**We thank the reviewers for taking the time to read our work. We here provide our answers and rebuttals.**

**Reply to RC1**

Dear Anonymous Referee #1,

Thank you for your comments.

- **Lack of clarity regarding the problem addressed:** we agree the specific real-world problem and benefits are not clearly stated. We have now modified the text in the abstract (lines 1 to 5 and 12 to 14), introduction (lines 24 to 34) and conclusion (lines 573 to 575) to add more clarity to the subject matter. Regarding previous research on the topic, we could not find any relevant papers. Therefore, in the introduction (lines 34 to 58) we described three approaches commonly used for detecting and monitoring faults on wind turbine components.
- **Incomplete analysis of AFS method performance:**
    - The actuator control signal is already included in the input signal used for the generation of the features (line 176)
    - Several parameters can affect the performances of the AFS. Due to time and resource constrains, we just want to show that the AFS method has some potential and, in some configurations, performs better than MFS. But it needs to be further investigated and developed to be usable. We added this consideration in the AFS discussion (lines 562 to 568) and in the conclusions (lines 607 to 609).
- **Potential improvement:** Ensemble modelling is a technique that has been used by the authors of this paper and can confirm the reviewer's comment that it very well might be an ideal approach to fusing the strength of multiple methods simultaneously. We will note this improvement in our future research. Due to time and resources constrains, it cannot be evaluated in this current version of the paper. The idea has been added as possible future development (lines 616 and 617).

**Reply to RC2:**

Dear Davide Astolfi,

Thank you for taking the time to review our work. Here are our responses to your questions:

- **Time resolution:** The data are obtained from aeroelastic simulations of 10 minutes length with a time resolution of 0.01 s. (line 137).
- **objective accomplishable for on site wind turbine with standard SCADA:** We developed this methodology taking into consideration it should be applicable to actual commercial wind turbines. The Manual Feature Selection approach with

reduced set of features relies only on 10 minutes statistical properties of commonly available wind turbine signals. Therefore, we believe this approach can be directly implemented to an actual prototype. The model must be trained with simulations based on the target wind turbine aeroelastic model and eventually tuned with transfer learning techniques using the wind turbine SCADA data. The MLS method with full features requires the calculation of additional features generally not included in the standard SCADA data. A cost benefit evaluation should be performed to decide which features are relevant to be captured in addition to the SCADA data. The Automatic Features Selection methodology does not use SCADA data. It requires instead the special postprocessing of the 10 minutes high frequency sampled time series. We included this consideration in the discussion (lines 546 to 551 and 569 to 571) and conclusion (lines 599 to 604 and 611 to 612) chapters.

**Paper updates:**

**Updated abstract:**

"Active trailing edge flap systems (AFlap) have shown promising results in reducing wind turbine (WT) loads. The design of WT relying on AFlap load reduction requires implementing systems to detect, monitor, and quantify any potential fault or performance degradation of the flap system to avoid jeopardizing the wind turbine's safety and performance. Currently, flap fault detection or monitoring systems are yet to be developed. This paper presents two approaches based on machine learning to diagnose the health state of an AFlap system."

……….

Instead, the AFS method can identify some of the AFlap health states for both asymmetrical and symmetrical faults when the WT is in normal power production. These results contribute to developing the systems for detecting and monitoring active flap faults, which are paramount for the safe and reliable integration of active flap technology in future wind turbine design.

**Updated introduction:**

….

Despite the potential benefits of AFlaps, this technology has yet to reach a sufficient level of maturity for its implementation in commercial WTs. To the authors' knowledge, only Siemens Gamesa Renewable Energy (SGRE) has publicly shared data of an AFlap system implemented on two different multi-MW WTs: a 4.0 MW WT prototype and a 4.3 MW WT prototype, both installed in Høvsøre (Denmark), see Gomez Gonzalez et al. (2022).

Every time a new component is included in a wind turbine's design, the safe and reliable continuous wind turbine operation must be ensured for the whole turbine's lifetime. To fulfill this requirement, additional components, systems, and controller strategies are needed to identify, quantify and resolve any potential issue deriving from the fault of the new component without compromising the WT safety.

Once the active flap reaches an adequate level of maturity, the wind turbine design will rely on the load reduction provided by the active flap. Therefore, any potential fault or performance degradation of the flap system may jeopardize the safety and performance of the wind turbine if not adequately managed. Therefore, a system will be needed to identify, monitor and handle active flap faults or degradation. Until now, the detection and condition monitoring of AFlap systems fault has not been detailed investigated, and to our knowledge, no literature is available on this topic.

**Updated discussion:**

… This transformation can be achieved with a flap check routine that activates the flap one blade at a time, which is like a 1B condition where the RF models can accurately estimate the flap health states. (line 535)

The reduced feature set of the MFS approach relies on statistical data commonly available in the commercial wind turbine SCADA data. This approach greatly facilitates the application of this methodology to commercial wind turbines. To do so, the MFS model must be trained with simulations based on the target wind turbine aeroelastic model and eventually fine-tuned with transfer learning techniques using the wind turbine SCADA data. Instead, the MLS method with full features requires calculating additional features generally not included in the standard SCADA data. For this method, a cost-benefit evaluation should identify which features are relevant to be computed in addition to the standard SCADA data…..

In the 3B scenarios, AFS RF models perform slightly better, especially for the Detailed flap health states. As shown in Figure \ref{F1score_comp}, for the 1B scenarios, AFS Ridge models perform similarly to the AFS RF models in 1B cases and slightly worst in the 3B cases (line 542)

The overall performances of the AFS models need to be further improved before the AFS models can be implemented in detecting all the AFlap health states. However, the AFS models performed better than the MFS models for two flap health states. For the NPP operation state, the AFS models can correctly identify the AF_Off and AF_OFF_Fault flap health states from the other states with Precision and Recall above 0.9. This result suggests that the selected input channels also carry the flap state information for the NPP state. The AFS method has the potential to detect this information, even if partially, for the flap state estimation. Further studies are needed to achieve acceptable Precision and Recall for all the flap health states. These studies should cover a comprehensive study on the impact of the different setup parameters on the model performance or explore other ML techniques like, for example, Multirocket (MiniRocket evolution) or HYDRA.

Regarding the implementation into the wind turbine controller, the AFS approach processes the whole 10 minutes signal data to generate the features. Therefore, it requires a dedicated feature generation algorithm that constantly computes the different features. As a result, implementing the AFS requires more resources (both hardware and software) than the MFS.

**Updated conclusions:**

The integration of active flaps in the wind turbine design has the potential to reduce loads and enhance wind turbine performances. However, this integration requires implementing systems to detect, monitor, and quantify any potential fault or performance degradation of the flap system to avoid jeopardizing the wind turbine's safety and performance. This paper investigated two approaches to identify the health state of a WT's active trailing edge flaps.

These approaches do not rely on specific sensors designated for AFlap's health monitoring but only on sensors commonly available on all commercial wind turbines.

….

For example, a flap check routine can activate the flap one blade at a time, generating a temporary asymmetrical flap activation that the MFS methodology can monitor. (line 572)

As the MFS approach with a reduced feature set relies only on 10 minutes statistical properties, we believe it can be directly implemented into an actual wind turbine. The model must be trained with simulations based on the target wind turbine aeroelastic model and eventually tuned with transfer learning techniques using the wind turbine SCADA data. Instead, the MLS method with full features requires calculating additional features generally not included in the standard SCADA data. For this method, a cost-benefit evaluation should be performed to identify which features are relevant to be computed in addition to the SCADA data.

Furthermore, we showed that, in general, the AFS method fails to classify most AFlap health states in asymmetrical and symmetrical flap faults. However, AFS can identify some specific flap health states better than the MFS method for the symmetrical case. This result suggests that the selected input channels carry the flap state information for the NPP state, but only the AFS method has the potential to detect them. We also tested a Ridge classifier in the AFS method, obtaining a similar performance to the random forest classifier with a consistently lower training time.

Compared to the MFS approach, implementing the AFS method will require more resources as it needs additional preprocessing to generate the features.

The methodologies described in this study contribute to developing the systems for detecting and monitoring active flap faults, which are paramount for the safe and reliable integration of active flap technology in future wind turbine design.
As future developments, we suggest further exploring the AFS method by applying different and more performing convolutional techniques. Also, the AFS and MFS methodology can be combined into a hybrid system to investigate if the combined system presents improved performances by leveraging the strengths of each method.
It is also of extreme interest to validate the capability of the MFS method with data from an actual wind turbine, to which the models can be adapted via transfer learning techniques.