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A comparative assessment of hierarchical control structures for spatiotemporally-varying systems, with application to airborne wind energy☆

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ABSTRACT

Optimal control in a spatiotemporally varying environment is difficult, especially if the environment is partially observable. Altitude optimization of an airborne wind energy (AWE) system, in which the tower and foundation of a contemporary wind turbine is replaced by tethers and a lifting body, is a challenging problem of this kind. The wind velocity changes both spatially and temporally, and it can only be measured at the altitude where the system is flying, making the problem partially observable. In this work, we propose and evaluate hierarchical structures for the aforementioned problem, which fuse coarse, global for the chosen grid resolution and prediction horizon, where applicable control with fine, local control. These controllers leverage the advantages of both fine, local and coarse, global control schemes, while addressing their limitations. We show through simulation, using the real wind velocity data, that the hierarchical structures outperform legacy control strategies in terms of net energy generation.

1. Introduction

Optimal control in environments that vary both in time and space is a challenging task. It becomes even harder when the environment is partially observable. In addressing this problem, the literature has traditionally focused on centralized control schemes, which are effective for a number of applications but are often limited in applicability and/or computationally burdensome. For example, a H_2-optimal control approach is used in Hinnen, Verhaegen, and Doelman (2007) for real-time compensation of the optical wave front distortions introduced by a turbulent medium. Optimization of multi-robot reconnaissance is another example of spatiotemporal optimization. In Quann, Ojeda, Smith, Rizzo, Castanier, and Barton (2017), the uncertainty of a spatiotemporal field prediction is minimized to optimize multi-robot waypoint while it is required to ensure that the robots can return to fueling spots before they run out of fuel. Autonomous soaring of unmanned aerial vehicles (UAV) also involves optimization in a spatiotemporally varying environment (Daugherty & Langelaan, 2013).

In addition to many other applications, altitude optimization of airborne wind energy (AWE) systems is an important partially observable, spatiotemporally varying problem. Available wind resources for contemporary wind turbines are limited by the hub height. Considering the fact that the tower and associated foundation of the wind turbine often represent as much as a quarter of the system cost, it is not economically viable to manufacture wind turbines with hub height greater than 220 m (MHI Vestas Offshore Wind, 2017). The idea of AWE systems is to utilize a lifting body (a kite, aerostat, or rigid wing) and tethers as a replacement for the relatively expensive tower and foundation of a contemporary wind turbine. This exposes the system to strong, consistent, high-altitude winds. Additionally, the altitude of the system can be adjusted to search for wind speeds that align more closely with the rated wind speed of the turbine.

A large body of research in the control and optimization of AWE systems has focused on kite- and wing-based systems that employ crosswind motion to harness significantly more energy than can be generated under stationary operation. For example, in Fagiano, Milanese, and Piga (2012), an optimal control law is applied to the KiteGen system, and the generator operating cycle is optimized. The authors of Gros, Zanon, and Diehl (2013) introduced fictitious forces and moments at critical stages of the dynamics to solve a modified and relaxed optimization problem instead of the non-convex optimal control problem of kite-based AWE systems. General crosswind path parameters are optimized in Zgraggen, Fagiano, and Morari (2015) and Zgraggen, Fagiano, and Morari, (2013) to maximize traction force and output power. Numerical

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optimization of an AWE system trajectory is studied in Horn, Gros, and Diehl (2013). The lab-scale evaluation of closed-loop optimal control of an AWE system in crosswind motion is studied in Cobb, Deodhar, and Vermillion (2017b). Combined plant/controller optimization of tethered AWE systems in crosswind motion is studied in Nikpoorparizi, Deodhar, and Vermillion (2017), where it is shown that the optimal performance under crosswind motion occurs when the system is on the verge of closed-loop instability. The waypoints that describe an AWE system's figure-8 crosswind path are optimized using iterative learning control in Cobb, Barton, Fathy, and Vermillion (2017a). A model predictive controller for autonomous figure-of-eight flight for a kite-based AWE system is developed in Wood, Hesse, and Smith (2017b). Similarly, a predictive guidance controller is designed in Wood, Ahbe, Hesse, and Smith (2017a) for autonomous flight of kites. The authors of Diwale, Faulwasser, and Jones (2017) propose a nonlinear path following MPC for a kite-based AWE system and guarantee the closed-loop stability by introducing a terminal constraint similar to vector field control schemes which are often used in aerial vehicles.

In contrast, a relatively small body of literature has focused on the use of strategic altitude adjustment to maximize the net energy generation of an AWE system. Within this body of literature, Vermillion (2013), Vermillion and Fagiano (2013) assume that wind shear profile is deterministic and monotonic, and therefore implicitly assume that it is possible to predict the optimal operating altitude. However, it has been observed, based on available wind speed data (see Bafandeh & Vermillion, 2016, 2017), that the wind shear profile changes stochastically with time. There, Bafandeh and Vermillion (2016, 2017) demonstrate the use of an extremum seeking (ES) controller to optimize the altitude of the AWE system. The size of the sinusoidal perturbation is decreased upon convergence to the optimum point, using a Lyapunov-based switch. A heuristic probability model of spatiotemporally changing wind speed, conditioned on previous observations, is introduced in Bin-Karim, Bafandeh, and Vermillion (2016), where a model predictive controller (MPC) uses the conditional probability model to search for the optimum operating altitude in real time. Bayesian optimization (BO) is another tool, used by Baheri and Vermillion (2017), for altitude optimization of AWE systems. Specifically, the underlying objective function is modeled by a Gaussian Process (GP); then, BO utilizes the predictive uncertainty information from the GP model to determine the best subsequent operating altitude.

The aforementioned MPC and Lyapunov-based switched ES (LSES) control strategies have their own pros and cons. While LSES is computationally inexpensive, it only guarantees local convergence to the optimum. Moreover, LSES as introduced in Bafandeh and Vermillion (2017) does not utilize the available wind velocity data, measured prior to or during the course of operation. On the other hand, MPC is capable of employing global optimization tools for minimizing its underlying cost function. However, the global nature of the solution is limited to the finite horizon length of the MPC optimization and the grid resolution used by the underlying dynamic programming or exhaustive search. This becomes particularly important when the optimization is performed over a partially-observable randomly-varying environment, where uncertainty (modeled through a standard deviation of variance of an estimated state) must be included as a part of the system state in order to use deterministic optimization tools. The MPC controller proposed in Bin-Karim et al. (2016) relies on sequential quadratic programming (SQP) for the minimization of the underlying cost function, thereby leading to computational efficiency, but only guaranteeing convergence to local optima.

A critical evaluation of the aforementioned previous results reveals a trade-off between coarse, global optimization techniques and fine, local ones. In this work, we propose three novel mechanisms for fusing coarse, global techniques with fine, local ones in a hierarchical framework. Specifically, we address the following questions:

- What data should be exchanged between different control levels?

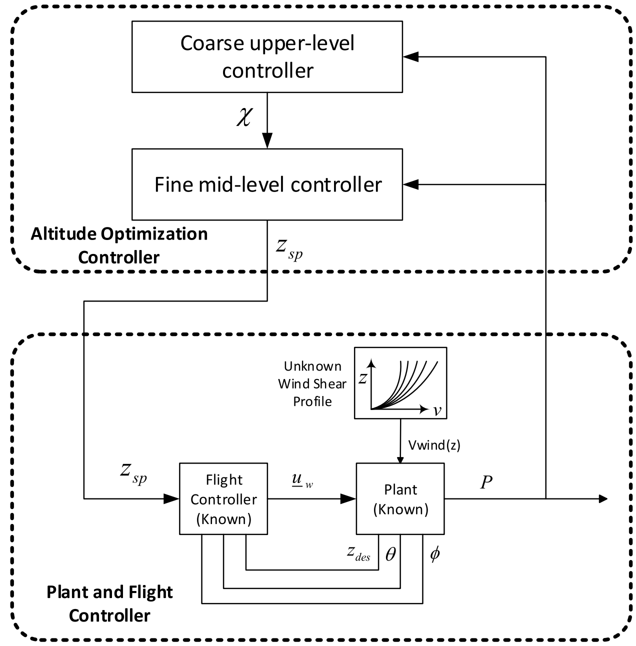

Fig. 1. Basic block diagram showing the common proposed hierarchical altitude control structure for an AWE system.

- What is the best hierarchical configuration based on MPC and LSES for the partially observable spatiotemporally varying problem at hand?

In fact, the answer to the first question depends on the choice of the controller for the different layers of the hierarchy. Fig. 1 provides a generic block diagram of the basic hierarchical control structure under consideration. In this block diagram, the variable χ, which is passed from the upper-level controller to the mid-level controller, represents a distinguishing feature between the three candidate control strategies.

The candidate hierarchical control strategies considered in this work build on our recent conference publication, Bafandeh, Bin-Karim, and Vermillion, (2017), which considers a simple hierarchical strategy wherein a global (up to the horizon length and grid resolution) MPC optimization acts as an advisory input to a fine, local LSES controller. For the hierarchical architectures considered in this work, Table 1 shows the controller options for upper and middle levels. In the first candidate control strategy, an upper-level coarse, global MPC selects an altitude set-point that dictates the local domain of altitudes that can be explored by a mid-level LSES controller. In the second candidate strategy, an upper-level coarse, global MPC selects an altitude that dictates the local domain of altitudes that can be explored by a fine mid-level MPC optimization. In these two controllers, the upper level MPC finds the global optimum up to the grid resolution and finite horizon length, and the mid-level controller explores within the optimal altitude "bin". Finally, in the third candidate strategy, the upper-level controller estimates the difference between the optimal power output of the system and the output at the present altitude; this estimated difference, termed the surrogate power deficit, is used to adjust the perturbation amplitude for a mid-level LSES controller.

The hierarchical control structure of Fig. 1 also includes a lower-level flight controller that regulates altitude to its set-point, along with a turbine torque controller. The turbine torque controller is similar to the system described in Pao and Johnson (2011), and the flight control system for the Altaeros BAT is discussed in Vermillion, Grunnagle, Lim, and Kolmanovsky (2014). Because these lower-level controllers have been validated through simulations and experiments in legacy work, they are not the focal point of this work.