

Abstract

Defect Detection in Wind Turbine Blades Using Infrared Thermography, Image Processing, and U-Net [†]

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Abstract: In this research, we developed and tested an automated defect detection system for wind turbine blades using infrared thermography (IRT) and a deep learning model U-Net.

Keywords: thermography; wind turbine blades; modelling, U-net.

1. Introduction

The inspection of wind turbine blades (1, 2) is really important for ensuring both the productivity and the safety of wind energy systems. In this paper, we present the development of an automated defect detection system that uses infrared thermography (IRT) to extract the database and U-Net deep learning model to identify defects in wind turbine blades. We start with a theoretical analysis using COMSOL simulations to study the best time of day for capturing infrared images in order to maximize the visibility of defects based on thermal conditions. Our second analysis allow to settle the limits of defect sizes in relation to their depths that can be detected using infrared thermography. The simulated defects are air cavities of different sizes which were analyzed to evaluate the ability of our system in detecting those defects at different depths. Next, we use U-Net deep learning model for the automatic detection of defects in wind turbine blade infrared images. We use U-Net for pixels segmentation of the defects which provides accurate identification of defect areas. Additionally, we employed image processing techniques in order to divide the images corresponding to different blades of the turbine. Then we compare the images of the blades at the same positions using masks to improve the reliability of defect detection. The findings of this work show that the proposed system identifies successfully defects of different sizes in turbine blades. But this detection system faces a challenge with identifying false positives mistaken for real defects caused by some external factors like blade contamination and variable sunlight reflections due to the clouds. Despite these limitations, the system provides a potential solution for automatically identifying defects in wind turbine blades which improves productivity and decreases the need to do manual, visual drone inspections.

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2. Thermal Modeling of Wind Turbine Blades

For the simulation process, a wind turbine blade model was used, including a full-scale blade with dimensions of 60 m in length, 5 m in height, and 2 m in width as shown in Figure 1. Our blade model contained four subsurface defects of different sizes.

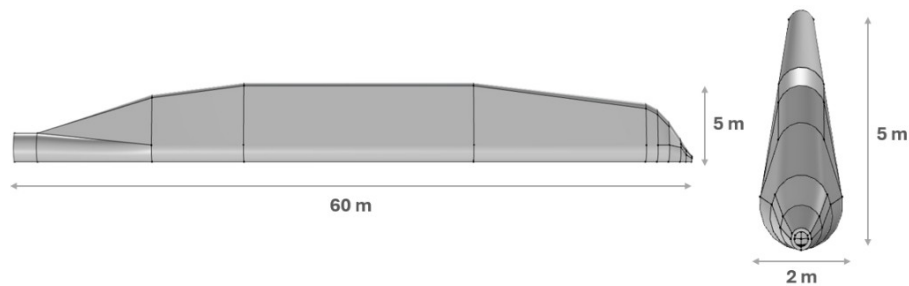


Figure 1. Geometric model of the wind turbine blade.

3. Results of the simulations

In order to study the best timing for capturing infrared images, we executed different simulations for the month of September. These simulations provided as results a sequence of infrared images that show clearly the appearance of (simulated) defects as shown in Figure 2. After this, we extracted the temperatures of the defected areas and the surface temperature from 10 consecutive points throughout the day, from 14:30 to 20:00, with measurements taken every 30 minutes. The choice of this time range was based on the solar radiation power being most ideal for defect detection during these hours. The results of these simulations are illustrated in Figures 3. The simulations were done in order to replicate a sunny day, and for the temperatures of the defected areas, we calculated the average temperature of the four defects simulated.



Figure 2. Infrared Image Showing the Appearance of Defects.

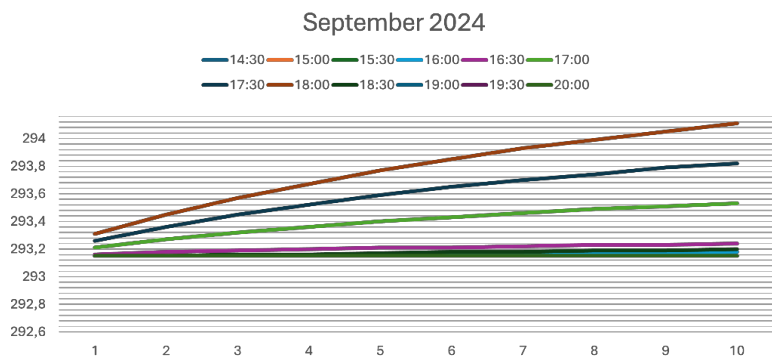


Figure 3. Temperature Curves for September Simulation Results.

4. Field Image Acquisition

Following our preliminary study and the availability of equipment, we conducted fieldwork at a windfarm South of Quebec City on Thursday, September 12, 2024. The weather was cloudy in the morning and sunny in the afternoon with some clouds, enabling infrared image capture between 16:00 and 18:00, timed to align with the optimal conditions identified in our COMSOL study. Using a cooled FLIR model A6701 MWIR camera with a 100 mm lens as shown in Figure 4.



Figure 4. Infrared Camera Setup with 100 mm Lens for Blade Inspection

We achieved a clear view of several sections of wind turbine blades. During this test, infrared image sequences were recorded for two wind turbines.

5. Methodology - Image Processing

We developed several image processing techniques in order to isolate and locate possible defects on the infrared images of the two wind turbine blades inspected. By employing these methods, we were able to clean the infrared images from the clouds in the background in order to prevent the detection of these clouds as defects and to improve the visibility of defects, this methodology served to guarantee correct study in different regions of the blades. We started by converting the raw infrared images to binary format to feature defect regions, followed by some morphological operations such as erosion and dilation in order to refine the images by eliminating noise and restoring defect regions. Next, we applied some image processing methods for identifying and grouping similar images to split the sequences of the images. The images were divided into sub-lists corresponding to specific blade sections (Blade 1, Blade 2, and Blade 3) for localized defect analysis. Furthermore, we operated a comparison of images from various blades (Blade 1, Blade 2, and Blade 3) at the same location using multiple thresholds to assist us in identifying defects on the blades. The creation of combined defect masks helped us in detecting minor variations between images. This resulted in more uniform defect detection in the dataset (3).

6. Automatic Defect Detection Using U-Net

The automatic defect detection method using U-Net has shown its success in detecting many defects that are already detected by the image comparison technique where blades were compared at the same positions as shown in Figure 5. Detection validation was done with another approach (3). Defects detected by both methods are considered as true defects. In contrast, defects detected only by one method and more specifically those not validated by U-Net are considered as false positives. This dual validation approach helped us in filtering out the errors caused by environmental conditions, like sunlight reflections or debris, reducing the chances of misinterpreting non-defect areas as actual

defects. This is a preliminary analysis and the network could be refined and better exploited.

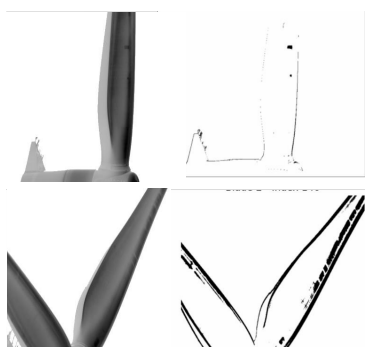


Figure 5. Potential Defects detected on blade edge of top right picture.

7. Conclusion

In this paper, we developed and tested an automated defect detection system for wind turbine blades using infrared thermography and deep learning model U-Net. We started our study with a theoretical study using COMSOL simulations in order to determine the best time of the day for capturing infrared images and to determine the limitations of defect detections in size and depth.

Our approach included two main detection methods: image comparison across turbine blade images (3) and U-Net segmentation. U-Net allowed us to achieve precise defect localization by segmenting the infrared images pixel-by-pixel. This approach, mixing image comparison and deep learning, allowed us to cross-validate the detected defects, confirming (possible) true defects and identifying false positives.

The data base will eventually be made available on our website.

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Conflicts of Interest: The authors declare no conflicts of interest.

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