

# Utilization of Wind Energy in Optimal Guidance Strategies VIDA Real-Time Nonlinear Control Methodologies

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By

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METHODOLOGIES

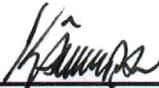
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# Utilization of Wind Energy in Optimal Guidance Strategies via Real-Time Nonlinear Control Methodologies

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In this paper, a real-time, on-board methodology to utilize wind energy associated with air currents is proposed for saving power, minimizing fuel consumption and increasing endurance during flight of an unmanned aerial vehicle (UAV). The UAV is modeled as a 3D dynamic point mass and a non-linear receding horizon control algorithm is investigated for implementation of real-time guidance strategies developed for wind energy utilization.

## Nomenclature

AR aspect ratio  
 $C_D$  drag coefficient  
 $C_{D_0}$  zero-lift drag coefficient  
 $C_L$  lift coefficient  
 $D$  aerodynamic drag  
 $e$  Oswald efficiency factor  
 $h$  inertial altitude  
 $J$  performance index  
 $K$  induced drag factor  
 $L$  aerodynamic lift  
 $m$  aircraft mass  
 $n$  g-load factor  
 $P$  power  
 $S$  wing reference area  
 $T$  thrust  
 $t$  time  
 $V$  airspeed  
 $W_{x,y}$  wind components (East, North)  
 $W_h$  wind component (Upwards)  
 $x; y$  position vectors (East, North)  
free-stream-relative flight path angle  
bank angle  
heading angle measured clockwise from the North  
air density  
normalized time  
 $( )_0$  initial value  
 $( )_f$  final value  
 $( )^r$  reference value  
 $( )^*$  optimal control value

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- ( $\dot{\phantom{x}}$ ) time derivative
- ( $\partial_{\tau}$ ) derivative w.r.t. normalized time

## I. Introduction

In 1903, the Wright brothers demonstrated powered aircraft flight for the first time in history. In a little over a hundred years from that date, mankind has gone from flying primitive wooden aircraft a few hundred feet at a time to sending flying metal marvels across the planet.

While there are many examples of aircraft that have grown in size and scope over history, there are also examples of aircraft that have been scaled down in size but still maintain a massive scope: unmanned aerial vehicles. Small-scale unmanned aerial vehicles (UAVs) exist in a variety of forms and are used to fulfill a multitude of needs. A glider that a pilot controls remotely, a drone the military uses for surveillance are just two examples of the roles UAVs take and the needs they fill. Moreover, UAVs are used in applications for search and rescue, science, leisure, training, surveillance, agriculture, military, recharging, policing and more.

In order to serve these applications as best as possible, the aircraft we create are usually optimized with respect to a desired performance objective. They have gone from composition of wood to metal and from metal to composite. They have been revised and redesigned based on advancements in theory and empirical data. Such advancements include winglets, which enhance aerodynamic efficiency and save fuel by reducing the downwash induced on the wing. Their recent implementation on commercial airliners is evidence that aircraft innovations are not at an end. An observation worth noting is that the ways in which aircraft have improved over the years are mostly due to advancements in technology and supporting theory and the changes manifest in ways that are mostly physical (e.g. appearance, structure, and composition).

A less investigated approach to improving aircraft is to ask how we may benefit from changing the way we approach flight itself, as opposed to changing the object that flies. Nature commonly serves as an example of what works in our world. Inventors, entrepreneurs, enthusiasts, and more have looked to nature for ideas or inspiration, and biomimicry has made an appearance in aviation. The prime example of flight in nature is the bird. Birds, like humans, seek efficiency. As a result, they take advantage of air currents (i.e. winds) to reduce the effort required to fly. Birds have been observed taking advantage of air currents like updrafts, thermals, microbursts, and the effects of wind shear. Before the onset of small aerial vehicles, taking advantage of the same air currents birds benefit from was not feasible with the size, speed, and overall scale of the aircraft available. With aircraft that have similarly low-mass and small-scale features to birds, near instantaneous changes in direction become practical. The possibility to take advantage of wind energy exists and simply needs a method of implementation for aircraft.

Modern day aircraft are on the verge of a major transformation. Autopilot technology has existed since the early 1900s. The advancements made to aircraft control systems, however, are as drastic as the changes to the aircraft themselves. Up until recent history, all aircraft have had a human pilot, regardless of any autopilot implementation. This precedent is nearing its end, with the onset of sophisticated autonomous control systems that enable aircraft to fly a pre-determined human-selected course without any human interaction.

The transition to primarily computer-controlled aircraft is here and applicable in nowadays. With autonomous technology for UAVs already commercially available, the next steps are in two directions: widespread implementation and improvements. The improvements of interest for this research include the application of biomimicry in flight patterns to UAV guidance algorithms.

### A. Background

The studies of flight in nature and improvements to aircraft cross paths from time to time and sometimes, evolutionary progress is made in the way we approach flight. Certainly, the observation of birds in flight spurred the inspiration for the Wright brothers to tackle the dream of human flight. While the first aircraft to fly had a set of fixed unmoving wings, aircraft with wings that flap like a bird have been proposed and studied throughout history. None have come to be as successful as their fixed wing counterparts but progress continues. In 2010, the Snowbird of the Human-Powered Ornithopter (HPO) Project at the University of Toronto officially became the world's first human-powered ornithopter.<sup>1</sup> The aircraft demonstrated the

ability to climb in altitude and maintain level flight with flapping wings as the only means of propulsion. Another way in which nature has influenced our understanding of and approach to flight is through tubercles, the bumps on the sides of Humpback whales. Research has found that tubercles act as vortex generators to produce turbulent flow over the whale's skin and improve stall performance.<sup>2</sup> Tubercles have been tested for applications in air with results indicating enhancement to lift properties.<sup>3, 4</sup> These examples of biomimicry hardly scratch the surface of the potential improvements we can harness from copying nature's approach to flight.

The ways nature approaches flight and the ways in which we might be able to benefit from a similar approach have been investigated in the past. Richardson<sup>5</sup> created a simple dynamical model of wind-shear soaring and found that an estimated 80-90% of the total energy required for sustained flight can be extracted from wind-shear soaring. The promise of energy benefits from dynamic soaring motivated other research on the topic. Zhao<sup>6</sup> formulated a glider's dynamic soaring as a 3D point mass with utilization of wind gradients as a non-linear optimal control problem and investigated various performance indices and terminal conditions to yield differing optimal flight patterns, each with their own prospective uses. Furthermore, using a 3D point mass and linear wind gradients, optimal powered dynamic soaring flights of UAVs utilizing wind gradients at low altitudes for reducing fuel consumption were studied by Qi and Zhao.<sup>7</sup> They were able to compare the characteristics of minimum thrust dynamic soaring cases with those of minimum power dynamic soaring to find similar fuel savings benefits between the two approaches. Additional air current research of Qi and Zhao<sup>8</sup> includes modeling a 2D point mass model of a UAV flying through a region of vertically flowing thermal air current. Their results suggest significant improvements in UAV fuel consumption are possible by taking advantage of thermal air energy. Enforcing the effectiveness of using thermal air currents, Akhtar et al.<sup>9</sup> created a positioning algorithm for autonomous thermal soaring where a simulated 6DOF model is used to estimate the interaction of a sailplane with thermal updrafts. In their study, a control system, based on classical theory, is used to guide the sailplane for maximum benefit from the thermal energy. A situationally unique approach to energy savings is taken by White, C. et al.,<sup>10</sup> who conducted a feasibility study for micro air vehicles (MAVs) saving energy by soaring near tall buildings. Provided issues of controllability could be overcome, the study findings indicated the prospect for soaring to be realistic. The current status of the technology in the field of miniature air vehicles and prospective future innovations were discussed by Gerdes et al.<sup>11</sup> in a review of miniature air vehicle designs with bird-inspired flapping wings.

The utilization of these air currents and flight strategies requires computer algorithms capable of providing real-time guidance solutions. Recently, Gao, X.-Z., et al.<sup>12</sup> proposed a guidance strategy for dynamic soaring of UAVs that could reduce computational time to less than one percent of what is required by the Gauss pseudo-spectral method, thereby increasing the possibilities for an on-board real-time guidance strategy. Previous work by Ohtsuka and Fujii<sup>13</sup> proposed a real-time optimization technique for optimal state-feedback control of general non-linear systems. The technique utilizes the backward-sweep method to reduce the computational cost of the solution. In another study, Turkoglu,<sup>14</sup> generated an approach for optimizing flight trajectory to benefit from wind energy using real-time guidance strategies. When using the algorithm in a real-time simulation, a 10 to 20 percent decrease in total power consumption was observed.

The aforementioned advancements in our understanding of wind energy and software implementation methods will be the basis for this research.

## B. Overview of the Research

The objective of this research is to investigate mathematical methodologies for achieving on-board implementation and function of real-time optimal guidance strategies in presence of wind. The optimal guidance strategies of focus for this research are those which utilize instantaneous wind information and adjust trajectory for efficiency accordingly. This requires the examination of not only computationally efficient and robust, but also on-board applicable, real-time optimization methods. An algorithm of nonlinear receding horizon control, proposed by Ohtsuka and Fujii,<sup>13</sup> is of main interest and will be implemented for the application of the real-time guidance strategies in presence of wind. The aim is to minimize fuel consumption and extend flight time benefiting from the wind conditions.

## II. Aircraft System Description

Properly defining the system at hand is critical to generating the parameters, equations, and algorithm so that the final results can emulate reality to the desired level of accuracy. The typical approach to modeling the aircraft dynamics include definition of a system with six degrees of freedom (6DOF). While this is common and serves as an accurate model, the computational burden induced by the highly complex system model is not ideal for real-time optimization applications. Furthermore, the accuracy required by the problem at hand can be achieved with an approach that boasts simplicity over the 6DOF system. For this research the aircraft is modeled as a three-dimensional (3D) dynamic point-mass with all the necessary flight trajectory parameters for trajectory analysis and optimization.

### A. Equations of Motion

In defining the aircraft as a 3D dynamic point mass, the equations of motion are:<sup>14</sup>

$$\bar{V} = (T - D) = m g \sin \gamma \quad (1)$$

$$\bar{V} \cos \mu = L \sin \alpha = m W \quad (2)$$

$$\bar{V} = L \cos \alpha = m g \cos \gamma + W \quad (3)$$

$$\dot{x} = \bar{V} \cos \mu \sin \gamma + W_x \quad (4)$$

$$\dot{y} = \bar{V} \cos \mu \cos \gamma + W_y \quad (5)$$

$$\dot{h} = \bar{V} \sin \mu + W_h \quad (6)$$

where

$$\bar{W}_V = W_x \cos \mu \sin \gamma + \bar{W}_y \cos \mu \cos \gamma + W_h \sin \mu \quad (7)$$

$$W = W_x \sin \mu \sin \gamma + W_y \sin \mu \cos \gamma + W_h \cos \mu$$

For these equations, the terms to be used as inputs are thrust  $T$ , lift  $L$ , and bank angle  $\mu$ . The states to be controlled are: the airspeed  $V$ , heading angle  $\psi$ , flight path angle  $\gamma$ , and the coordinates  $(x; y; h)$  of the aircraft relative to the inertial coordinate system location.

For this research, the UAV is assumed to be propeller-driven by an electric motor with a known power output and the UAV's mass  $m$  is assumed to remain constant over time. Given these assumptions, the thrust  $T$ , power  $P$ , and velocity  $V$  of the aircraft can be related as shown below.

$$T = P/V \quad (8)$$

The lift  $L$  and drag  $D$  forces experienced by the aircraft can be defined as

$$L = \frac{1}{2} V^2 S C_L; \quad D = \frac{1}{2} V^2 S C_D \quad (9)$$

and the drag coefficient is modeled by the parabolic drag polar<sup>15</sup>

$$C_D = C_{D0} + K C_L^2 \quad (10)$$

The induced drag factor  $K$  can be determined from the Oswald efficiency factor  $e$  and the wing aspect ratio-AR as

$$K = \frac{1}{eAR} \quad (11)$$

## B. Motion Constraints

Since the aircraft has real limitations to its movement, constraints are applied to the system to better resemble realistic aircraft flight parameters. The bounded trajectory states are power  $P$ , velocity  $V$ , flight path angle, bank angle, and coefficient of lift  $C_L$ . The specified limitations are shown below.

$$\begin{aligned} V_{\min} \leq V \leq V_{\max}; \quad j \leq j_{\max} \\ C_{L_{\min}} \leq C_L \leq C_{L_{\max}}; \quad 0 \leq P \leq P_{\max}; \quad j \leq j_{\max} \end{aligned} \quad (12)$$

To further improve realism, the g-loading of the aircraft is limited as well.

$$n = \frac{L}{W} = \frac{V^2 S C_L}{2W} \quad n_{\min} \left( \frac{S}{2W} \right) \leq V^2 C_L \leq n_{\max} \left( \frac{S}{2W} \right) \quad (13)$$

The minimum allowable airspeed is set as the aircraft stall speed and the maximum airspeed is chosen to be the desired cruise speed.

$$V_{\min} = s \sqrt{\frac{2W}{S C_{L_{\max}}}}; \quad V_{\max} = s \sqrt{\frac{2W}{S C_{L_{cr}}}} \quad (14)$$

where  $C_{L_{cr}}$  is the coefficient of lift required for steady level flight at the cruise velocity.

## III. Problem Definition

The main effort of this research is to make a reduction in power consumption possible through use of wind energy via in-situ, on-board and instantaneous wind measurements. To do this, we will adopt a method for use of instantaneous, in-situ wind measurements to influence and optimize trajectory. The work of Turkoglu<sup>14</sup> focuses on development of such real-time, optimal trajectory guidance strategies based on gradient methods. This work builds on the previous work of Turkoglu<sup>14</sup> with a novel extension of applying the strategies with an advanced real-time optimization algorithm from the work of Ohtsuka and Fujii<sup>13</sup> (i.e. non-linear receding horizon control) that will serve for on-board, in-situ, real-time trajectory optimization routine.

### A. Nonlinear Receding Horizon Control Based Real-Time Optimization Algorithm

The problem in hand is an optimal control problem, which is to be solved for a non-linear system in real time through minimizing the cost function over a receding time horizon. The corresponding form of the differential equation and the performance index for such a problem are shown below for convenience.

$$\begin{aligned} \frac{dx(t)}{dt} = f[x(t); u(t); p(t)] \\ J = [x(t+T); p(t+T)] + \int_t^{t+T} L[x(t^0); u(t^0); p(t^0)] dt^0 \end{aligned} \quad (15)$$

Here,  $x(t)$  represents the state,  $u(t)$  represents the system input, and  $p(t)$  represents parameters that vary over time. With this problem setup, we seek an optimal control input and a resulting trajectory that will minimize the cost function, which is associated with minimum fuel consumption via the utilization of the wind energy. If we introduce a fictitious time axis, as defined by Ohtsuka,<sup>16</sup> where the present time  $t$  corresponds to  $\tau = 0$ , then the aforementioned problem becomes a set of problems with a fixed horizon.

$$\begin{aligned} \dot{x} = f[x(\tau); u(\tau); p(\tau)] \\ x(0; \tau) = x(t) \end{aligned} \quad (16)$$

The new problem set has the form of a typical optimal control problem where we formulate the Hamiltonian,

which consists of the terminal cost function and the Lagrangian. It follows that the necessary condition for optimal control takes the form of the two-point boundary value problem shown in Eq.(17).

$$\begin{aligned} \dot{x} &= H^T = f & \text{where } x(0; t) &= x(t) \\ &= H_x^T & \text{where } (T; t) &= x^T \\ H_u &= 0 \end{aligned} \quad (17)$$

In Eq.(17),  $\lambda$  represents the costate vector and H is the aforementioned Hamiltonian as defined by

$$H = L + \lambda^T f \quad (18)$$

Based on this approach, the control methodology is obtained as

$$u(t) = \text{argf} H_u[x(t); (t); u(t); p(t)] = 0 \quad (19)$$

A backward sweep method is implemented, and the TPBVP is to be regarded as a nonlinear equation with respect to the costate at  $t = 0$  as

$$F(\lambda(0); x(0); T; t) = (\lambda(T); t)^T [x(T; t); p(t+T)] = 0 \quad (20)$$

In order to reduce the error associated with the integration, a stabilized continuation method is used as follows:

$$\frac{dF}{dt} = A_s F \quad (21)$$

where  $A_s$  denotes a stable matrix to make the solution converge to zero.

Here, a linear differential equation is produced based on the previous equations:

$$\begin{aligned} \frac{d}{dt} \begin{bmatrix} \lambda \\ x \end{bmatrix} &= \begin{bmatrix} C & A^T \\ A & B \end{bmatrix} \begin{bmatrix} \lambda \\ x \end{bmatrix} \end{aligned} \quad (22)$$

where  $A = f_{xx} - f_u H_{uu}^{-1} H_{ux}$ ,  $B = f_u H_{uu}^{-1} f_u^T$ ,  $C = H_{xx} - H_{xu} H_{uu}^{-1} H_{ux}$ .  $p_t$  and  $p$  are canceled in Eq.(22).  
The derivative of the nonlinear function F with respect to time is given by

$$\frac{dF}{dt} = (\lambda; t)^T \begin{bmatrix} f_{xx} & f_{xp} \\ f_{xp} & f_{pp} \end{bmatrix} \begin{bmatrix} x(T; t) \\ p(t+T) \end{bmatrix} + [(\lambda; t)^T \begin{bmatrix} f_{xx} & f_{xp} \\ f_{xp} & f_{pp} \end{bmatrix} \begin{bmatrix} x(T; t) \\ p(t+T) \end{bmatrix}] \frac{dT}{dt} \quad (23)$$

The relationship between the costate and other variables is expressed as:

$$\begin{bmatrix} \lambda \\ x \end{bmatrix} = S(\lambda; t) \begin{bmatrix} x_t \\ x \end{bmatrix} + c(\lambda; t) \quad (24)$$

where

$$\begin{aligned} S &= A^T S + SA + SBS + C \\ c &= (A^T + SB)c \end{aligned} \quad (25)$$

The following conditions must hold:

$$\begin{aligned} S(T; t) &= f_{xx}^{-1} j = T; \\ c(T; t) &= (H^T + f_{xx}^{-1} f_{xp} + f_{pp}^{-1} p) j \left(1 + \frac{dT}{dt}\right) + A F; \end{aligned} \quad (26)$$

$$\frac{d}{dt} \begin{bmatrix} \lambda \\ x \end{bmatrix} = \begin{bmatrix} H^T \\ f_{xx} \end{bmatrix} + c(0; t); \quad (27)$$

The basic idea of the backward sweep method is to integrate Eqs.(17) forward and integrate Eqs.(25) backward along the axis at each time t. Then the differential equation of  $\lambda(t)$  is integrated for one step along the t axis so as to determine the optimal control effort from Eq.(19)

## IV. Implementation Method

To demonstrate the outcomes and assess the capabilities of proposed algorithm, the computational power of Simulink and Matlab are utilized. For demonstration of the algorithm, the system at hand has been simplified to a xed-direction 2D level flight. The wind is defined as a constant eastward wind, with a heading of 90° from true North.

Based on these assumptions, for steady-level flight, the coefficient of lift can be redefined as:

$$C_L = \frac{2mg}{V^2S} \quad (28)$$

Additionally,  $\delta = 0$ ,  $\sigma = \bar{\sigma}$ ,  $h$  is a constant and  $\dot{h}$  is zero. Eqs.(1-6) are rewritten with the aforementioned changes incorporated.

$$\frac{P}{V} = \frac{2m}{V^2S} C_{D0} + \frac{2mg^2K}{V^2S} + W_V \quad (29)$$

$$\frac{w}{V} \quad (30)$$

$$\underline{x} = V \sin(\theta) + W_x \quad (31)$$

$$\underline{y} = V \cos(\theta) + W_y \quad (32)$$

The aircraft parameters used for this simulation are similar to those of an MQ-1 Predator drone, however, the powerplant is assumed to be electric so there is no change in mass over the duration of the flight. The aircraft parameters are as follows:

$$m = 2250(\text{lb})$$

$$b = 48.7(\text{ft})$$

$$S = 123.3(\text{ft}^2)$$

$$C_{D0} = .01$$

$$e = .9$$

$$P_{\max} = 63250 \left( \frac{\text{ft} \cdot \text{lb}}{\text{s}} \right)$$

$$C_{L_{\max}} = 2.2$$

Using weighting matrices and reference trajectory tracking parameters, a simulation is conducted to evaluate the desired performance of the proposed real-time optimization algorithm.

## V. Results

Through implementation of the real-time non-linear receding horizon control algorithm, the following simulation results are obtained. For this specific scenario, we demonstrated a constant heading angle flight ( $\theta = 90[\text{deg}]$ ) with a constant East wind (20[ft/sec]). The preliminary results clearly demonstrate the applicability of the algorithm to the system at hand and the power saving benefits. Given a cost function that penalizes fuel consumption (i.e. power), in presence of any deviation from a desired reference trajectory, the system attempts to minimize the power used to fly the aircraft. If the minimum velocity is reached, the aircraft will adjust its power to keep from losing more speed, and maintain minimum power flight, when applicable.

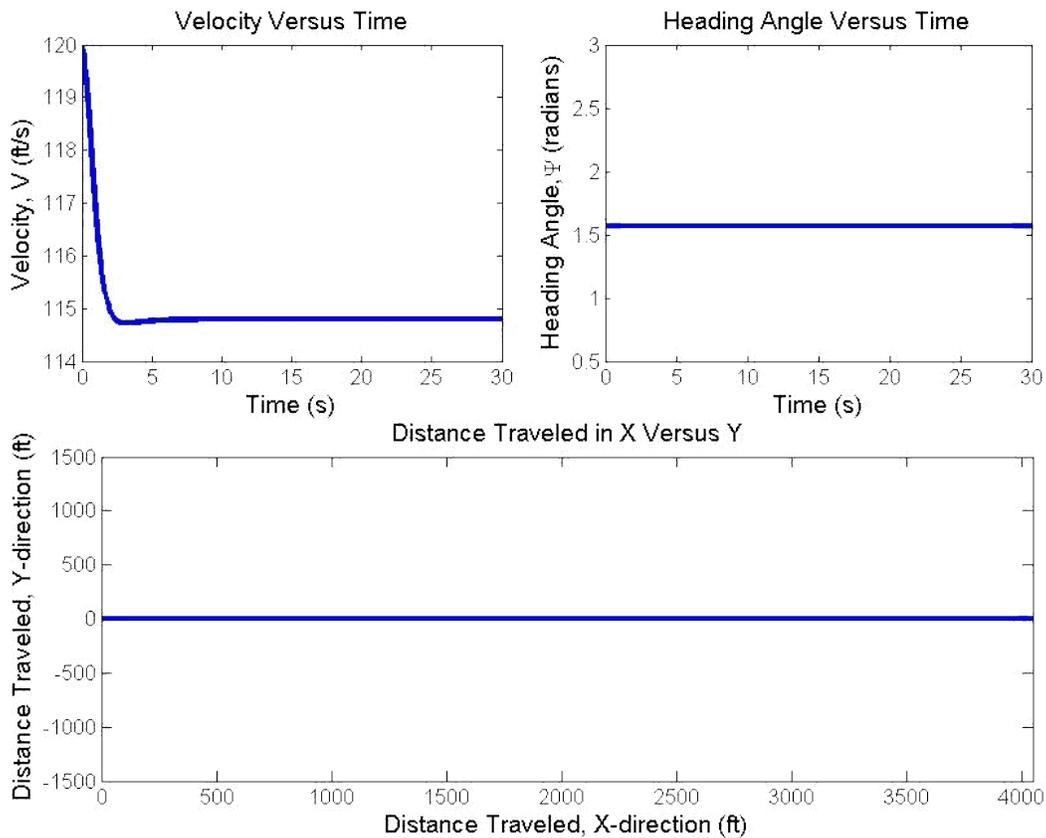


Figure 1. Velocity Versus Time

As can be seen from the Figure-1, for the flight scenario where the wind speed is defined as 20[ft/sec] (East), aircraft is able to minimize its airspeed and therefore reduce its power consumption, through Eq. (8), while still maintaining its flight course (i.e. fixed heading angle). This demonstrates the applicability and benefits of the concept for power minimization in optimal guidance strategies in the presence of wind.

## VI. Conclusion

This paper has presented an approach for a UAV to take advantage of the energy gains available in flying optimal trajectories with respect to current air currents. Aircraft dynamics are modeled by a 3D point mass model, where constant wind is taken into account for level flight conditions. With the utilization of nonlinear receding horizon control methodology and in presence of favourable wind conditions, we demonstrated the reduction in airspeed, which corresponds to minimized value of power, thus fuel savings throughout the flight. In future work, the approach suggested will be extended to include the time varying nature of the wind.

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