On Wind Speed Sensor Configurations and Altitude Control in Airborne Wind Energy Systems

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Abstract—Real-time altitude control of airborne wind energy (AWE) systems can improve performance by allowing turbines to track favorable wind speeds across a range of operating altitudes. The current work explores the performance implications of deploying an AWE system with sensor configurations that provide different amounts of data to characterize wind speed profiles. We examine various control objectives that balance trade-offs between exploration and exploitation, and use a persistence model to generate a probabilistic wind speed forecast to inform control decisions. We assess system performance by comparing power production against baselines with few sensors, control strategies that reward exploration are favored. We also show that with comprehensive sensing, such as omniscient control and stationary flight, we show that performance by comparing power production against baselines. We assess system performance by comparing power production against baselines that provide different amounts of data to characterize wind speed profiles. We examine various control objectives that balance exploration and exploitation. More specifically, these objectives balance the trade-off between capitalizing on known wind resources (exploitation) and collecting observations at altitudes where wind speed estimates are uncertain (exploration), given that wind speed profiles are only partially observable and that altitude adjustments are costly to make. Over time, control decisions favoring exploration can reduce uncertainty in wind speed models, though doing so may come at a cost to near-term performance. We refer readers to [12] for information on Bayesian optimization and a more detailed discussion of the trade-off between exploration and exploitation.

In the context of AWE system altitude control, this trade-off is directly related to uncertainty in wind speed estimates that inform control decisions. A survey of state-of-the-art algorithms for forecasting wind power production is given in [13]. Many of the algorithms cited require large training data sets. Training such algorithms may not be possible for AWE systems which typically rely on sparse data streams collected online. Observations are sparse because wind speeds are recorded by a single sensor that tracks (vertically) with the operating altitude of the turbine. A simpler persistence model is also shown to perform quite well, and is recommended as a benchmark for evaluating the performance of more complex wind forecasting algorithms.

Aside from using complex forecasting algorithms, uncertainty in wind speed can be reduced by increasing the spatial coverage of wind speed sensors. For example, if wind speeds were recorded continuously at all altitudes, a simple forecasting model (e.g. the persistence model) may be able to outperform a system that uses a more sophisticated forecasting model trained on single sensor data. This possibility motivates a comparative analysis of different sensor configurations and forecasting methods for AWE altitude control, an issue currently unexplored in the literature.

The main contribution of the current work is to develop a framework for evaluating performance gains achievable using different wind speed sensor configurations. We demonstrate this framework with a case study of a particular wind field. We use the control objectives proposed in [11] to determine the optimal altitude trajectory. Questions related to the performance gains from coupling sensor data with different statistical forecasts are reserved for future research.

This paper is organized as follows. Section II provides methodological details. Section III outlines the sensor configurations. Section IV details the forecasting methods. Section V formulates the altitude control objectives. Section VI describes the comparative analysis benchmarks and metrics. Section VII provides the results and discussion. Finally, Section VIII summarizes the paper’s main conclusions.
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A. Single-sensor configuration
sophisticated wind forecasting methods.
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objectives presented in [11] to do so, and leave it to future
50 meters in 30 minute intervals. We use the same spatial
and temporal discretization in simulation.
We examine single-sensor, multiple-sensor and remote
sensor configurations. We track the wind speed measure-
ments that would be recorded online given a particular
sensor configuration and the altitude trajectory followed up
to a particular point in time. Observations are used to
train a persistence model that generates a probabilistic wind
speed forecast. We use three different control objectives
to determine the optimal altitude trajectory given the current
wind speed forecast.
Altitude trajectories are generated for a range of scenarios,
each of which uses:
1) One of three control objectives
2) One of three sensor configurations
3) A persistence forecast
The current work examines differences in power production
with each sensor configuration. We build on the control
objectives presented in [11] to do so, and leave it to future
work to explore the performance implications of using more
sophisticated wind forecasting methods.

II. METHODS
In this work we simulate the altitude trajectory of a
buoyant airborne turbine (pictured in Fig. 1) in a spatially
and temporally varying wind field. The simulation relies on wind
speed data recorded by a 915-MHz wind profiler between
July 1, 2014 and August 31, 2014 at Cape Henlopen State
Park in Lewes, DE [5]. Wind speed data are measured every
50 meters in 30 minute intervals. We use the same spatial
temporal discretization in simulation.
We examine single-sensor, multiple-sensor and remote
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speed forecast. We use three different control objectives
to determine the optimal altitude trajectory given the current
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Altitude trajectories are generated for a range of scenarios,
each of which uses:
A. Single-sensor configuration
AWE systems are typically designed with a single
anemometer to measure the wind speed at the current op-
erating altitude. The vertical position of these measurements
changes when altitude adjustments are made.
B. Multiple sensor configuration
A novel sensor design would be to record wind speed
measurements along the length of the tether. The system is
still considered partially observable as wind speeds are not
measured above the hub height. However, flying the turbine
at the highest altitude within operating bounds would provide
a complete wind speed profile.
The focus of the current work is to assess the performance
implications rather than to explore sensor technologies them-
sehves. However, we have identified several technologies that
could collect these measurements. One option is to affix
anemometers in regular intervals along the tether, which
provides reliable wind speed measurements at altitudes below
the AWE system but requires a winch system to house the
anemometers upon spool-in. Another alternative is to attach
telltales to the tether and use image processing to estimate
wind speeds from the angle of the telltale relative to the
tether. Finally, one could potentially compute local wind
velocities based on the catenary geometry of the tether,
though to do so would require a detailed characterization
of the tether’s structural and aerodynamic properties. Further
research is needed to assess the technical and economic feas-
ibility of specific solutions for collecting these measurements.

C. Remote sensor configuration
The third configuration relies on a remote sensor to record
wind speed measurements in discrete intervals across a
wide range of altitudes simultaneously. For example, the
wind data we use to inform our simulation was collected
using a vertical profiler that measures wind speeds in 50
meter increments. With remote sensing wind speed profiles
are fully observable at each time step. Because the same
measurements are recorded regardless of the current position
of the turbine, this configuration decouples data acquisition
from altitude control. The implication is that exploring the
wind field for data acquisition is not necessary, and that
control decisions can focus instead on exploitation of known
wind resources.

IV. PERSISTENCE FORECAST
We use a persistence model adapted from [13] to generate
a probabilistic wind speed forecast. We extend the model
to extrapolate wind speeds into the spatial domain, and to
characterize uncertainty. The persistence model is based on
the premise that wind speeds change very little (or not at all)
from one time step to the next. The spatial extension of this
model presumes that there is little (or no) change vertically
either. Based on this premise, the forecast mean \( \mu \) at altitude
\( h \) and \( s \) time steps into the future is given by:

\[
\mu_{h,t+s} = X_t(h')
\]

where \( X_t(h) \) describes the wind speed observation recorded
at time \( t \) and altitude \( h \). We define \( h' \) to be the measurement
altitude in \( X_t \) that is either equal to the forecast altitude
\( h \), or is nearest to it. For example, with multiple sensors, \( h' \)
would be equal to \( h \) for altitudes below the current operating
altitude, and would equal the current altitude (i.e., the highest
observable altitude) otherwise. The fundamental assumption
is that the measurement \( X_t(h') \) recorded at \((h', t) \) persists
across all unobserved times and altitudes.
We characterize uncertainty by estimating how erroneous the assumption of persistence could be based on past observations. We define $\Delta$ to be a matrix composed of column vectors $\Delta X/\Delta h$ and $\Delta X/\Delta t$ describing the finite differences between measurements in $X$ in space and time. Based on an exploratory analysis of the data, we characterize $\Delta$ as a joint Gaussian distribution with zero mean.

Next, we define the vector $d$ describing the distance in space $(h-h')$ and in time $(s)$ between the current observation ($X_t(h')$) and the forecast. We can then characterize forecast uncertainty ($\sigma^2$) as:

$$\sigma^2_{h,t+s} = \Sigma (d\Delta T) = d\Sigma(\Delta)d^T$$

Here $\Sigma(\Delta)$, for example, is the covariance of $\Delta$.

Where forecast uncertainty is high, we truncate the distribution between 0 and 17 m/s to ensure that high uncertainty does not lead to unrealistic predictions. We find that 98% of all observations in the data are within these bounds. We assume that the underlying distribution of $\Delta$ is stationary, though characterizing non-stationarity in wind speed dynamics presents an interesting opportunity for future work.

V. CONTROL METHODS

We describe altitude control using the following simple integrator dynamics:

$$h(t + 1) = h(t) + u(t)$$

where $h(t)$ is the altitude at discrete time index $t$, and $u(t)$ is the controlled altitude adjustment.

The control objective at a given time $t$ is to select the trajectory of optimal future operating altitudes $\{h^*(t + 1), h^*(t + 2), \cdots\}$ and controlled altitude adjustments in $\{u^*(t), u^*(t + 1), \cdots\}$ that maximize some objective function, given the wind speed forecast $V_t$. We express this objective $J$ mathematically as:

$$\max_{h(t), u(t)} J = \sum_{s=t}^{t+T} g(h(s), u(s), V_{th,s})$$

Here $V_{th,s}$ refers to a random wind speed forecast for all candidate altitudes $h$ at time $s$, and $T$ is the planning horizon.

The problem is constrained such that operating altitudes are bounded within $h_{\min}$ and $h_{\max}$, and the rate of change in altitude is below $r_{\max}$.

$$h_{\min} \leq h(t) \leq h_{\max}$$

$$|u(t)| \leq r_{\max}$$

Table I provides numerical values for operating constraints.

This formulation uses model predictive control to optimize the control and state trajectories over the upcoming $T$ time-steps given the current state $h(t)$, dynamical model $\beta$ and wind speed forecasts for all altitudes. Only the first control action $u^*(t)$ is physically implemented, and the process is repeated using the measured state in the next time step.

We use a planning horizon of 90 minutes (or three 30-minute time steps). Given the values listed in Table I, the planning horizon is sufficient for the turbine to travel between any two operating altitudes. We use dynamic programming to solve for the optimal trajectory at each time step.

We examine three formulations of $g(h, u, V)$ that aim to maximize power production. These formulations differ in how they account for uncertainty in power production (which stems from uncertainty in wind speed forecasts). Although the objective function differs for each formulation, the long-term goal is always to maximize power production.

Equation (6) lists the system of equations used to calculate power production, as described in [10]. Here power production $p(u(t), v)$ is a function of the altitude adjustment during some time interval $u(t)$ and the true wind speed $v$.

$$p(u, v) = p_1 - p_2 - p_3$$

$$p_1 = k_1 \cdot \min\{v_r, v\}^3$$

$$p_2 = k_2 v^2$$

$$p_3 = k_3 v^2 \cdot |u|$$

In words, the total power production $p(u, v)$ is the difference between the amount of energy the turbine generates ($p_1$) and the amount of energy required to maintain ($p_2$) and to adjust ($p_3$) the operating altitude. The rated wind speed of the turbine is given by $v_r$, and $k_1$, $k_2$ and $k_3$ describe lumped parameters representing the mechanical and aerodynamic properties of the system. Numeric values for these constants are provided in Table I.

We highlight that $p_1$ is maximized when $v$ is equal to $v_r$. However, $p_2$ and $p_3$ continue to increase at wind speeds greater than $v_r$. The implication is that $p(u, v)$ increases as $v$ approaches $v_r$, but decreases if $v$ increases beyond $v_r$.

The wind speed $v$ can represent either a measurement reported in the data, or some realization of the wind speed forecast. In order words, if $V_{th,t}$ is a random variable describing the wind forecast at altitude $h$ and time $t$, then we can use the function $p(\cdot)$ to derive a probabilistic forecast of power production, denoted by $P_h$.

In the following sections we describe three candidate formulations of $g(h, u, V)$. Though the specific objective functions are different, the aim of all three formulations is to maximize overall power production. The objective functions are borrowed from Bayesian optimization, and their

| Variable | Value |
|----------|-------|
| $h_{\min}$ | 0.15 km |
| $h_{\max}$ | 1.0 km |
| $r_{\max}$ | 0.01 km/min |
| $v_r$ | 12 m/s |
| $\Delta t$ | 30 min |
| $T$ | 90 min |
| $k_1$ | 0.0579 kW s/m$^3$ |
| $k_2$ | 0.09 kW s/m$^2$ |
| $k_3$ | 1.08 kW s/m$^2$ \cdot km |
application to real-time control of AWE systems is motivated in [11].

Though the formulations we use are conceptually the same as the control objectives presented in [11], we have adapted them in two important ways. First, we optimize over a finite planning horizon extending $T$ time steps into the future. Second, we use a probabilistic wind speed forecast to compute a probability distribution of power production. Since power production is a nonlinear function of wind speed, the power production is not Gaussian, and generally does not follow a parametric distribution. As shown below, our approach handles non-parametric distributions directly, and does not require parametric approximations.

A. Maximize Expected Energy

The first control strategy chooses the altitude trajectory that maximizes expected power production across time steps within the planning horizon. This can be viewed as an exploitative control approach, in the sense that no reward within the planning horizon. This can be viewed as an alternative to purely explorative methods, except insofar as they reward acquisition of new data that reduces long-run uncertainty in the wind speed forecasts. As uncertainty bounds become narrow, the difference in power production between control objectives favoring exploration and exploitation also decreases.

B. Performance baselines

The omniscient baseline (described below) provides just harvesting in the omniscient baseline. We refer to this quantity as the “actualized power ratio” (as in Figs. 3 and 4).

C. Maximize Probability of Improvement

The last control strategy selects the altitude trajectory with the highest probability of improving performance relative to maintaining the current altitude. We calculate the probability of improvement by taking the log probability that power production for a particular trajectory will exceed power production if the altitude were to remain fixed at current altitude $h$. Mathematically, this is expressed in (10).

\[ g(h, u, V) = \log \Pr (P_{h+u,t} > p(0, v)) \]  

where $P_{h+u,t} = p(u, V_{h,t})$ is a random variable describing power generation at altitude $h + u$, and $p(0, v)$ is the current power output (i.e., no altitude adjustment $u = 0$ and assuming wind speed $v$ stays constant).

VI. PERFORMANCE METRICS AND BASELINE SCENARIOS

In the current section we define metrics and benchmarks to evaluate the performance of each sensor configuration and control strategy. We calculate these metrics and benchmarks by simulating the altitude trajectory over the course of three months.

A. Performance metrics

The most fundamental metric we use to evaluate performance is average power production (in kW). Though power production could be compared against the nameplate capacity (in this case 100 kW), this is not a practical target as it is not physically possible to achieve that level of performance. A more practical target would need to account for the physics of the simulation environment, including variations in wind speed and the energy required to adjust and maintain altitude. The omniscient baseline (described below) provides just such a target. In addition to reporting power production, we express performance as a ratio (between 0 and 1) of the energy harvested in a particular scenario and the energy harvested in the omniscient baseline. We refer to this quantity as the “actualized power ratio” (as in Figs. 3 and 4).

B. Performance baselines

1) Omniscient baseline: The omniscient baseline is obtained by simulating the altitude trajectory the AWE would follow if perfect information were available to inform control
decisions. The result provides an upper limit on power production, given the characteristics of the wind field and the specified operating constraints.

2) **Fixed altitude baseline:** We also compare our results against baselines where the altitude is fixed for the entire simulation at the altitudes that would achieve the highest ($h_{\text{max}}$) and lowest power production ($h_{\text{min}}$). Though these provide a useful basis for comparison, we note that it is not possible to know $h_{\text{max}}$ or $h_{\text{min}}$ without omniscient information about the wind speeds at each altitude.

Unlike the omniscient baseline, fixed altitude trajectories do not bound system performance. Instead, they provide a benchmark against a naïve, but possibly effective, control strategy. A real-time control scheme can under-perform relative to a fixed altitude trajectory if control decisions are made based on sufficiently erroneous wind speed forecasts, or if the power production observed at the new operating altitude does not compensate for the energy expended in making the altitude adjustment.

### VII. Results and Discussion

Here we summarize the performance of an AWE system evaluated in simulation for nine scenarios. What differentiates each scenario is the specific combination of sensor configuration and control scheme used to inform altitude adjustments. A persistence forecast is trained on observational data collected in simulation, given the sensor configuration and altitude trajectory up to that point. We examine a range of values for $\alpha$ in the upper confidence bound (UCB) control and report results for the value that achieves the highest performance in each sensor configuration. We compare the performance in each scenario against the omniscient and fixed altitude baselines.

Fig. 2 shows the altitude trajectory over one week in August for the omniscient baseline and four control schemes in the multiple-sensor scenarios. Commenting on the similarities and differences between trajectories highlights the merits (and pitfalls) of using a particular control scheme with each sensor configuration.

**Observation 1:** Though altitude trajectories follow very different patterns at times when the wind speed is low (e.g., July 11-13), they all follow a relatively fixed course when wind speeds are high (e.g., July 8-9). The reason for this is that $p_1$ is constant for wind speeds in excess of $v_r$, while $p_2$ and $p_3$ continue to increase. The incentive to explore is only in place if the potential increase in power production exceeds the cost of making altitude adjustments. When the wind speeds are near or in excess of $v_r$, a fixed altitude is favored because exploration comes at a relatively high cost without the possibility of increasing power production.

**Observation 2:** Maximizing the probability of improvement leads to a fixed altitude trajectory in both the single- and multiple-sensor cases. The reason for this is that wind speed forecasts are centered around the current observation. In other words, the forecast estimates that exploring some unobserved altitude is equally likely to reduce performance as to improve performance. Thus the probability of improvement is only 50%, and control decisions favor maintaining a constant altitude to avoid power loss from making altitude adjustments.

Though the objective to maximize expected energy is also centered about the current observation, control decisions in that case are informed not only by the probability but also the magnitude of improvement potential. Since the magnitude of improvement scales with $v^4$, the distribution of $p$ is skewed to the right and there is some incentive to explore.

**Observation 3:** In the multi-sensor case, when the objective is to maximize the upper confidence bound (UCB), trajectories tend towards higher altitudes rather than lower altitudes. This happens because the uncertainty is greater at unobserved altitudes above the current hub height than at altitudes where current measurements are available. This high uncertainty creates a strong incentive to explore higher altitudes. However, once the highest altitude is reached, the system becomes completely observable and uncertainty is equal at all altitudes, so exploitation is favored.

At this point the trajectory will tend downwards if the best wind resource is below the uppermost altitude. Decreasing the hub height also makes the system only partially observable, reinstating the reward to explore higher altitudes. This process repeats, causing the oscillations observed in the lowermost panel in Fig. 2. These oscillations come at a high energy cost and do not necessarily lead to gains in overall performance. We examine how energy is allocated when $\alpha$ is set to 0.7, and compare it against energy allocation when the optimal value (0.54) is used. Although the higher incentive to explore leads to a 4% increase in power production ($p_1$), the system expends twice as much energy on altitude adjustments ($p_3$). The additional energy cost leads to a 3% reduction in overall performance. Fig. 3 shows that performance tends to decrease as $\alpha$ increases.

Fig. 4 summarizes overall power production across the
Performance declines as system with only a single sensor. Fig. 3 shows that although multiple sensors, and by 15% compared with deploying the system with three-month simulation in all nine scenarios, and compares the best (dashed line) and worst (dotted line) fixed altitude trajectories. Performance is measured in terms of average power production (left y-axis) and in terms of the “actualized power ratio” between power production and the omniscient baseline (right y-axis).

Our results show that the remote sensor improves performance by 11% compared with deploying the system with multiple sensors, and by 15% compared with deploying a system with only a single sensor. Fig. 3 shows that although performance declines as $\alpha$ increases, the remote sensor consistently outperforms the other two sensor configurations. In all scenarios the multiple and single-sensor cases perform about on par with the optimal altitude ($h_{best}$) for stationary control. In practice, however, it is not possible to know $h_{best}$ in advance.

These results are based on the highest performing control strategy for each sensor configuration. However, the optimal value for $\alpha$ is not known a priori, and likely depends on many factors such as the spacing of sensors and the characteristics of the wind field. Fig. 3 shows that the consequences of choosing a sub-optimal control strategy are particularly severe in the multiple sensor configuration.

Finally, Fig. 3 shows that heavily rewarding exploration may slightly improve performance in the single-sensor configuration, but actually decreases performance in the multi-sensor configuration. This decline in performance is due to the altitude oscillations discussed in Observation 3.

VIII. CONCLUSIONS AND FUTURE WORK

In this work we report on differences in AWE performance achieved in simulation using various different control strategies and wind speed sensor configurations. The key difference between the control strategies is how (or if) uncertainty in the forecast is incorporated into the control objective.

We demonstrate that an AWE system with remote sensing equipment can achieve a high level of performance using the most recent measurement to inform control decisions. As the amount of information available to characterize wind speed profiles decreases, forecast uncertainty increases and performance declines.

Both results are related to the quality of the wind speed forecast, raising the question: Can a high-fidelity statistical model improve performance and/or close the gap in performance between different sensor configurations? Our work underscores the need for further research exploring statistical methods for characterizing vertical wind speed profiles.

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