Enhancing Control System Resilience for Airborne Wind Energy Systems Through Upset Condition Avoidance

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Airborne wind energy (AWE) systems are tethered flying devices that harvest wind resources at higher altitudes which are not accessible to conventional wind turbines. In order to become a viable alternative to other renewable energy technologies, AWE systems are required to fly reliably for long periods of time without manual intervention while being exposed to varying wind conditions. In the present work a methodology is presented, which augments an existing baseline controller with a prediction and prevention methodology to improve the resilience of the controller against these external disturbances. In the first part of the framework, upset conditions are systematically generated in which the given controller is no longer able to achieve its objectives. In the second part, the generated knowledge is used to synthesize a model that predicts upsets beforehand. Eventually, this allows to trigger an avoidance maneuver which keeps the AWE system operational, however, leads to a lower power production. The methodology is applied to the specific case of tether rupture prediction and prevention. Simulation results are used to demonstrate that the presented methodology leads indeed to a predictable economic benefit over systems without the proposed baseline controller augmentation.

I. Introduction

Operating airborne wind energy (AWE) systems reliably requires sophisticated control strategies that try to exploit the full physical capabilities of the system for maximum power generation without compromising safety. The major part of the existing literature about AWE control systems focuses on the former part, to optimize the power output using trajectory optimization, see for instance [1–4]. The only recent publication that analyses reliability and safety of AWE systems is [5], which presents a failure mode and effect analysis along with a fault tree analysis for a flexible wing kite power system. This imbalance between performance optimization and reliability analysis indicates that more research is necessary to investigate how the resilience and robustness of AWE control systems can be improved, which motivates the present work.

AWE systems need to operate in varying environmental conditions such as slowly varying wind speeds due to the
wind shear effect but also need to cope with rapid changes due to wind gusts and turbulence. Because of the inherent stochastic nature of the wind conditions it is difficult to explicitly include them in the control design process. In practice, the closed loop system is verified a posteriori for randomly generated wind conditions, as presented, for instance, in [6]. If the controller fails to satisfy all requirements, it needs either to be re-tuned or completely re-designed. To create enough confidence that the controller achieves its objective, a large amount of simulations is necessary. This approach belongs to the classical Monte Carlo simulation methods [7, p. 83f]. Besides the challenging verification task it is also difficult to accumulate knowledge about certain rare conditions that lead to a failure of the control system using classical Monte Carlo simulations. For example a wind gust with a certain shape, that occurs with a probability of $10^{-6}$, requires on average $10^6$ simulation runs until it is encountered once. Especially for computationally expensive simulation runs this can quickly lead to practical limitations of generating such rare events. Naturally, the more information about the condition that leads to a control system failure is available, the more reliably it can be predicted and prevented in the future. Hence, if enough information is available, a model that runs in parallel to the control system can be constructed that monitors the current flight state and predicts how likely it is that the current flight condition leads to an upset and if necessary triggers a maneuver that avoids it.

Creating such a predictor requires data that can not be generated efficiently using simple Monte Carlo simulations due to the aforementioned computational burden. Therefore, a different road is taken here based on Subset Simulations (SS) which is an algorithm that has been developed originally to estimate small failure probabilities of high dimensional stochastic systems [8]. The algorithm is usually used to predict the probability that a certain critical but rare event occurs. Recently SS has already been applied to rare event prediction in the context of flight control system analysis (see [9] and [10]). In the context of this work the algorithm will not only be used to estimate a certain rare event probability but also to generate systematically a knowledge base for external disturbances that lead to a specified control system failure, denoted as an upset. The generated conditions will then be used to train a binary time series classifier using a Support Vector Machine (SVM) that is able to predict and eventually prevent the occurrence of a failure beforehand with the overall goal to improve the fail-operational characteristic of the AWE system.

The contribution of this work can be summarized as follows. First, two control system modifications to a previously published work of the authors (see [6]) that helped to improve the control systems reliability in turbulent wind conditions are proposed. Second, a generic framework is presented that allows to systematically maximize a cost function that drives the control system towards its limits and eventually prevents the controller from achieving its objective. Third, based on the generated knowledge different prediction strategies are discussed that rely on the one hand on a statistical analysis of the controller performance and on the other hand uses time series classification techniques to predict upset conditions. Fourth, a loss rate function is derived that allows to trade off the prediction performance with respect to the induced economic loss of false positives and false negatives. Finally, the framework is applied to predict and prevent tether rupture, a common failure scenario in the context of AWE. A tailored avoidance maneuver is proposed that
prevents this specific upset and keeps the system operational. The framework is build up in a generic way such that it allows to analyze a variety of different upset conditions and can augment different control strategies in the future beyond the single example that is presented in this work.

Ultimately, the following research questions are answered: How can upset conditions in the context of AWE be defined and systematically generated if the probability of encountering one per pumping cycle is low? Further, is it justifiable from an economic point of view to prevent these conditions if that comes at the cost of false positives or is more reasonable to simply accept them? Finally, how can the practical impact of different prediction strategies be used to measure classification performance beyond classical metrics?

To that end, the paper is structured as follows. In section II the closed loop system is presented including a brief description of the utilized models and controller as well as a modification to the baseline control architecture. In section III the generic parts of the novel framework are presented and in section IV it is applied to the specific case of predicting and preventing tether rupture in turbulent wind conditions. Finally, section V concludes the paper.

II. Closed-Loop System Description

In this study a model of a generic AWE system operated in pumping cycle mode is used along a modified version of the control system presented in [6] in order to demonstrate the effectiveness of the proposed framework. In the first part of this section the main components of the model will be reviewed. In the second part the key elements of the controller will be presented with a focus on the modification with respect to the baseline architecture as presented in [6].

A. Aircraft, Ground Station and Wind Models

The aircraft is modeled as a six degrees of freedom rigid body and its geometric and aerodynamic properties are based on the values in [11] and [12]. The translational dynamics are given by

\[
\begin{align*}
\left( v^G_k \right)_B &= \left( \omega \right)_B^{OB} \times \left( v^G_k \right)_B + \frac{(F_{tot})_B}{m_a} \\
\end{align*}
\]

with

\[
(F_{tot})_B = (F_a)_B + (F_g)_B + (F_t)_B + (F_p)_B
\]

where \( \left( v^G_k \right)_B, \left( v^G_k \right)_B, \left( \omega \right)_B^{OB} \) and \( m_a \) represent the kinematic acceleration, the kinematic velocity, the rotational rate of the aircraft with respect to the North-East-Down reference frame and the total mass of the aircraft, respectively. The subscript \( B \) indicates vectors given in the conventional body-fixed frame of the aircraft. The total force acting in the center of mass \( G \) of the aircraft consists of the resulting aerodynamic force \( (F_a)_B \), the weight \( (F_g)_B \), tether force \( (F_t)_B \) as
well as propulsion force \((F_p)_B\). The rotational dynamics are given by

\[
(\dot{\omega})_{OB}^B = -J^{-1}\left((\omega)_{OB}^B \times J (\omega)_{OB}^B - (M_a)_B\right)
\]

where \((\dot{\omega})_{OB}^B\), \(J\) and \((M_a)_B\) denote the rotational acceleration, inertia tensor and resulting aerodynamic moment acting in the center of mass, respectively. Furthermore, the actuator dynamics for ailerons, elevator and rudder are approximated as first order filters including rate and deflection limits. These values are summarized in Table 1. For the post-takeoff phase a simple propeller model is implemented as defined in [13, p.53f]. Note, the propeller is only used in the beginning of each simulation to initialize the pumping cycle operation.

The ground station is modeled as in [6] and relevant parameter values are summarized in Table 2. Furthermore, the discretized tether model of [14] is implemented, the utilized values are displayed in Table 3. Wind conditions are simulated using the shear wind model and the discrete Dryden turbulence model provided by the Matlab Aerospace Toolbox [15]. The utilized wind shear profile in the present work as a function of altitude is depicted in Fig. 1.

![Wind shear profile as a function of altitude.](image)

Table 1  
First order actuator models.

| Parameters                  | Values | Units   |
|-----------------------------|--------|---------|
| Bandwidth aileron \(\omega_{\text{a,0}}\) | 35     | rad s\(^{-1}\) |
| Aileron deflection limit \(\delta_{\text{a,lim}}\) | ±20   | \(^{\circ}\) |
| Aileron rate limit \(\dot{\delta}_{\text{a,lim}}\) | ±115  | \(^{\circ}\) s\(^{-1}\) |
| Bandwidth elevator \(\omega_{\text{e,0}}\) | 35     | rad s\(^{-1}\) |
| Elevator deflection limit \(\delta_{\text{e,lim}}\) | ±20   | \(^{\circ}\) |
| Elevator rate limit \(\dot{\delta}_{\text{e,lim}}\) | ±115  | \(^{\circ}\) s\(^{-1}\) |
| Bandwidth rudder \(\omega_{\text{r,0}}\) | 35     | rad s\(^{-1}\) |
| Rudder deflection limit \(\delta_{\text{r,lim}}\) | ±30   | \(^{\circ}\) |
| Rudder rate limit \(\dot{\delta}_{\text{r,lim}}\) | ±115  | \(^{\circ}\) s\(^{-1}\) |
B. Control System Description

In the following the control objective for an AWE system operated in pumping cycle mode is described. A pumping cycle usually results in a trajectory similar to the one displayed in Fig. 2. The control objective for such a system can be subdivided into a radial and a tangential direction control task. On the one hand, the controller needs to keep a high tension in the tether during the traction and a low tension during the retraction phase. This radial direction control objective is achieved using the rotational speed of the winch and the aircraft angle of attack and bank angle as control variables. On the other hand, the aircraft needs to follow a prescribed flight path, for instance a figure of eight pattern during the traction phase and a straight line glide path during the retraction phase similar to the ones visualized in Fig. 2. This objective will be achieved using only the flight controller. It is implemented in a cascaded form with three loops. In the first loop the guidance commands in form of course and flight path angle rates are calculated with respect to the path curvature for the figure of eight flight while during the retraction phase command shaping filters are used. These commands are then translated into bank angle and angle of attack commands that are tracked by the attitude controller. In the inner most loop the output of the attitude controller is translated into rate commands that are tracked by the rate controller and eventually allocated to the actuator deflections. Additionally, in each loop pseudo control hedging is implemented to comply with aircraft state and input limits.

In this section two modifications to [6] will be introduced that improved the robustness of the controller in strong turbulent wind condition. The first modification consists of an improved guidance strategy for the transition between the retraction and the traction phase. The main challenge here is represented by the rising tether tension i.e. from low tension in the retraction to high tension in the traction phase. Furthermore, since both phases are fundamentally different

| Table 2 Ground station parameters. |
|-----------------------------------|
| Parameters | Values | Units |
| Inertia $J_W$ | 0.08 | kg m$^2$ |
| Viscous friction $\kappa_W$ | 0.6 | kg m s$^{-1}$ |
| Acceleration limits $a_{W,\text{min/max}}$ | ±5 | m s$^{-2}$ |
| Maximum speed $v_{W,\text{max}}$ | 20 | m s$^{-1}$ |
| Minimum speed $v_{W,\text{min}}$ | -15 | m s$^{-1}$ |

| Table 3 Tether Parameter. |
|----------------------------|
| Parameters | Values | Units |
| Particles $n_T$ | 5 | - |
| Mass Density $\rho_T$ | 0.0046 | kg m$^{-3}$ |
| Diameter $d_T$ | 0.0025 | m |
| Drag coefficient $C_{d,T}$ | 1.2 | - |
| Stiffness $c_T$ | 10243 | N m$^{-1}$ |
| Damping $d_T$ | 7.8833 | N s m$^{-1}$ |
from a control perspective a transition strategy from straight line following (retraction) to path following on a virtual sphere (traction) needs to be achieved. In the following several solutions will be discussed before the final method is presented.

One possible approach is to directly switch into the figure of eight path following mode as soon as the end of the retraction path is reached which does not require any intermediate guidance strategy. Another option is to include a planar circular arc at the end of the retraction phase that defines the turning radius for the transition phase. This delays the activation of the traction mode until the aircraft is steered sufficiently back into the wind which can be defined by a way-point on the arc. The drawback of the first approach is the reduced level of guidance and hence it is difficult to shape the transient behavior. Since the same controller for the transient as for the traction phase is used to avoid unnecessary switching between different controllers, tuning of the controller for better transient behavior would also alter the controller for the traction phase. The downside of the second approach is that it requires additional parameters to be tuned such as the length and curvature of the arc. Modifying the figure of eight would most likely also requires to modify the geometry of the arc. It can be seen that both approaches are complementary in terms of additional complexity and level of guidance.

The advantages of both approaches can be combined in the following third alternative. Instead of defining a new arc in the horizontal plane the same but rotated figure of eight curve as for the traction phase is used. This is similar to the first approach where the traction phase is directly triggered at the end of the retraction phase. However, instead of directly approaching the traction phase path at a low elevation angle (power zone) a figure eight curve at a high elevation angle (limit is 90 degrees) is used for better guidance in the turning phase (advantage of the second approach). During
the transient the curve is rotated towards the desired elevation angle for the traction phase. The time constant that defines
the speed with which the path is rotated turns out to be an important parameter which trades of robustness (large value)
and performance (small value) since it defines how fast the aircraft will fly into the power zone. In combination with a
shaped set point change for the tether force tracking a smooth transition from a straight path with low tether tension to
figure of eight flight path following with high tether tension can be achieved. The mathematical implementation of this
approach is discussed in the following.

As in [6] the figure of eight flight path is parameterized using the definition of a Lemniscate in spherical coordinates
on a unit sphere. Concretely, the longitude and latitude of each point on the path is then given by

\[
\lambda_p = \frac{b \sin(s)}{1 + \left(\frac{a}{b} \cos(s)\right)^2}
\]

\[
\phi_p = \frac{a \sin(s) \cos(s)}{1 + \left(\frac{a}{b} \cos(s)\right)^2}
\]

(4)

where the \(a\) and \(b\) define the specific shape of the path and \(s \in [0, 2\pi]\) defines a specific position on the path. Transforming
the path definition from spherical into Cartesian coordinates yields

\[
(p)_p = \begin{pmatrix}
\cos \lambda_p \cos \phi_p \\
\sin \lambda_p \cos \lambda_p \\
\sin \phi_p
\end{pmatrix}
\]

(5)

where the subscript \(p\) denotes the path frame. It is essentially defined in the same way as the Wind reference frame \(W\)
(see [6]) but is tilted by an angle \(\phi_t\) around the \(y_W\) axis. The reference path in the \(W\) frame is then defined by

\[
(p)_W = \begin{pmatrix}
\cos \phi_t & 0 & -\sin \phi_t \\
0 & 1 & 0 \\
\sin \phi_t & 0 & \cos \phi_t
\end{pmatrix}
(p)_p
\]

(6)

Note that this redefinition of the path requires also a small modification in the algorithm in [6] that finds the closest
point on the path with respect to the current position. In [6] the path is fixed at a certain elevation angle. However, since
the rotation matrix in Eq. (6) is constant with respect to \(s\) the derivatives are not impacted and only the final result in [6]
needs to be changed. Concretely, the target on the path as well as the tangent and its derivative with respect to \(s\) (see [6])
eed to be rotated by \(\phi_t\) using the same rotation matrix as utilized in Eq. (6).

The transient of the rotation angle \(\phi_t\) is shaped using a first order filter with time constant \(\tau_r\) and set point \(\phi_{set}\) which
corresponds to the reference elevation angle during the traction phase:

\[
\phi_t = \begin{cases} 
0 & \text{if } \Delta_\phi > \bar{\Delta}_\phi \\
-\frac{1}{\tau_r} \phi_t + \frac{1}{\tau_r} \phi_{set}, & \phi_t(t = 0) = \phi_0 \text{ else}
\end{cases}
\]  

(7)

In order to avoid that the path is rotated too quickly $\phi_t$ is set equal to zero as soon as the arc length on the unit sphere $\Delta_\phi$ between the path and the current projected position of the aircraft exceeds a certain threshold $\bar{\Delta}_\phi$, which is set to one degree for the subsequent simulations. $\Delta_\phi$ is given by

\[
\Delta_\phi = \tilde{\phi}^G - \tilde{\phi}^I \\
\tilde{\phi}^G = \arccos \left( \frac{\left( \mathbf{p}^G_{xy} \right)_w \left( \mathbf{p}^G \right)_w}{\left\| \left( \mathbf{p}^G \right)_w \right\|_2 \left\| \left( \mathbf{p}^G \right)_w \right\|_2} \right) \\
\tilde{\phi}^I = \arccos \left( \frac{\left( \mathbf{p}^I_{xy} \right)_w \left( \mathbf{p}^I \right)_w}{\left\| \left( \mathbf{p}^I \right)_w \right\|_2 \left\| \left( \mathbf{p}^I \right)_w \right\|_2} \right)
\]  

(8)

where $\left( \mathbf{p}^G_{xy} \right)_w$ and $\left( \mathbf{p}^I_{xy} \right)_w$ are the normal projections into the $x_wy_w$ plane of the aircraft position $\left( \mathbf{p}^G \right)_w$ and the target on the path $\left( \mathbf{p}^I \right)_w$, respectively. All vectors are given in the wind reference frame. The time constant $\tau_r$ in Eq. (7) is a tuning parameter that defines how quickly the path is rotated into the power zone. In the limit, as $\tau_r$ goes to zero the transition scenario without guidance is reached. On the contrary, for large time constants the aircraft will fly most of the time at high elevation angles which will reduce the power output. Hence, the parameter value reflects the trade-off between robustness (large $\tau_r$) and maximum power output (small $\tau_r$). Note, the initial condition is usually chosen smaller than 90 degrees (between 70 and 80 degrees) otherwise this would cause the aircraft to overfly the ground station. The
filter is reset at the beginning of the transition phase.

For the retraction phase the straight glide path is defined as the connecting line of the point at which the retraction mode got triggered and a waypoint on the rotated reference path defined by \( s = \{ \frac{\pi}{2}, \frac{3\pi}{2} \} \) and the initial value for \( \phi_r \). The \( s \) value is chosen depending in which part of the figure of eight (positive or negative \( y_W \) coordinate) the traction phase got triggered. The retraction phase is triggered if two conditions are met. First, a specified tether length needs to be reached, second, the aircraft needs to pass the point on the path specified by \( s_1 = \frac{\pi}{2} \) or \( s_2 = \frac{3\pi}{2} \). As opposed to directly triggering the retraction phase if the maximum tether length is reached, this approach reduces the possible retraction points on the path to two, which is more convenient for robustness analysis. The downside of this approach is that the maximum length of the tether can vary in one pumping cycle since the increment in tether length per half figure of eight flight varies with the reeling speed. To mitigate this effect the increment in tether length for each half figure flight is predicted based on the previous increment. If the aircraft reaches one of the two possible retraction points the increase in tether length until the other retraction point is reached will be estimated. If the estimated tether length is higher than the maximum tether length the retraction phase will be already triggered at the current retraction point. This feature leads to more consistent tether lengths in high wind conditions which require high reeling-out speeds.

Finally, a minor modification of the winch controller is presented. In contrast to [6] the winch controller was simplified since the feed-forward part turned out to be too aggressive in highly turbulent wind conditions leading to instabilities due to the acceleration limits of the winch. Instead, a simple PI controller is implemented that calculates a reference torque based on the difference between the tether force set point and the measured tether force on the ground. Based on the reference torque the winch will adapt the reeling speed. This strategy works for traction and retraction phase and requires only different set points.

### III. Upset Generation, Prediction and Avoidance Framework

The framework consists of three parts. The different parts can be designed to a large extend independently, which allows to further improve the framework in the future in a modular manner. First, a formal definition of the upset conditions that are considered in this work is given. Second, the Subset Simulation algorithm is presented that can generate samples that lead to a specific upset condition, which represents the first part of the framework. The second part consists of the prediction model that takes as input the created samples from the first part as learning examples which allows to build a prediction model. Both modules can be applied to different upset conditions without major modification. The third part consists of the avoidance maneuver which needs to be tailored to the specific upset. For instance, an upset condition that leads to a tether rupture might require a different prevention strategy than the upset that leads to a divergence of the aircraft from the flight path. The complete framework is visualized in Fig. 4, where the blocks enclosed by the red dotted rectangle belong to the upset generation part and the blocks enclosed by the blue dashed rectangle belong to the prediction part of the framework. Note, the connecting arrows to and from the avoidance
maneuver block are dashed in order to indicate that on the one hand the avoidance maneuver is triggered by the predictor and on the other hand is an active entity within the closed-loop AWE system. The individual blocks are discussed in detail in the subsequent section.

A. Theoretical Preliminaries

In this section a concise description of the utilized classification and SS algorithm is given. For a detailed description it is referred to the literature, for instance [16] and [17, p.383-387] for a detailed derivation of the SVM algorithm. The introduction of SS follows [18]. Further details about SS and proofs can also be found in [8].
1. Support Vector Machines

The goal of the SVM algorithm is to find a hyperplane for each class such that the margin between the two planes is maximized. The two hyperplanes can be defined as

\[
\mathbf{w}^\top \phi_{f,i} + b \begin{cases} 
  \geq 1 & \text{if } \phi_{f,i} \text{ belongs to class 1} \\
  \leq -1 & \text{otherwise}
\end{cases}
\]  

(9)

where \( \mathbf{w} \) is the normal vector of both hyperplanes and \( b \) is a bias. The distance between the two hyperplanes is given by \( \frac{2}{\sqrt{\mathbf{w}^\top \mathbf{w}}} \). In order to maximize the distance between the two planes the scalar product \( \mathbf{w}^\top \mathbf{w} \) needs to be minimized which leads to the following quadratic programming problem [17, p.384]:

\[
\minimise \frac{1}{2} \mathbf{w}^\top \mathbf{w}
\]

subject to \( y_i (\mathbf{w}^\top \phi_{f,i} + b) \geq 1, \ i = 1, ..., n \)  

(10)

The optimization problem can be rewritten in terms of its Lagrangian as defined in [17, p.386]. It will contain the input vector only as the scalar product \( \phi_{f,i}^\top \phi_{f,i} \) which allows to apply the kernel trick. The kernel function essentially maps the input parameter into a higher dimensional space in which both classes are linearly separable [17, p.382]. A common kernel is the radial basis function, or Gaussian kernel, which is also used in this work. Ultimately, the SVM is used to solve a binary classification problem where a given data set \( \mathcal{D} = \{(\phi_{f,i}, y_i), i = 1, ..., n\} \) with \( y_i \in \{-1, 1\} \) is used to construct a model that can predict if a certain input vector belongs to class -1 or class 1. The predictor equation that augments the control system is given by

\[
\hat{f} = \sum_{j=1}^{m} \alpha_j y_j e^{-\frac{(\phi_{f,i} - \phi_j)^\top (\phi_{f,i} - \phi_j)}{\sigma^2}} 
\]

(11)

where the \( \alpha_j \)'s are the \( m \) non-zero Lagrange multipliers of the corresponding support vectors \( \phi_j \) as well as their class labels \( y_j \) and \( \sigma^2 \) is the variance of the Gaussian kernel which is a hyperparameter that needs to be tuned. \( \phi_{f,i} \) corresponds to the current feature vector. The class label is then determined based on the condition

\[
\hat{y} = \begin{cases} 
  1 & \text{if } \hat{f} \geq 0 \\
  -1 & \text{else}
\end{cases}
\]

(12)

In this work the two classes indicate either an upset (\( \hat{y} = -1 \)) or a nominal flight condition (\( \hat{y} = 1 \)). In the present work the SVM is trained using the Matlab Statistics and Machine Learning Toolbox [19].
2. Subset Simulations

Subset Simulations (SS) is a popular algorithm to estimate small event probabilities for high dimensional systems [8]. An event, or failure, probability as a function of a multidimensional random variable $\Theta$ and its probability density function $f_{\Theta}$ can be written as

$$p_f = \int \mathbb{1}_{F}(\theta) f_{\Theta}(\theta) \, d\theta$$

(13)

where $\mathbb{1}_{F}(\theta)$ is the indicator function that is either one if a certain realization $\theta$ leads to a failure or zero otherwise. Furthermore, it is usually assumed in this context that the random variables are identically and independently (iid) distributed hence

$$f_{\Theta}(\theta) = \prod_{k=1}^{d} f_{\Theta_k}(\theta_k)$$

(14)

In addition, it is assumed that the random variables are transformed such that the transformed variables are iid standard normal random variables with probability density function $f'$.

Directly evaluating the integral in Eq. (13) analytically or even numerically is not feasible for complex high dimensional systems due to the curse of dimensionality [8]. One approach to calculate this integral is using direct Monte Carlo methods that randomly sample from the parameter marginal distributions, evaluating the indicator function by simulation and using eventually the sample average to approximate the failure probability. If $p_f$ is small this can require an unfeasible amount of simulation runs which is especially critical if one simulation run is time consuming i.e. several minutes or more. Contrarily, in the context of SS $p_f$ is written as a product of conditional probabilities which involves the definition of intermediate failure domains. The main idea behind this strategy is that transitioning from one intermediate failure domain to the next has a higher chance than directly transitioning from nominal conditions into the failure domain. The failure probability can then equivalently be expressed as

$$p_f = \Pr(F_1) \prod_{i=1}^{m-1} \Pr(F_{i+1} \mid F_i)$$

(15)

The first intermediate failure probability $\Pr(F_1)$ is obtained via a direct Monte Carlo approach where $n_s$ samples are generated at random and a limit function $g$ that characterizes how close the current sample is too the failure is evaluated for each sample. On the other hand, the conditional probabilities $\Pr(F_{i+1} \mid F_i)$ are obtained using a Markov chain Monte Carlo method. The intermediate failure thresholds are selected adaptively by taking a certain fraction of the samples that lead to the highest limit function value. If the threshold values of the limit function are arranged in descending order then the intermediate threshold value is defined by

$$g_{i+1} = \frac{n_p^i \cdot g_i + n_p^{i+1} \cdot g_i}{2}$$

(16)
where $g_i^{n \cdot p_s}$ and $g_i^{n \cdot p_s+1}$ denote the $n \cdot p_s$-th and $(n \cdot p_s + 1)$-th largest sample with respect to the limit function. In that case, the transition probabilities $\Pr(F_{i+1} \mid F_i)$ is per definition equal to $p_s$. The remaining task is to construct the Markov chain using for instance the modified Metropolis algorithms (Algorithm 1) which will be briefly reviewed based on [8].

In the context of SS the task of the Metropolis algorithm is to repopulate an intermediate failure domain with samples $\tilde{\theta} \in F_i$. As soon as enough, i.e. $n_s$ samples, are contained in the domain $F_i$ the subsequent intermediate failure domain will be defined. This procedure is repeated until the actual failure domain is reached. New samples, conditioned on an existing sample $\theta$ in an intermediate failure domain $F_i$, are created by centering a symmetric proposal function $\tilde{f}$ around each coordinate $\theta_k$ of $\theta$. In this work a Gaussian proposal function is used with fixed standard deviation $\sigma = 0.234$. This results in $n_s \cdot p_s$ Markov chains with $\frac{1}{p_s} - 1$ elements. An accept/reject strategy, as defined in line 5 of the algorithm, leads to a non-greedy random walk around the previous state in the Markov chain. Since the intermediate thresholds are selected adaptively with respect to the most promising samples (higher limit function value) and new samples are only accepted if they are contained in the current intermediate failure domain (line 7) the algorithm will return at every stage inputs that drive the system more towards an upset condition (critical limit function value).

Algorithm 1: Modified Metropolis Algorithm

1: Pick $\theta \in F_i$
2: for each coordinate $k = 1...d$ in $\theta$ do
3: Sample $\tilde{\theta}_k \sim \tilde{f}(\cdot|\theta_k)$
4: Compute $\alpha = \frac{\tilde{f}(\tilde{\theta}_k)}{f(\theta_k)}$
5: Accept $\tilde{\theta}_k$ if $\alpha > 1$ or if $\alpha > u$ with $u \sim \mathcal{U}(0, 1)$
6: end for
7: Accept $\tilde{\theta}$ if $\tilde{\theta} \in F_i$ o.w. set $\tilde{\theta} = \theta$
8: return $\tilde{\theta}$

B. Module 1 of the Framework: Upset Condition Generation

The first step in the upset generation framework consists of defining the upset formally. Since upset conditions are generated using the SS algorithm an upset is defined with respect to a certain limit function value. All samples that yield limit function values that are beyond this threshold value are considered as upset conditions. The crucial part in modeling an upset condition is the allocation of the upset condition to a reasonable signal value or combination of different signal values. For instance, if the analyzed upset is stall, the angle of attack represent the obvious choice as a limit function. Since this framework is mostly applicable to control system failure finding the right limit function is usually done by taking the complement of the control objective. For instance, as described in section II the control objective for AWE systems operated in pumping cycle mode can be decomposed into a path-following problem (tangential direction control) and a tether force tracking problem (radial direction control). Hence, the limit function should be able do describe a failure in the tangential or radial direction control objective. The performance of the tangential direction control objective is reflected by the path-following tracking error, which suggest to choose this signal as a limit function.

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to generate conditions in which the controller is not able to keep the aircraft close enough to the flight path. Similarly, in the radial direction the controller needs to track a high tension in the tether for optimal power production while keeping the tether force below the maximum tensile force that the aircraft and the tether itself can still support. An upset condition in this case can then be defined as a condition where the tension in the tether exceeds this critical value. Depending on the model fidelity, more complex upset conditions such as too high wing bending or vibrations with certain amplitudes in a certain frequency range can be analyzed, where the external excitations are generated using SS. Ultimately, a wide range of different upset conditions can be converted into a scalar function with a threshold value beyond which the upset occurs. In general, this leads to a linear combination of measured signals (e.g. angle of attack, airspeed, wing bending, tether tension,...) that can be used to construct the limit function. The general form of the limit function is then defined by

$$g(\Theta) = \sum_{i=1}^{N_s} w_{x,i} x_i + \sum_{j=1}^{N_o} w_{z,j} z_j$$

(17)

where the $w_{x,i}$ allow to associate a weight to each of the $N_s$ AWE system states $x_i$. Similarly $w_{z,j}$ defines the weight of the $j$th output signal of the AWE system. The argument of $g$ indicates that for multiple simulation runs its value differs only according to the components of the uncertainty vector $\Theta$. Note, that the implicit dependence of the states and outputs on the uncertainties is not displayed. Having defined the limit function the SS algorithm can be applied to sample $\Theta$ in order to to drive $g$ into the specific upset $g > g^*$. 

C. Module 2 of the Framework: Upset Condition Prediction

In this section two prediction approaches are presented. Since it is assumed that an upset can be defined by the value of the corresponding limit function, as for instance defined in Eq. (17), a reasonable prediction approach is to predict an upset also based on the current functional value of $g$. Due to the stochasticity of the system the values of $g$ will fluctuate according to the joint distribution of the uncertainties. Threshold values can then be selected based on a quantile analysis using a direct Monte Carlo simulation approach. For instance, the results in Fig. 5 are obtained from simulations with 5000 input samples which displays the limit function value (blue line) as a function of its quantiles. The limit function in this case corresponds to the maximum tether force in one pumping cycle and the uncertainties stem from fluctuations in the wind speed. The dashed green lines in Fig. 5 indicate the 0.95-, 0.98-, 0.994- and 0.999-quantiles respectively. Assuming that the critical limit function value is reached at $g^* = 2$ these quantiles are all viable intermediate threshold candidates but are also from right to left increasingly conservative predictors. Figure 6 displays the corresponding fitted probability density function.

For the sole purpose of classification it is obvious that selecting a threshold value arbitrarily close to the maximum supported tensile strength of the tether will yield the highest accuracy (least conservative). However, due to the inertia of the system as well as time delays this will in most cases not allow to prevent tether rupture. Contrarily, if the threshold
value is decreased the false positive rate will grow (more conservative). The probability of a false positive can be estimated using the fact that the SS algorithm provides an estimate for the failure probability \( p_f \). In that case the false positive probability is given by

\[
\Pr(\hat{y} = -1, y = 1) = 1 - F_{g(\Theta)}(q^*) - p_f
\]  

(18)

where \( q^* \) represents the chosen threshold quantile and \( F_{g(\Theta)} \) the cumulative distribution function of the limit function \( g(\Theta) \). Contrarily, the false-negative rate can only be estimated by simulating randomly upset scenarios generated by the SS algorithm for different threshold values and counting the not prevented upset cases. The false negative probability is then given by

\[
\Pr(\hat{y} = 1, y = -1) = \Pr (\hat{y} = 1 \mid y = -1) \Pr (y = -1)
\]

\[
= \frac{n_{FN}}{n_{FN} + n_{TP}} p_f
\]  

(19)
where \( n_{FN} \) denotes the number of false negatives and \( n_{TP} \) the number of true positives i.e. encountered and avoided upsets.

In addition to the fixed threshold approach a time series classifier is constructed to predict upsets. The main motivation for this approach is that also the time history of certain states and outputs can be taken into account for prediction and not just a single point in time. The goal is to detect patterns in the flight conditions prior to an upset such that the upset can be predicted earlier compared to a simple non-conservative fixed threshold value approach. The input to the predictor will be specific estimations of aircraft states and wind conditions. Note, it will be assumed that the utilized signal values can be measured at a specific rate, no state estimation is performed. The approach can however be extended by including a state estimator in between the predictor and the sensor outputs. The predictor is build as a binary classifier that decides if a certain flight condition might lead to an upset in the close future by analyzing specific signals in a specified time window. Concretely, based on the generated upset conditions using the SS algorithm the SVM is trained. Instead of capturing the complete time history of each signal, specific signal statistics are extracted and collected in a feature vector that is used to train and predict the signal class. To do that each signal is cut into smaller pieces according to the selected time window size. For instance, the highlighted area in Fig. 7 indicates a time window with length 10 seconds. At 67 seconds simulation time the signal content between 57 and 67 seconds, denoted with \( s_1 \) is translated into a feature vector. To create the training examples the time window will be moved from either the final logged data point to the first data point, or if the complete signal contains an upset i.e. \( g(\Theta) > g_\ast \), in this example \( g(\Theta) = F_t > F_{t,\text{max}} \) (orange dashed line), the segmentation is started where the first upset occurred minus a shift \( \Delta T_r \) as depicted in Fig. 7. The additional shift is required otherwise the predictor might fail to forecast an upset prior to its occurrence. The signal segmentation contains overlaps between the segments, hence the first time window is only shifted by \( \Delta T_s \) and not by the window length. Note, only the first segment in Fig. 7 would be labeled as an upset i.e. \( y = -1 \), the segments starting with \( s_2 \) belong all to the non-upset class and are labeled with \( y = 1 \).

If a binary classifier is trained based on the generated data, the prediction accuracy can be improved by balancing the training data set. Although the SS algorithm will generate upset condition, the segmentation of the logged signals within a pumping cycle will always lead to more non-upset than upset conditions and hence to an extremely imbalanced data set. In fact, most of the simulated pumping cycles will not contain a single upset. One approach, which belongs to the data-level methods of learning from imbalanced data (see [20]), suggest to use a similar amount of samples from both classes. In this case randomly chosen non-upset samples are removed from the training data set (undersampling). Another more sophisticated approach is to synthetically create more samples of the minority class. This can be achieved using the SMOTE algorithm (see [21]). The algorithm randomly picks a sample from the minority class, determines its k-nearest neighbors, picks one of the k neighbors at random and interpolates again randomly between the two samples to synthesis a new minority class sample. Since the variances vary strongly between the different features the k-nearest neighbors are determined based on the Mahalanobis distance which normalizes the Euclidean distance between two
samples using the sample covariance matrix of the training set. This process is repeated until a specified amount of minority class samples has been created. Note, SMOTE can also be applied to the turbulence model input vector. In that case the synthesized input vectors can be tested by simulation if they indeed lead to an upset and hence belong to the minority class. This is not guaranteed if SMOTE is applied to the training data set in the feature space, but requires significantly more time. In this work SMOTE is applied directly to the feature space to save training time. Based on the balanced training set a greedy forward feature selection algorithm as described in [22] is proposed to identify the most relevant features. The relevance of a feature is determined using 10-fold cross-validation and the achieved average Matthews correlation coefficient to measure classification performance.

$$MCC = \frac{n_{TP} \cdot n_{TN} - n_{FP} \cdot n_{FN}}{\sqrt{(n_{TP} + n_{FP})(n_{TP} + n_{FN})(n_{TN} + n_{FP})(n_{TN} + n_{FN})}}$$  \hspace{1cm} (20)$$

where \(n_{TP}, n_{TN}, n_{FP} \) and \(n_{FN} \) denote the number of true positives, true negatives, false positives and false negatives, respectively. The MCC is the preferred performance measure since it condenses information of all four quadrants of the confusion matrix in one single number, in contrast to other measures such as accuracy or F1 score as for instance discussed in [23]. Ultimately, each continuous time series segment is condensed in a \(\mathbb{R}^m \) dimensional vector \(\phi_{I,i} \) and the predictor is trained based on the relationship

$$\begin{pmatrix} \phi_{I,1}^T \\ \phi_{I,2}^T \\ \vdots \\ \phi_{I,n}^T \end{pmatrix} \rightarrow \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}$$  \hspace{1cm} (21)$$

Fig. 7 Training example with reaction time definition.
where $y_i \in \{-1, 1\}$.

The key challenge in selecting the right predictor is to trade off the false positive and false negative probabilities. Since in practice both have a different impact on the overall system performance, ranking predictors simply based on their prediction accuracy is not a recommended approach. A solution is to weight both terms proportionally to the resulting economic loss. In case of a false positive this loss equals the power loss due to the triggered emergency maneuver $P_{FP} = P_{em}$. The loss stemming from a false negative $P_{FN}$ is more difficult to find since it requires a cost model that is able to predict the power loss due to system downtime and repair costs in case the upset damaged the system. In order to combine both false negative and false positive contributions in a single number, an economic loss rate is introduced which is defined as the weighted linear combination of power loss due to a FP and power loss due to a FN

$$L = w_1 P_{em} + w_2 P_{FN}$$ (22)

The weights $w_1$ and $w_2$ are derived in the following based on the probabilities of FPs and FNs. The occurrence of either a FP or a FN is modeled as two Poisson processes running in parallel. The Poisson process that models the arrivals of FPs runs until the first arrival of the Poisson process that models the arrival of the FNs. The expected value of the arrival time of a FN allows to estimate the amount of FPs until that point in time and hence the resulting power loss. The rate for the process that models the occurrence of a FN is given by

$$\lambda_{FN} = \Pr(\hat{y} = 1, y = -1) = \Pr(\hat{y} = 1 \mid y = -1) \Pr(y = -1)$$ (23)

The conditional probability is simply given by the false positive rate of the prediction strategy, the probability that $y = -1$ is the upset condition probability which is independent of the prediction approach. Estimating the conditional probability is done by re-simulating upset conditions for the different predictors using the results from the SS run that generated the test set data. With the estimated FN rate the number of pumping cycles until the first expected FN occurs is given by

$$n_{pc} = \frac{1}{\lambda_{FN}}$$ (24)

In this time interval the expected number of FP is then given by the expected value of the corresponding Poisson process defined by

$$n_{FP} = \lambda_{FP} n_{pc}$$ (25)

$$= \Pr(\hat{y} = -1, y = 1) n_{pc}$$

The probability of encountering a false positive per pumping cycle can be estimated by counting falsely predicted upsets.
using a Monte Carlo simulation approach for each prediction strategy.

If a FN occurs the system will not be operational for a specific time $\Delta T_{nop}$. It reflects the time for a possible emergency landing, maintenance and relaunching. This mainly leads to a power loss in terms of missed pumping cycles. Assuming an average pumping cycle time of $t_{PC}$ the number of missed pumping cycles is

$$n_{mpc} = \frac{\Delta T_{nop}}{t_{PC}}$$

(26)

Finally, the expected power loss per pumping cycle due to predictions errors is given by

$$L = w_1 P_{em} + w_2 P_{FN} = \frac{n_{FP}}{n_{pc} + n_{mpc}} P_{em} + \frac{1}{n_{pc} + n_{mpc}} (n_{mpc} P_{pc} + P_{misc})$$

(27)

$P_{misc}$ combines all additional losses involved with a FN such as replacement costs of damaged parts. Equation (27) allows to rank different predictors with respect to their expected power loss. Note, at this stage only educated guesses about the average downtime $\Delta T_{nop}$ as well as the additional involved costs summarized in $P_{misc}$ can be made. In practice, a sensitivity analysis such as the one used in the subsequent section IV can be used to rank the importance of each parameter in $L$ for a specific upset case.

As a concluding remark of this section, note that the feature ranking is done using the MCC to measure prediction performance. One could also choose directly the loss rate as a performance measure. However, this would require to rank the features as a function of the parameter values in the loss function for which only rough estimations are available at the moment. Moreover, it would require a significantly higher training time since for each feature candidate the false positive and false negative probabilities need to be estimated based on simulations.

IV. Application of the Framework to Predict and Prevent Tether Rupture

In this section the presented framework will be applied to generate conditions that lead to tether rupture, hence $g(\Theta) = F_t$. The quantile as well as the SVM prediction strategy is used to predict tether rupture beforehand and their individual performance is assessed with respect to classical accuracy measures as well as the economic loss rate. Additionally, a prevention strategy is presented that will be triggered as soon as a tether rupture is predicted. In the presented example the stochastic excitation is limited to the uncertainties in the wind conditions. It is arguably also the highest uncertainty that makes AWE systems notoriously difficult to control. Of course, the framework can be easily extended by considering also model parameter uncertainties, sensor noise or hardware failures. The wind conditions are generated using the Dryden Turbulence model that has as input standard Gaussian distributed random variables $\theta_k$ that are filtered to recover the Dryden turbulence spectrum. In total $d = T_{sim} f_s$ random variables are sampled per run where
$T_{\text{sim}}$ is the simulation runtime and $f_s$ the sampling frequency which is set to 10 Hz. Further possible variations in the wind field such as discrete gusts or changes in the shear profile and the wind directions are not considered in this work, but leave room for future research directions.

### A. Application of Module 1 and 2 of the Framework for Tether Rupture Prediction

In general, upset conditions for a complete pumping cycle, or even several pumping cycles in a row can be generated with the proposed framework. However, since the dimension of the joint probability density function from which the wind condition is sampled grows linearly with simulation time all the results are generated only for one pumping cycle. Moreover, traction and retraction phase are considered separately to further reduce the input dimension. Due to space limitations only the results for a tether rupture during the traction phase are presented. Eventually, initializing the SS algorithm with 5000 samples yields a tether rupture probability of approximately $p_t \approx 10^{-4}$.

As described in section III the first step after the convergence of the SS algorithm consists of selecting reasonable states and outputs that are used to predict the upset. For the considered case of tether rupture the following signals are chosen:

- wind speed components $v_{w,x,W}$, $v_{w,y,W}$, and $v_{w,z,W}$
- aircraft acceleration in radial direction $a_{z,\tau}$
- Tether force $F_t$
- angle of attack $\alpha$
- path following error $e_p$

In the next step, each signal is discretized into smaller overlapping time windows and statistical properties in the time and frequency domain are calculated. The utilized features that are calculated for each of the signals in the time domain are: mean, median, rms-value, variance, maximum, minimum, maximum peak-to-peak ratio, skewness, kurtosis, crest factor, median absolute deviation, range of the cumulative sum, the time-reversal asymmetry statistic given by Eq. (28) and the maximum signal slope. The time-reversal asymmetry statistic is defined by [22]:

$$p = \frac{\mathbb{E}\left(\left(s(t) - s(t - \tau)\right)^3\right)}{\left(\mathbb{E}\left(\left(s(t) - s(t - \tau)\right)^2\right)\right)^{3/2}}$$

(28)

where $\tau = 1$ s is chosen. In the frequency domain the following characteristics are calculated: median and maximum amplitude, and additionally the maximum amplitude above 1 Hz using a fast Fourier transform. The feature selection algorithm is applied to reduce this feature space which eventually yields the subset of features displayed in Table 4 (ordered according to significance). Note, the MCC value in the third row is the cumulative MCC value. In Fig. 8 the convergence of the selection process is displayed.
B. Module 3 of the Framework: Upset Condition Prevention

In order to avoid the upset once it is predicted an augmentation of the baseline control system is necessary, which is implemented for the present example as follows. As soon as an upset is predicted the state machine of the AWE control system switches to a defined contingency maneuver state. In case of a predicted tether rupture the contingency maneuver must reduce the current tension in the tether as quickly as possible. It turns out that with the underlying control system only a set point change for the tether force is sufficient. On the one hand, the tension in the tether is tracked by the winch controller via the reeling out/in speed of the tether and on the other hand by the flight path controller through the angle of attack and bank angle. Therefore, changing the set point for the tether force leads to an adaptation of the angle of attack and bank angle command $\alpha_c$ and $\mu_a$, respectively. As derived in [6] both attitude commands are determined by inverting the flight path dynamics which yields

\[
\begin{align*}
    f_{y,m} &= m_a v_{x,k} \cos \gamma_k v_k - f_{y,K} \\
    f_{z,m} &= m_a v_{y,k} v_k + \cos \gamma_k m_a g + f_{z,K}
\end{align*}
\]  

(29)
\[ \mu_{a,c} \approx \mu_{k,c} = \arctan \left( \frac{f_{y,m}}{f_{z,m}} \right) \]

\[ C_{L,c}(\alpha) = \sqrt{f_{y,m}^2 + f_{z,m}^2} \left/ \frac{0.5 \rho v_a^2 S_w}{\alpha_c} \right. \]

\[ \alpha_c = C_{L,c}^{-1} \ldots \]

where the tether force set point components \( f_{x,K} \) and \( f_{z,K} \) are obtained by

\[
\begin{pmatrix}
  f_{x,K} \\
  f_{y,K} \\
  f_{z,K}
\end{pmatrix} = -M_{K\mathbf{O}}(\chi_k, \gamma_k) \frac{(||\mathbf{p}^G\|_2)}{F_{t,c}} \]

\( (\mathbf{p}^G)\mathbf{O} \) is the position of the aircraft in the North-East-Down frame \( \mathbf{O} \) and \( M_{K\mathbf{O}}(\chi_k, \gamma_k) \) transforms a vector from the \( \mathbf{O} \) frame into the kinematic frame \( K \) (see [6]).

Essentially, Eq. (29-31) calculate the angle of attack and bank angle commands based on the desired path curvature represented by the pseudo-control inputs \( \nu_{\chi_k} \) and \( \nu_{\gamma_k} \) as well as the tether force set point \( F_{t,c} \). Note, for consistency the kinematic bank angle should in general be converted into the aerodynamic bank angle (banking around the aerodynamic instead of the kinematic velocity vector) but the effect is negligible here which leads to the approximation \( \mu_{a,c} \approx \mu_{k,c} \).

The angle of attack command reflects the required lift magnitude which is estimated by the required forces \( f_{y,m}, f_{z,m} \) and involves the inversion of the lift coefficient as shown in Eq. (30). Furthermore, \( \chi_k \) is the aircraft course angle, \( \gamma_k \) is the flight path angle, \( g \) denotes gravity, \( v_a \) is the airspeed, \( \rho \) is the air density and \( S_w \) is the wing reference area. Note, in order to track the tether force the angle of attack and bank angle commands are calculated using the tether force set point \( F_{t,c} \) and not the measured tether force currently acting on the aircraft. During nominal operation this allows to effectively keep the tether under the desired tension. As soon as an upset is predicted this set point will be reduced to a low value (\( F_{t,c} = 10 \) N). As a result the aircraft will correct the current bank and angle of attack commands accordingly.

Even if the winch controller is currently working at its limits, which is indeed a result of the upset in the first place, this allows to reliably reduce the tension in the tether quickly. As soon as the tether force drops below the threshold value i.e. \( F_t \leq 10 \) N and the predictor output switches from \( \hat{\gamma} = -1 \) to \( \hat{\gamma} = 1 \) the force set point is increased again to the original traction phase set point. The corresponding transient is shaped using a first order filter.

**C. Results**

The performance of the different prediction and avoidance strategies is tested on a separately generated data set that is not used to construct the predictors. The test data set is generated in the same manner as the training data set using the SS algorithm. From the obtained results 1000 pumping cycles are selected randomly and the same conditions are
re-simulated with the prediction and prevention strategy in the loop. In the first part of this section the effectiveness of the avoidance maneuver is analyzed, this is done with only the SVM prediction strategy. Subsequently, the prediction and prevention performance among different predictors is assessed with respect to their expected economic loss rate.

As explained in section IV.B the contingency maneuver does not require a separate control strategy but can be achieved by a simple set point change of the tether force. According to Eq. (29) and Eq. (29) this translated in an adaptation of the angle of attack and bank angle command. The tension in the tether is mainly produced by the lift force of the aircraft. Hence, the force in the tether can be reduced in two different ways. On the one hand, the magnitude of the lift can be reduced, on the other hand the lift vector can be rotated such that the majority of the lift points perpendicular to the tether direction. From a flight dynamic point of view this directly translates into a pitching and banking maneuver into the tangential plane. Indeed, this can be observed in the simulation results. In Fig. 9 and Fig. 10 the evolution of the tangential plane roll angle $\Phi_T$ and tangential plane pitch angle $\Theta_T$ for a falsely triggered contingency maneuver at around 53 seconds (blue, solid line) and the nominal flight (orange, dashed line) is displayed. The corresponding tether force is displayed in Fig. 11. Since no upset occurs in this situation it reflects the aircraft behavior in case of a false
positive. As soon as the contingency maneuver is triggered the controller commands a large negative angle of attack (see Fig. 12) as well as a decreased aerodynamic bank angle (see Fig. 13), which essentially rotates the lift vector away from the tether direction. In terms of the aircraft orientation with respect to the tangential plane these commands lead to a large negative pitch angle (see Fig. 10) of almost -30 degrees and a large roll angle command up to 50 degrees (see Fig. 9). In this condition the aircraft flies for a short period of time with nearly leveled wings with respect to the ground. This combined pitching down and rolling maneuver effectively reduces the tension. As soon as the tether force drops below its minimum value the set point for $F_t$ will be increased again to its nominal traction phase value and the system continuous with the power generation phase as visualized for instance in terms of the tether force in Fig. 11.

A similar behavior can be observed in the case where the predictor prevents a tether rupture. The same argumentation as before holds, the contingency maneuver leads to a combined pitching down (see Fig. 17) and rolling maneuver (see Fig. 18) caused by the change in angle of attack (see Fig. 15) and aerodynamic bank angle (see Fig. 16) commands. In this case the simulation without avoidance maneuver results in a tether rupture as soon as the tether force exceeds the critical value (here 2 kN) as can be observed in Fig. 14 and Fig. 19, whereas the contingency maneuver avoids the tether

\[ F_t \text{ (kN)} \]

\[ \alpha \text{ (deg)} \]

\[ \text{Time (s)} \]

\[ \text{Time (deg)} \]

**Fig. 11**  Tetherforce evolution for false positive case.

**Fig. 12**  Angle of attack with contingency maneuver (solid) and without (dashed).
rupture. In Fig. 20 and Fig. 21 the flight paths with and without avoidance maneuver are displayed. The aircraft visualization in Fig. 20 changes from blue to orange as soon as the contingency maneuver is triggered. The resulting attitude change is especially visible in the area highlighted with the dashed circle. The aircraft rolls positively into the tangential plane leading to a loss in the tether force which results in a visible tether sag compared to the nominal case. For the case with upset the resulting trajectory is displayed in Fig. 22 and the contingency maneuver is able to avoid the upset by banking and down pitching (dashed circle) while continuously following the figure of eight pattern.

In the following the performance of different predictors will be investigated with respect to classical performance measures as well as the introduced economic loss rate. In total, five different predictors are analyzed including four different quantile based and one SVM based predictor. For the fixed thresholds the FP rate and the FN rate are negatively correlated, hence decreasing the FP rate leads to a significant increase in FN rate. The closer to the critical level the threshold value is selected the more likely it is that the tether rupture cannot be prevented. In contrast to that the more conservative the threshold is chosen the more likely it is to prevent a tether rupture but at the cost of an increasing false positive rate. Concretely, selecting the $q_{0.95}$-quantile has a 100% success rate of preventing a tether rupture but on
average 4.4% pumping cycles contain a falsely triggered avoidance maneuver. Opposite to that is the \( q_{0.999} \)-quantile which achieves the lowest false positive rate of 0.1% but fails to prevent more than a third of the encountered tether ruptures. Selecting the right threshold based solely on these results is difficult because no reasonable acceptable FP and FN rate can be defined a priori. Similarly, using a performance measure such as the MCC which is displayed in the third row can be misleading since it tries to find the predictor that can achieve low FP as well as low FN rates at the same time without considering their respective relevance to the overall system performance.

Table 5  Upset Detection Performance.

| Method       | FP Rate | FN Rate | MCC  |
|--------------|---------|---------|------|
| \( q_{0.95} = F_{t_{\text{set}}} + 10\% \) | 4.4%    | 0%      | 0.49 |
| \( q_{0.98} = F_{t_{\text{set}}} + 12\% \) | 2%      | 0.26%   | 0.75 |
| \( q_{0.994} = F_{t_{\text{set}}} + 15\% \) | 0.6%    | 3.5%    | 0.83 |
| \( q_{0.999} = F_{t_{\text{set}}} + 20\% \) | 0.1%    | 33.6%   | 0.76 |
| Predictor    | 1.52%   | 0.2%    | 0.78 |
The economic loss rate that is proposed in section III tries to solve this issue by assigning weights to the FP and FN rate based on their associated power loss. Since the loss rate depends on heuristically chosen parameters a sensitivity analysis is performed based on Sobol’s variance decomposition approach (see [24, p.159-166]) to identify the parameter with the highest impact on the loss for further analysis. The first-order sensitivity and total effect indices are displayed in Fig. 23 and Fig. 24, respectively. The considered parameter intervals are displayed in Table 6. It can be observed that the first order effects are similar to the total-effects, hence the discussion can be continued by only considering the individual effects. The sensitivity results reinforce the intuition that for predictors with a high false positive rate with respect to the false negative rate the required power for the emergency maneuver dominates the loss rate. Contrarily, for predictors with a high false negative rate the average downtime after a false negative has the highest impact on the power loss. Additionally, in both cases the average pumping cycle power as well as the duration of one pumping cycle has a marginal effect.

In the following the concrete impact of different downtimes and power losses due to the avoidance maneuver is analyzed. For both cases the chosen average pumping cycle power is 6 kW and the average pumping cycle time is set to
2 minutes whereas the additional losses represented by $P_{\text{misc}}$ are neglected. In Fig. 25 and Fig. 26 the economic loss rate $L$ per average pumping cycle power $P_{\text{pc}}$ is displayed as a function of system downtime where $P_{\text{em}}$ is set to 1 kW. The results displayed in Fig. 25 show that without prevention strategy (dashed line, square markers) the relative power loss quickly grows, for instance with a downtime of 2 days already a power loss of more than 10% per pumping cycle is expected. Less severe but still significant is the resulting loss for the $q_{0.999}$-quantile approach (solid line, triangles) where the power loss grows linearly and results in a power loss per pumping cycle of approximately 5% after 3 days of downtime. In Fig. 26 the same results with a higher resolution are displayed. Since the $q_{0.95}$-quantile results in zero false negatives the power loss is independent of the system downtime hence the only contribution is a result of the

| Table 6   | Parameter ranges.                                                                 |
|-----------|-----------------------------------------------------------------------------------|
| Parameter | Range                          | Unit     |
| $P_{\text{em}}$ | [0.1, 1] kW                    |          |
| $P_{\text{pc}}$ | [4, 10] kW                     |          |
| $t_{\text{pc}}$ | [1, 3] minutes                  |          |
| $\Delta T_{\text{nop}}$ | [0, 7] days                    |          |
false positives. The $q_{0.994}$-quantile threshold that achieved the highest MCC score grows linearly and leads to a higher loss than the predictor and the $q_{0.95}$-quantile approach after half a day and 2.5 days, respectively. In the depicted time window the SVM based predictor achieves the lowest loss if a downtime of more than half a day is assumed.

The dependence of the power loss rate on the maneuver induced loss is depicted in Fig. 27 for three prediction approaches with an assumed downtime of one day. The $F^*_t + 20\%$ and the case without prevention are not displayed since they caused for every $P_{em}$ a higher loss. In the chosen interval the SVM based predictor leads to the lowest power loss independent of $P_{em}$. For $P_{em} < 29$ W the $F^*_t + 10\%$ threshold yields the best predictor performance however achieving such a low cost maneuver is practically not feasible.

D. Discussion Model Validity and Future Work

The presented framework uses models of the AWE system as well as the wind to create, predict and prevent upset conditions. The accuracy of the models is critical in order to be able to project the results to reality. The aircraft model has been validated to some extent as described in [12] and [11] but especially for quick changes in the wind conditions the aerodynamic model is probably too aggressive since changes in the local flow immediately change the resulting lift force. It is expected that with a more realistic aerodynamic model an additional time delay between changes in the local flow field around the aircraft and the resulting rates of the tether force is present which might alter the presented results.
Fig. 23  First order sensitivities: No prevention (squares), $F_1^* + 20\%$ (triangles), $+15\%$ (crosses), $+10\%$ (asterisks) and SVM (circles).

Fig. 24  Total-effect indices: No prevention (squares), $F_1^* + 20\%$ (triangles), $+15\%$ (crosses), $+10\%$ (asterisks) and SVM (circles).

in the previous section. The present model can hence be regarded as conservative and it is expected that the prediction accuracy can be further improved with a more realistic model. Testing the framework with a more realistic aircraft model is therefore regarded as the main suggestion for future work. This will also allow to investigate further upset conditions related to the structural and aerodynamic integrity of the aircraft. For instance, wind conditions that lead to critical wing bending or severe vibrations can be generated using the SS algorithm and a data-driven predictor such as the SVM predictor can be used to trigger a load and/or vibration alleviation strategy if necessary. Finally, it needs to be emphasized that the presented results are strongly dependent on the specific controller. In order to investigate how well the results generalize it is recommended to apply the presented methodology to a different closed loop system model in the future. Moreover, additional data-driven methods for the predictor can be tested to further decrease both false positive and negative rates and hence the economic loss.
V. Conclusion

This paper proposes a framework to generate, predict and prevent upset conditions that jeopardize the long term reliability of Airborne Wind Energy (AWE) systems. The framework is applied to the specific case of tether rupture prediction and prevention.

The results demonstrate that the Subset Simulation (SS) algorithm allows to efficiently generate wind conditions in which the controller is no longer able to keep the tether force within acceptable limits. The samples generated by the SS algorithm can be used to construct a prediction model that is able to detect tether rupture before it occurs. In order to trade off false positive and false negative rates an economic loss rate is introduced that is better suited to rank predictor performances than conventional classification measures since it allows to associate a power loss to prediction errors. Furthermore, predictors with a higher false negative rate lead on average to a higher power loss which depends especially on the system downtime due to a false negative.

Naturally, for well tuned control systems upset conditions have a low occurrence probability which poses the question
if accepting upsets is better than preventing them and therefore avoiding any prediction error induced costs. However, the results show that in the long run also rare upset conditions can have a significant impact on the average power output, hence augmenting AWE baseline control systems with an upset tailored prediction and prevention strategy is recommended.

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