

# Improved Multirotor UAV Flight Controller using Nonlinear Model Predictive Position Control

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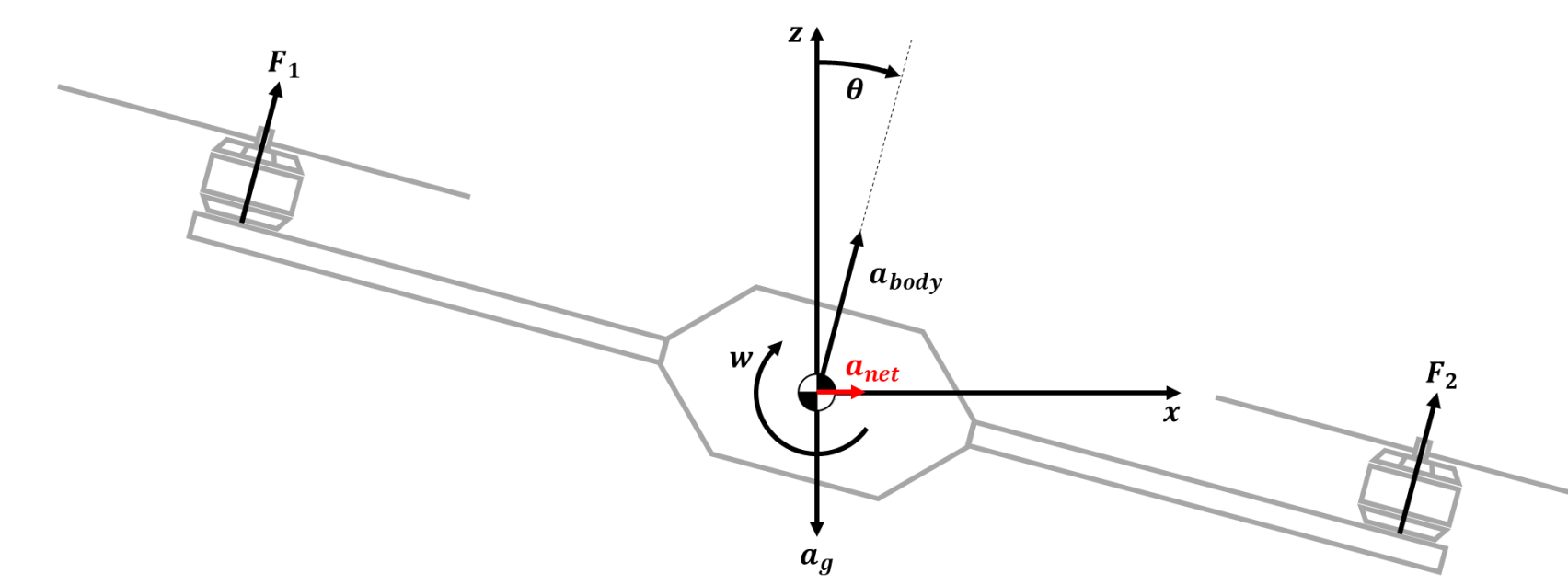
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## Background

Over the last decade, autonomous Unmanned Aerial Vehicles (UAVs or “drones”) have seen increased usage in industrial, research, and academic applications. They are appealing for commercial or military tasks such as precision agriculture, search and rescue, surveillance, surveying, and film making where the position of the UAV needs to be highly controllable. Quadrotor UAV flight dynamics are a highly nonlinear, strongly coupled, and unstable; Quadrotors are also underactuated systems. This makes developing precision control systems a particularly challenging task.

Therefore, an optimal control law has been developed to advance the state of the art in position control of multirotor UAV’s. A Nonlinear Model Predictive Position Controller (NMPC) was developed. A weighted basis function method of optimization is introduced to reduce the computational complexity of the NMPC algorithm. Simulation results show the feasibility of such a control law being implemented on a prototype UAV.

$\dot{\phi} = b_1 U_2 + a_1 \dot{\theta} \psi - a_2 \dot{\theta} \Omega_r + \Gamma_\phi(X, u, t, F_d)$	(1)
$\dot{\theta} = b_2 U_3 + a_3 \dot{\phi} \psi + a_4 \dot{\phi} \Omega_r + \Gamma_\theta(X, u, t, F_d)$	Attitude (2)
$\dot{\psi} = b_3 U_4 + a_5 \dot{\phi} \dot{\theta} + \Gamma_\psi(X, u, t, F_d)$	(3)
$\ddot{x} = \frac{U_1}{m} (\sin\phi \sin\psi + \cos\phi \cos\psi \sin\theta) + \Gamma_x(X, u, t, F_d)$	(4)
$\ddot{y} = \frac{U_1}{m} (\cos\phi \sin\psi \sin\theta - \cos\psi \sin\phi) + \Gamma_y(X, u, t, F_d)$	(5)
$\ddot{z} = \frac{U_1}{m} (\cos\phi \cos\theta) - g + \Gamma_z(X, u, t, F_d)$	Position (6)

Equation 1: Quadrotor Dynamics

## Control Law Outline

The dual loop controller applying SMC and NMPC is shown in Figure 1. In this configuration, the position controller provides setpoints to the attitude controller which in turn actuates the system. Sliding mode is ideal for the inner attitude loop since it is robust enough to account for unmodeled dynamics and deficient actuators.

NMPC is based on an iterative optimization of a set of control inputs over a finite prediction horizon – a finite window of time in the future. It is capable of finding an exact solution to a trajectory tracking control problem for a predefined, desired trajectory.

The NMPC-SMC dual loop controller is expected to provide precise control over the UAV position and attitude dynamics, and can be applied to quadrotor research platforms used for spacecraft simulation.

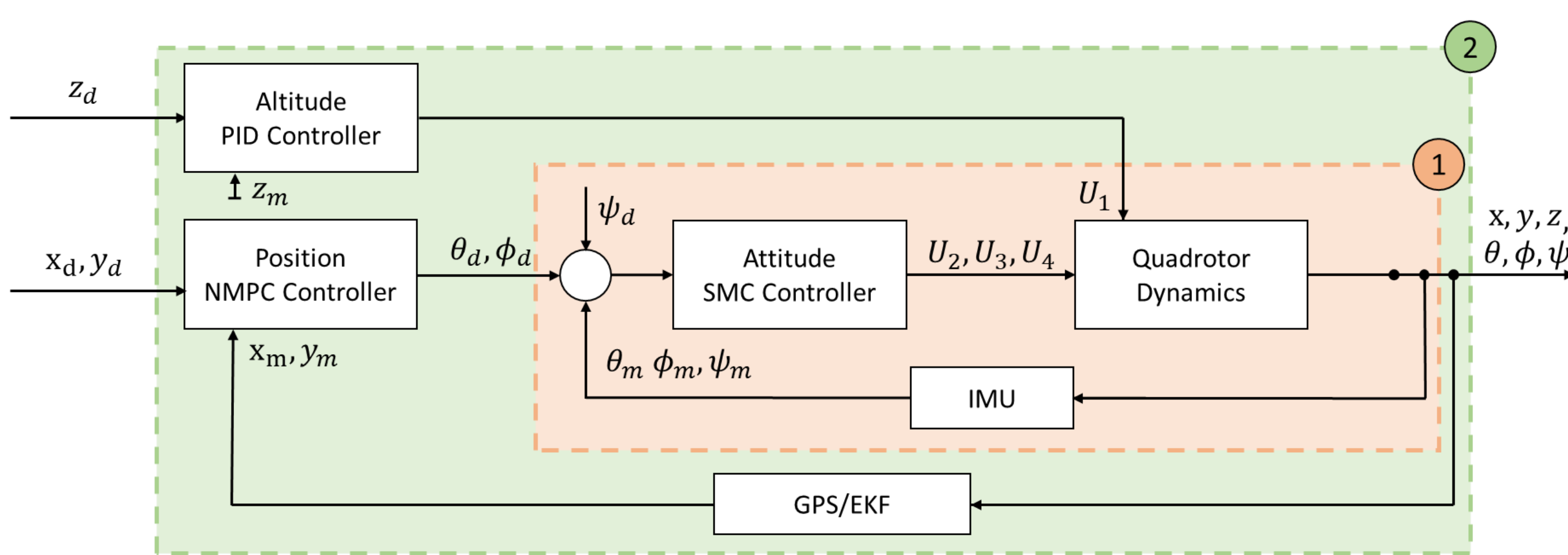


Fig. 1: Dual loop NMPC-SMC control law (1) Inner SMC attitude control loop, currently implemented on experimental platform. (2) Outer NMPC position control loop, developed in simulation.

## NMPC with Weighted Basis Functions

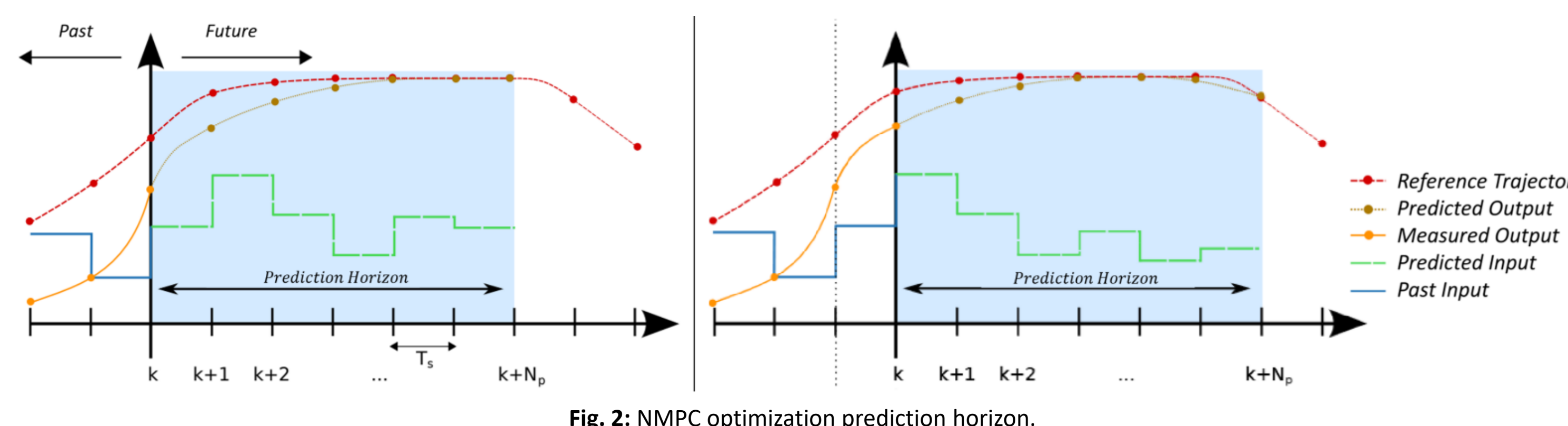


Fig. 2: NMPC optimization prediction horizon.

### Advantages:

- Control inputs are optimized over the full nonlinear model
- Future actions are accounted for
- Different cost functions for different applications

### Disadvantages:

- The large computational cost of nonlinear optimization
- The difficulty to prove stability
- The need for an extremely accurate model of the quadrotor

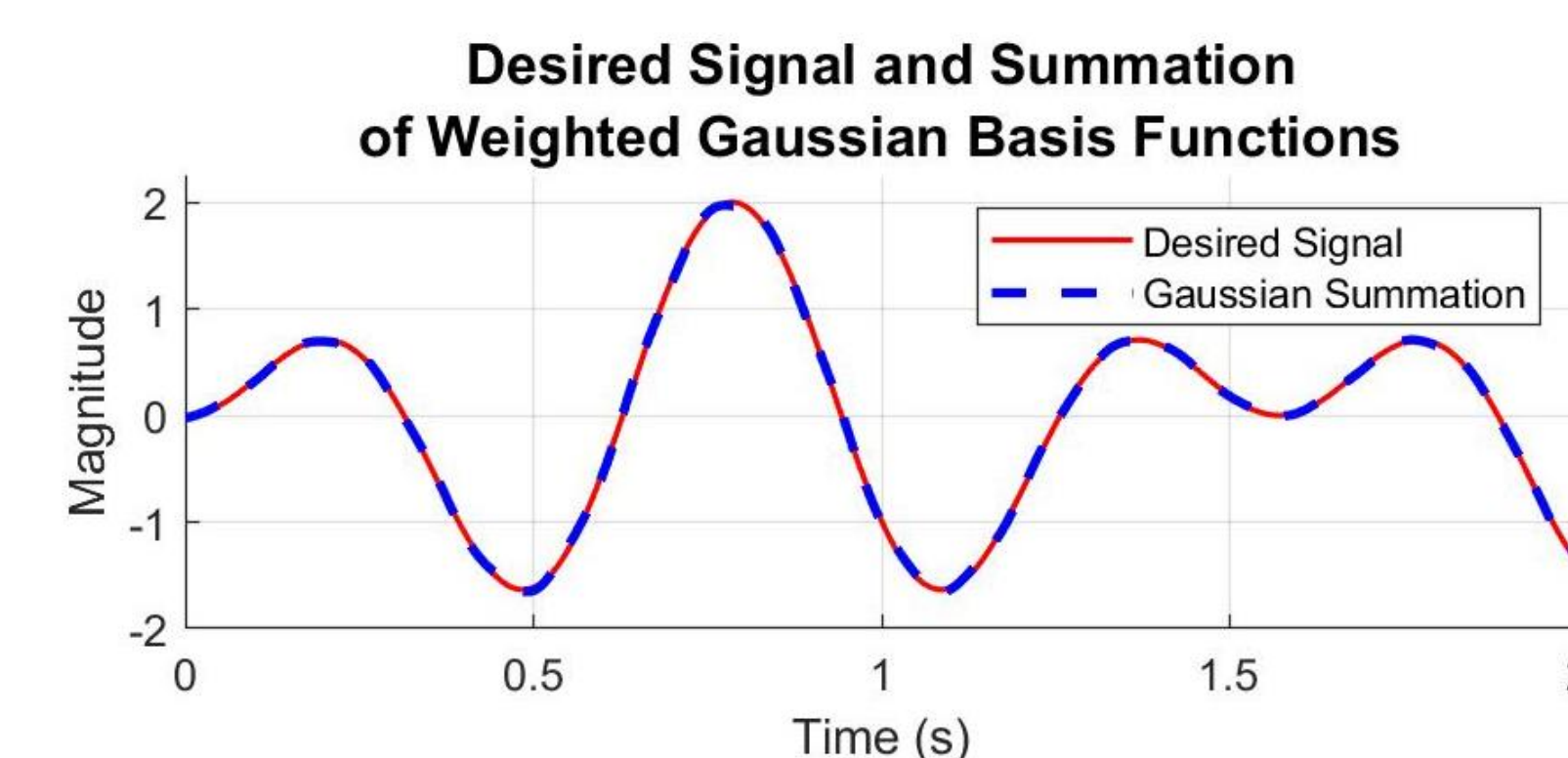
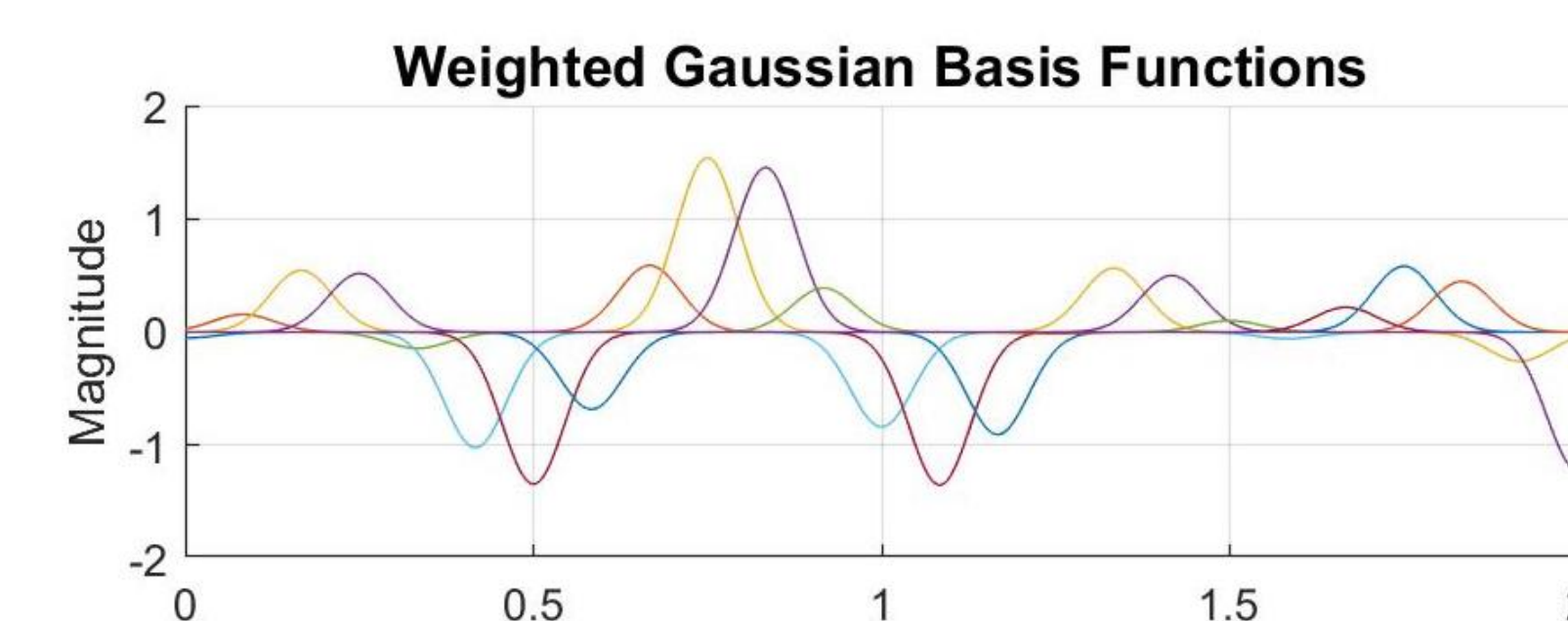
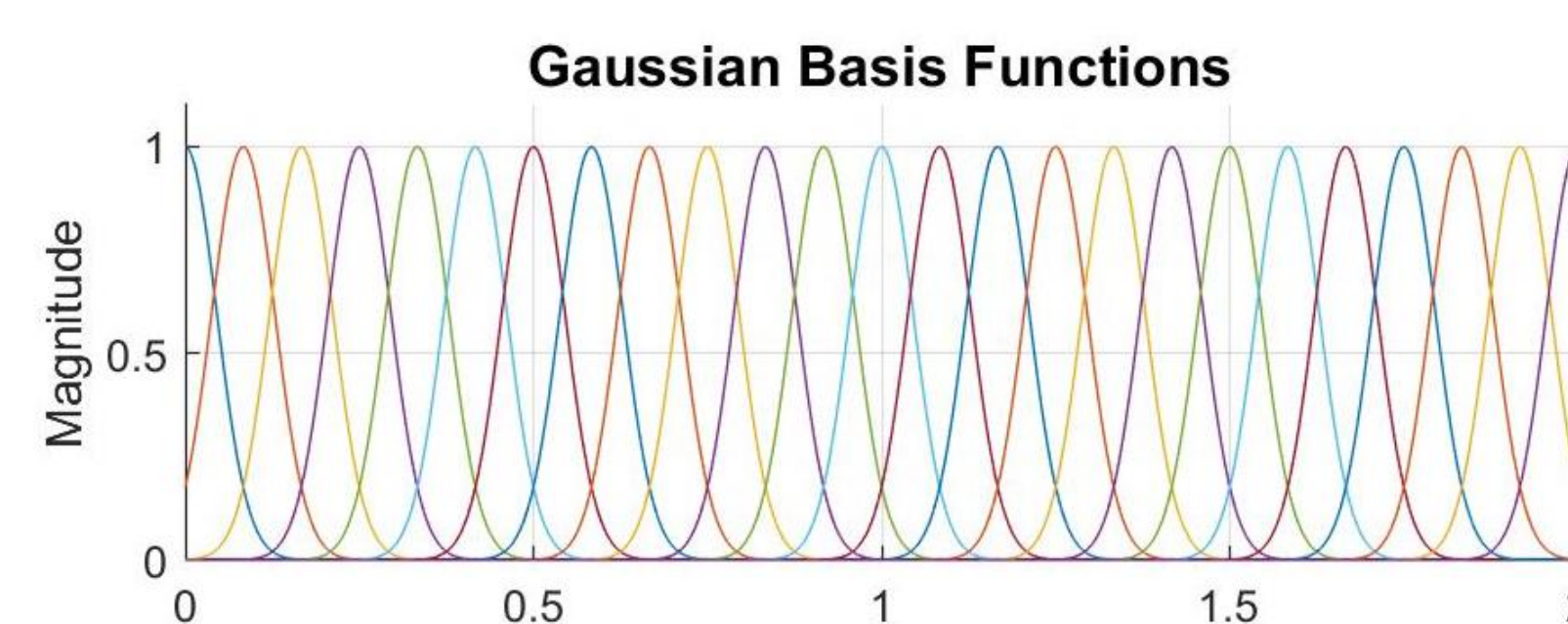


Fig. 3: Gaussian basis function method for fast optimization.

### Algorithm 1: NMPC with Weighted Basis Functions

```

Generate Basis Function
Choose n, h, s
for i = 1: n
    for j = 1: N_pred
        BF(i, j) = exp(h * (t_pred(j) - s(i))^2);
    end
end
NMPC Basis Function Algorithm
Given:
Knowns: X_init, X_des, t_manue ver, t_pred, F, BF;
Unknowns: W_t, U_t
while p < (N - N_pred):
    Measure initial state:
    X_init = X_meas;
    Shift Prediction Horizon:
    t_pred = t_manue ver (p: p + N_pred);
    X_des_PH = X_des (p: p + N_pred);
    W_0 = [W_t(:; 2: end), 1^{2x1}];
    Reformulate executable cost function using [X_init, X_des_PH, BF]
    J(W_t) = J(W_t, X_init, X_des_PH, BF);
    Perform optimization:
    W_t = min_{W_t} J s.t. {A_1 W_t = C_1, A_2 W_t <= C_2} w/ W_0
    Convert W_t, BF into U_t, execute U_t(1):
    U_t = (BF)(W_t^T);
    U_t(1) -> Attitude controller
end

```

$$J = \left[ \sum_{i=1}^{N_{pred}} |X_{des}(i) - X_{meas}(i)| + |Y_{des}(i) - Y_{meas}(i)| \right] + \left[ \sum_{i=1}^{N_{pred}} |\dot{\theta}(i)| + |\dot{\phi}(i)| \right]$$

Equation 2: NMPC Cost Function

By taking advantage of the quadrotor’s generally sinusoidal angular inputs, basis function can be developed to approximate these input signals using far less optimization parameters. Using this method with a two second prediction horizon at 50Hz, the quadrotor NMPC optimization is reduced from 200 to 20 parameters.

## Simulations

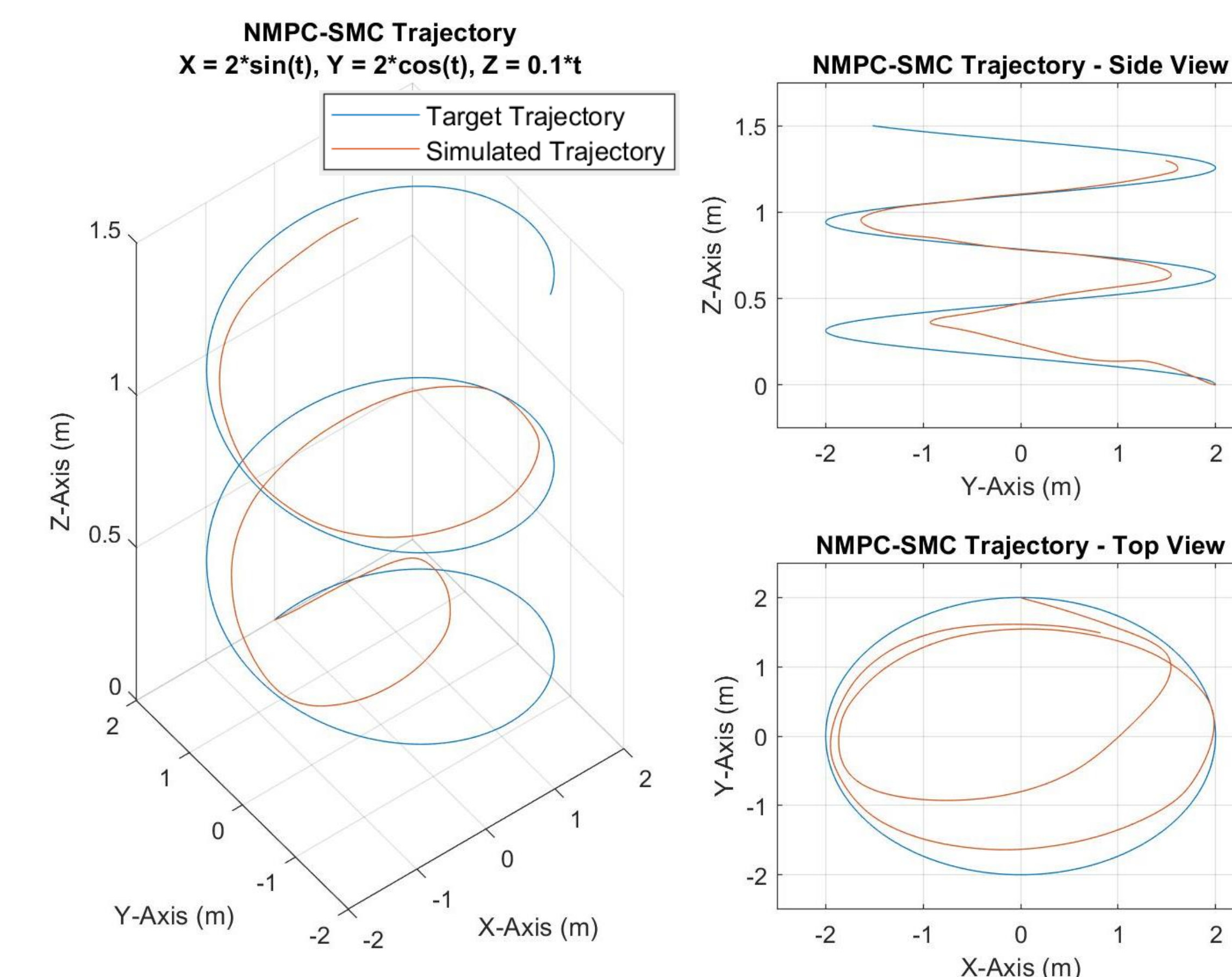


Fig. 4: NMPC Position Control and SMC Attitude Control. 15s simulation, 50Hz controller frequency, 2s prediction horizon w/ 10 basis functions per axis

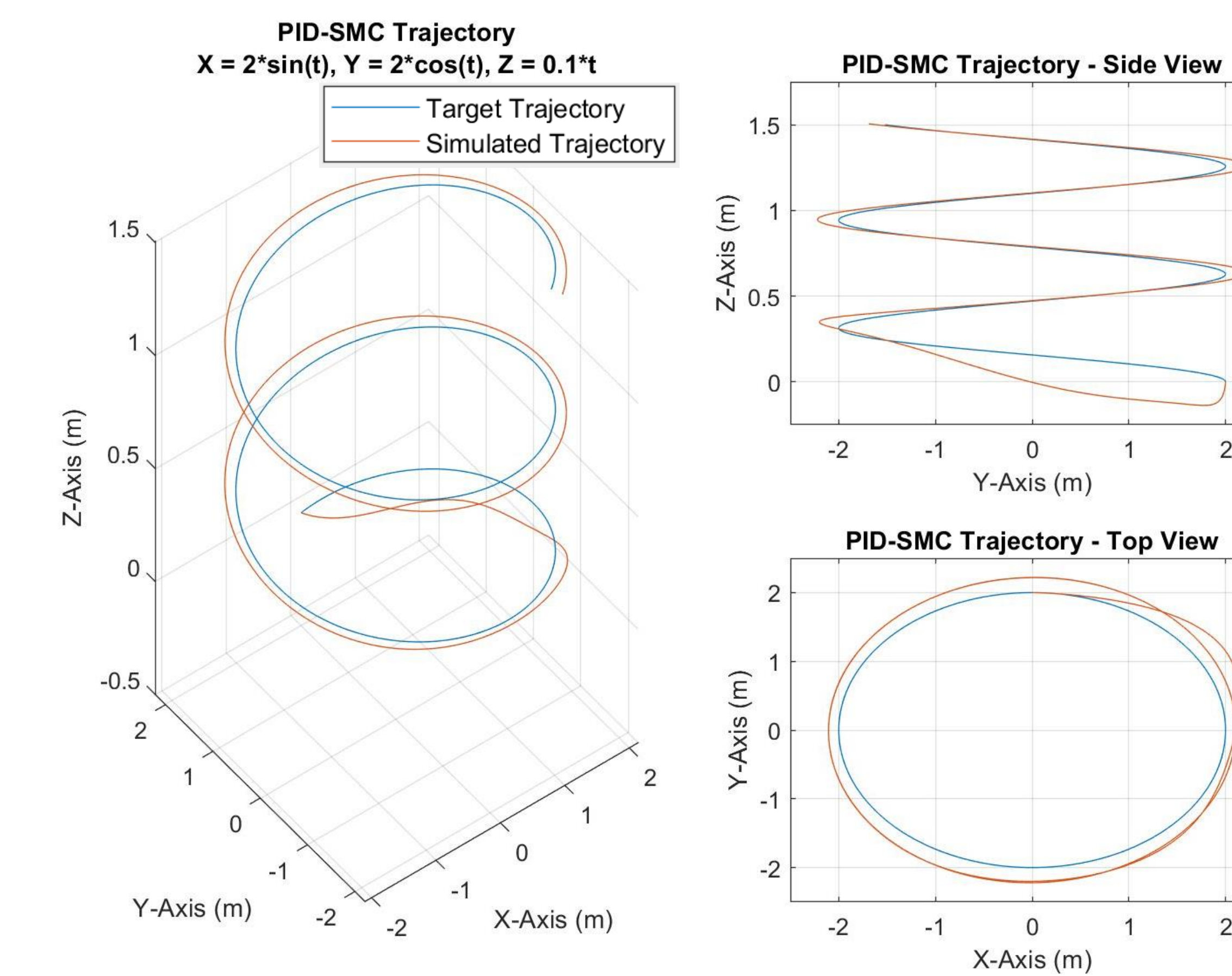


Fig. 5: PID Position Control and SMC Attitude Control. 15s simulation, 50Hz controller frequency

## Conclusions and Future Work

This work shows the feasibility of an NMPC algorithm using weighted basis functions that reduces optimization parameters and increase operating frequency and prediction time. Next, the NMPC algorithm will be thoroughly tuned and evaluated in simulations over more trajectories. Then, it will be implemented on a quadrotor and evaluated experimentally.

### References

S. Khatiwada, A. Masters, A. Cantara, M. Goulet and M.W. Thein. “Control of an Earth-Based Satellite Test Platform through Vision-Based Position Measurement.” AAS/AIAA 29th Spaceflight Mechanics Meeting, Hawaii, 2019.