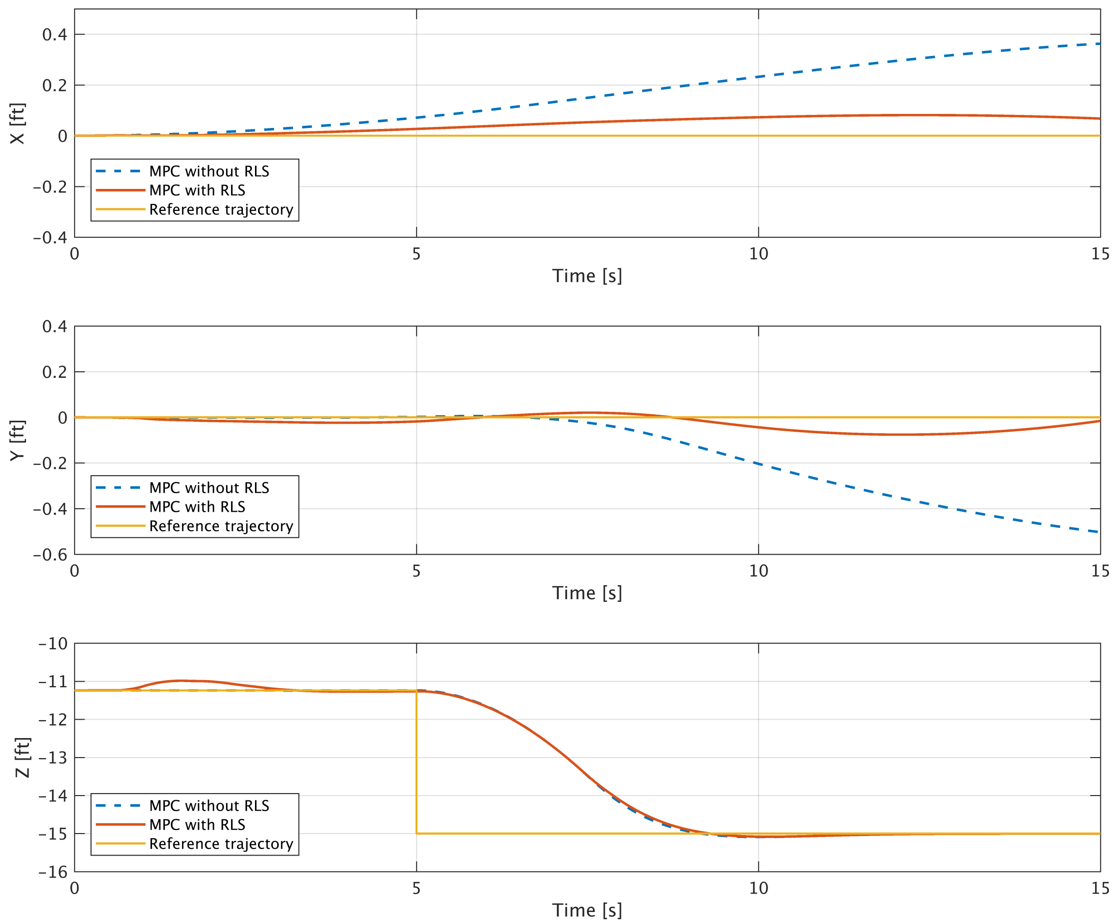

Figure 3 – Case 1, flight level change using MPC with and without RLS model parameter estimation

In Case 2 (shown in Figure 4), the ARCHER helicopter increased its forward flight velocity along the X-axis in the inertial coordinate system. The increase in forward velocity caused minor perturbations in the altitude and Y-axis position, which were compensated by the flight control system.
Simulation results, presented below (figure 4), were obtained for a system without RLS and with the use of the RLS algorithm, composing a final mathematical model in proportions of 20% of the continuously estimated model and 80% of the model obtained from linearization prior to simulation start. In this case, enhancing linear MPC algorithm with RLS model parameter estimation was not as succesful as in previous case, but resulted with limiting disturbances in position on Y axis. Step response of the system while changing reference value of forward flight velocity from 0 ft/s to 5 ft/s resulted with slight overshoot of measured signal on level about 8% of reference value. In both cases helicopter successfully maintained its initial altitude.

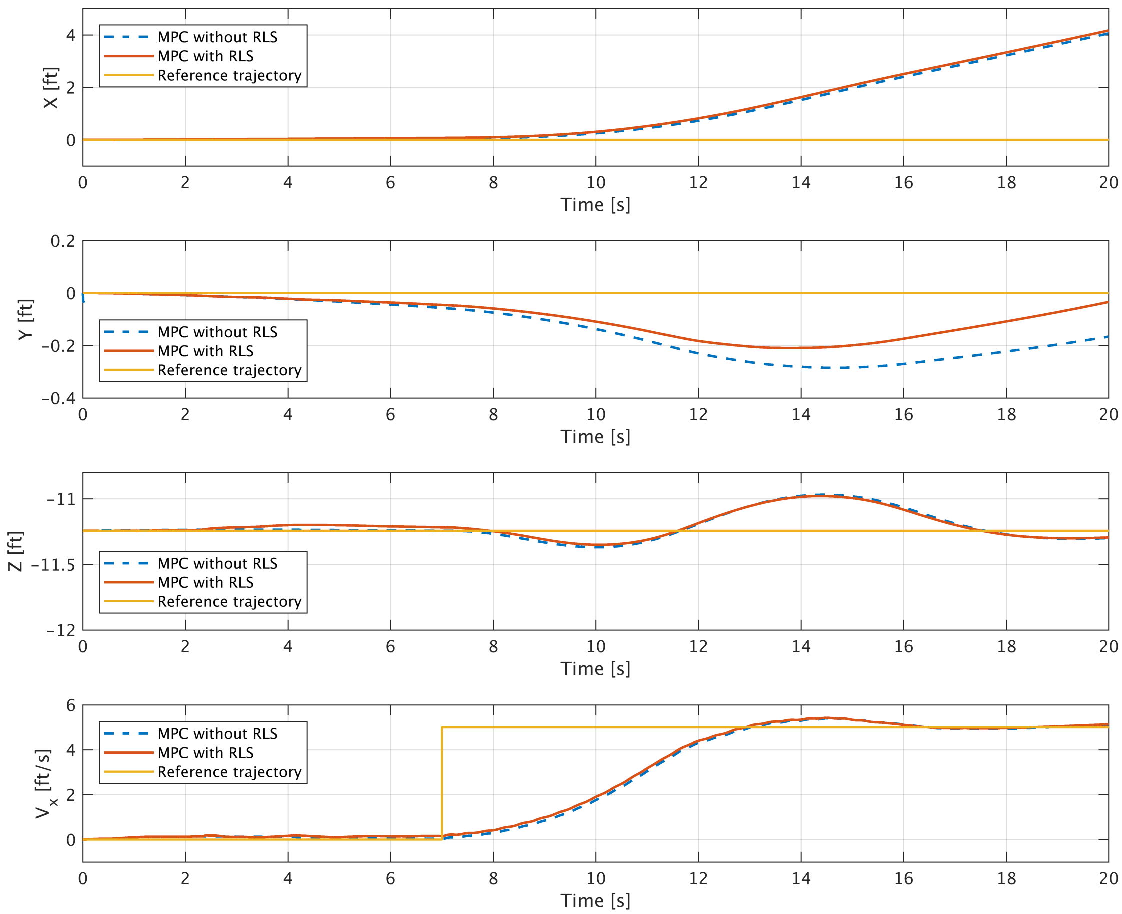

Figure 4 – Case 2, forward flight velocity increase using MPC with and without RLS model parameter estimation

In Case 3 (shown in Figure 5), the ARCHER rotorcraft successfully completed the task of rotating around its Z-axis, changing its yaw angle from 0 to 90 degrees. The change in yaw was achieved by increasing the pitch angle of the tail rotor blades, which caused a slight shift in the Y-axis due to incerasing thrust of the tail rotor. This shift was compensated for by the control system. Using RLS model parameter estimation algorithm and mixing initial mathematical model with estimated one in proportion of 20% and 80% resulted with faster compensating the disturbance on the Y axis and keeping helicopter closer to the desired position on X axis rather than in the scenario without utilizing RLS. Both cases resulted in changing yaw angle from 0 to 90 degrees, whithout overshoot. What is worth mentioning, using RLS created slight disturbances, which can be observed in time window of 2-5 seconds, where system is switching from initial mathematical model to mixed one and returns to the equilibirum point.

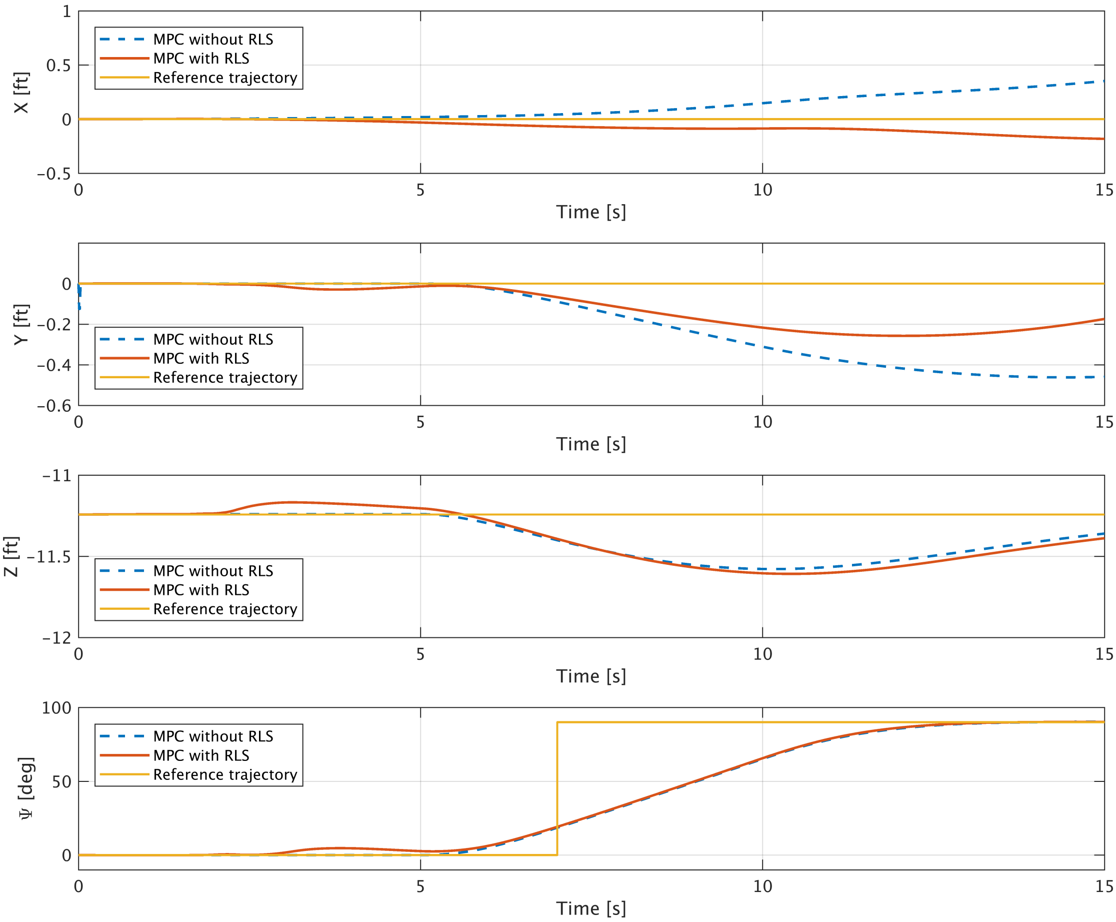

Figure 5 – Case 3, yaw angle change increase using MPC with and without RLS model parameter estimation

5. Conclusions

This paper presents the development of an automatic flight control system for an unmanned rotorcraft using a linear Model Predictive Controller (MPC) enhanced with Recursive Least Squares (RLS) model parameter estimation. Since the effectiveness of the MPC algorithm is highly dependent on the accuracy of the mathematical model of the system, the results demonstrate that the linear MPC algorithm performed successfully. The addition of RLS for online model parameter estimation further improved the system's accuracy, particularly during altitude changes while maintaining the helicopter's horizontal position.

The transition from hovering to forward flight is inherently nonlinear due to changes in aerodynamic conditions. Despite this, the proposed Model Predictive Control algorithm effectively managed these nonlinearities.

The main conclusion of this study is that incorporating online parameter estimation with MPC can significantly enhance the accuracy of unmanned helicopter flight control, where focus relies on controlling many states of the plant. As case 1 has shown [3], using RLS parameter estimation did not have effect on signal describing altitude with respect to time, this algorithm significantly helped with maintaining helicopter's position on X and Y axis of inertial coordinate system.

Future research could explore alternative online model parameter identification methods to further improve the accuracy and performance of the system when using a linear MPC controller for rotorcraft. Additionally, investigating the efficiency of nonlinear MPC algorithms for controlling unmanned helicopter flight could be another direction for further study.

References

[1] Bauersfeld L., Spannagl L., Ducard G. J. J. and Onder. C. H. "MPC Flight Control for a Tilt-Rotor VTOL Aircraft", *IEEE Transactions on Aerospace and Electronics Systems*, Vol. 57, Issue 4, pp. 2395-2409, 2021.

[2] Yi S. H., Shamsudin S. S. and Pairan M. F. "Flight Control System Design for a Rotorcraft-Based Unmanned Aerial System using Pole Placement and LQR-Based PID Tuning Techniques" *Journal of Aeronautics, Astronautics and Aviation*, Vol. 56, No. 3, pp. 615-636, 2024

[3] Gadewadikar J., Peng K., Subbarao K. and Chen B. M. "H-Infinity Static Output-Feedback Control for Rotorcraft" *Journal of Intelligent & Robotic Systems*, April 2009.

[4] Yuan W. and Katupitya J. "6-DOF Design of a μ-synthesis Controller to Stabilize an Unmanned Helicopter" *28th International Congress of the Aeronautical Sciences*, Brisbane, Australia, pp 6123-6128, 2012.

[5] Topczewski S. and Bibik P. "LQR and LQG control of the helicopter during landing on the ship deck" *Aircraft Engineering and Aerospace Technology*, Vol. 95, No. 9, pp 1344-1352, 2023.

[6] Topczewski S., Narkiewicz J. and Bibik P. "Helicopter Control During Landing on a Moving Confined Platform" *IEEE Access*, Vol. 8, pp 107315-107325, 2020.

[7] de Wagter C. and Dellemann L. F. A. "Hybrid UAV Attitude Control using INDI and Dynamic Tilt-Twist." *12th International Micro Air Vehicle Conference*, Puebla, Mexico, Vol. 1, 16, pp 1-7, 2021.

[8] Flores G., Lozano R. and Lugo-Cárdenas I. "6-DOF Hovering Controller Design of the Quad Tiltrotor Aircraft: Simulations and Experiments" *53rd IEEE Conference on Decision and Control*, Los Angeles, California, USA, pp 6123-6128, 2014.

[9] Rothe J., Zevering J., Strohmeier M. and Montenegro S. "A Modified Model Reference Adaptive Controller (M-MRAC) Using an Updated MIT-Rule for the Altitude of a UAV" *Electronics*, Vol. 9, 11045, 2020.

[10] Allenspach M. and Ducard G. J. J. "Nonlinear model predictive control and guidance for a propeller-tilting hybrid unmanned air vehicle" *Automatica*, Vol. 132, 109790, 2021.

[11] Kadmiry B. and Driankov D. "Fuzzy Control of an Autonomous Helicopter" *IFSA World Congress and 20th NAFIPS International Conference*, Vancouver, BC, Canada, 2001.

[12] Ng A., Kim H., Jordan M. I. and Sastry S. "Autonomous Helicopter Flight via Reinforcement Learning" *Neural Information Processing Systems*, 2003.

[13] Wang L., Tan G. and Meng J. "Research on Model Predictive Control of IPMSM Based on Adaline Neural Network Parameter Identification" *Energies*, Vol. 12, 4803, 2019.

[14] Chikasha P. N. and Dube C. "Adaptive Model Predictive Control of a Quadrotor" *IFAC 2017 World Congress*,Toulouse, France, pp 157-162, 2017.

[15] Campbell S. F., Nguyen N. T., Kaneshige J. and Krishnakumar K. "Parameter Estimation for a Hybrid

Adaptive Flight Controller" *AIAA Infotech@Aerospace Conference*,Seattle, United States of America, 2009.

[16] Wagener N., Cheng C. A., Sacks J. and Boots B. "An Online Learning Approach to Model Predictive Control" *Robotics: Science and Systems*, Freiburg, Germany, 2019.

[17] Fan Y., Shi H., Wang S. and Fernandez C. "A Novel Adaptive Function—Dual Kalman Filtering Strategy for Online Battery Model Parameters and State of Charge Co-Estimation" *Energies*, Vol. 14, 2268, 2021.

[18] Yu H., Wang J. and Xin Z. "Model Predictive Control for PMSM Based on Discrete Space Vector Modulation with RLS Parameter Identification" *Energies*, Vol. 15, 2022

[19] Brunton S. L. and Kutz N. "Data-Driven Science and Engineering - Machine Learning, Dynamical Systems, and Control" *Cambridge University Press*, 2019

[20] Camacho E.F. and Bordons C. "Model Predictive Control" *Springer*, London, second edition, 2004

[21] Tatijewski P. "Effectiveness of Dynamic Matrix Control algorithm with Laguerre functions" *Archives of Control Sciences*, Vol. 31, No. 4, pp. 795-814, 2021

[22] Ławryńczuk M. "Computationally Efficient Model Predictive Control Algorithms, A Neural Network Approach", *Springer*, Studies in Systems, Decision and Control Vol. 3, 2014

[23] Żugaj M., Edawdi M., Iwański G., Topczewski S. and Bibik P. "An Unmanned Helicopter Energy Consumption Analysis", *Energies*, Vol. 16, 2067, 2023