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A Diagnostic and Predictive Framework for Wind Turbine Drive Train Monitoring

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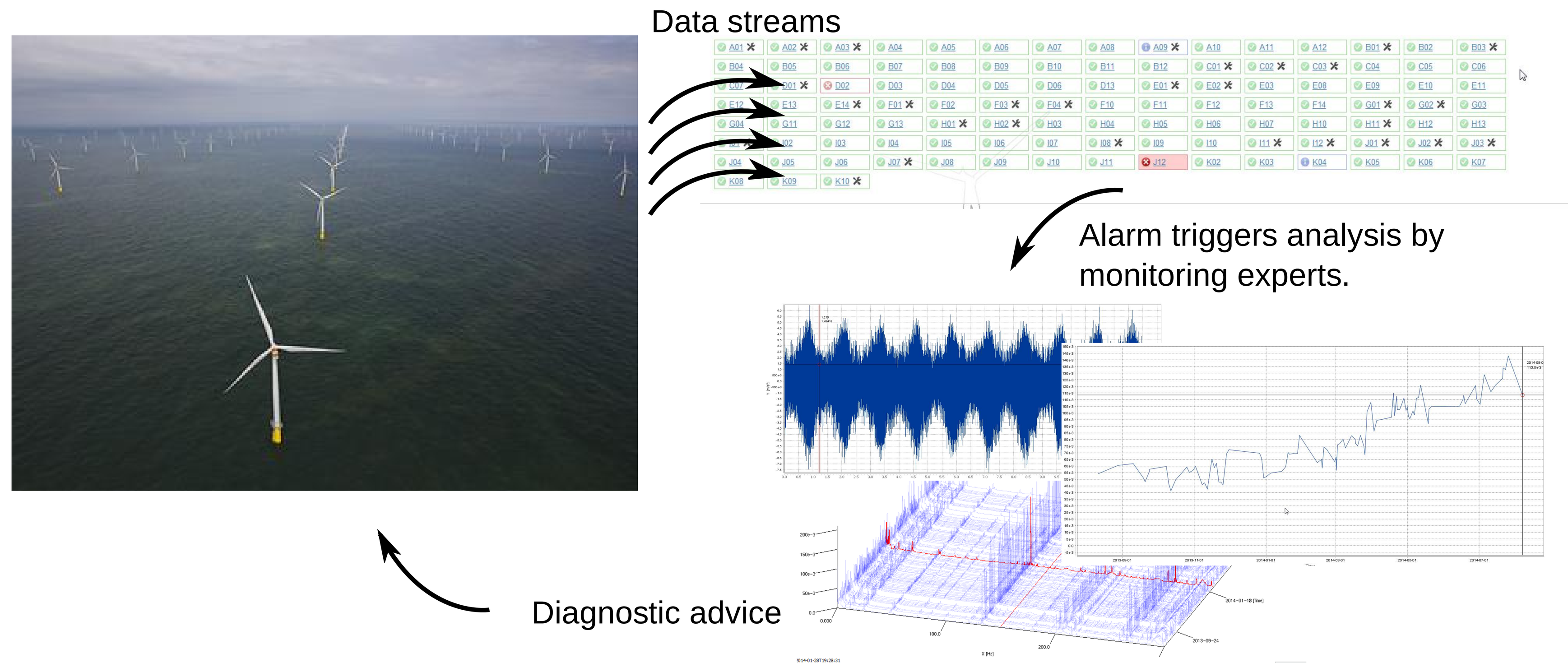
Introduction

- The wind power industry is strongly focused on reducing the cost of wind energy to achieve subsidy independence. An important goal is to reduce the operation and maintenance costs accumulated during the lifetime of the turbines.
- Advanced remote diagnostic systems supports this effort by reducing the risk of severe equipment failure and downtime, lowering the costs of spare parts and optimizing the planning of component exchange and repairs.
- The Siemens Diagnostic Center operates the world's largest advanced wind turbine condition monitoring setup (7500+ turbines worldwide). The system relies on a combination of in- and off-turbine alarm triggers and a team of experienced turbine monitoring experts.

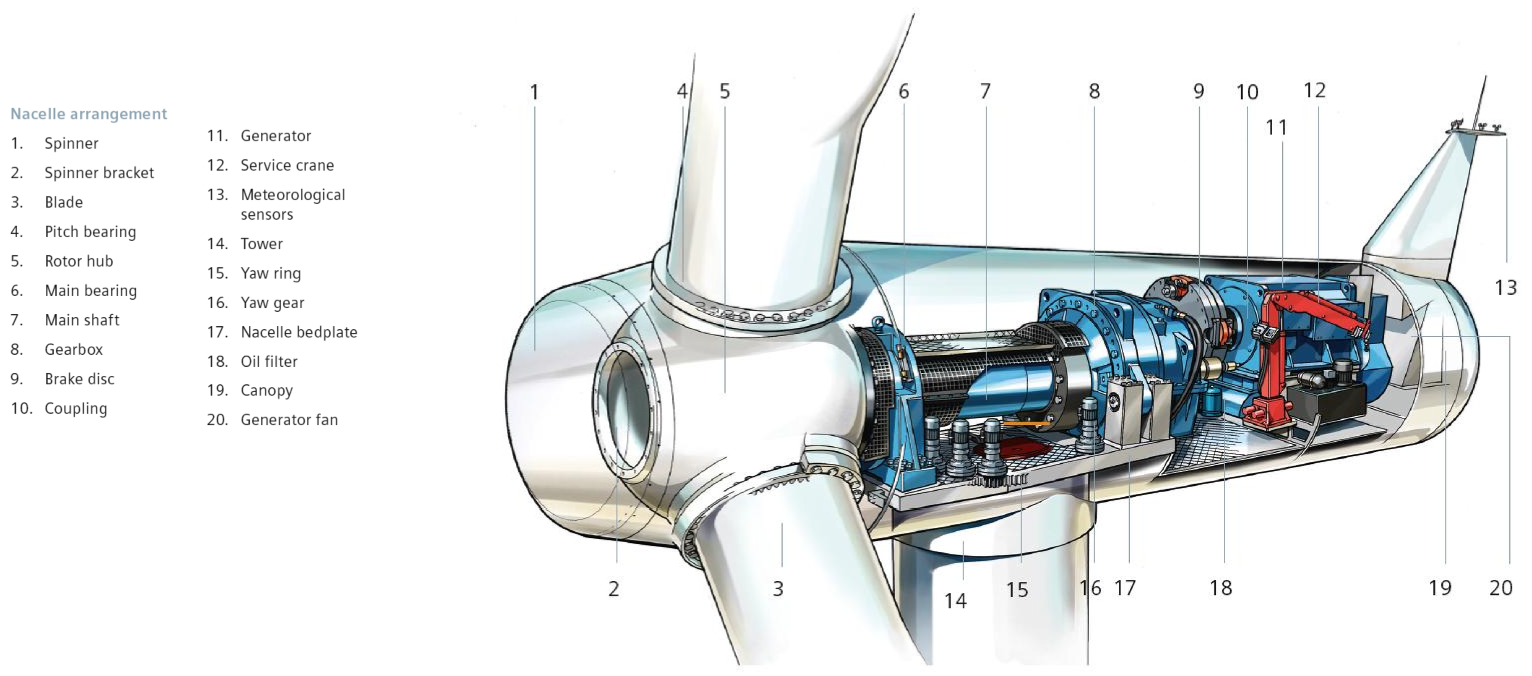
Project motivation

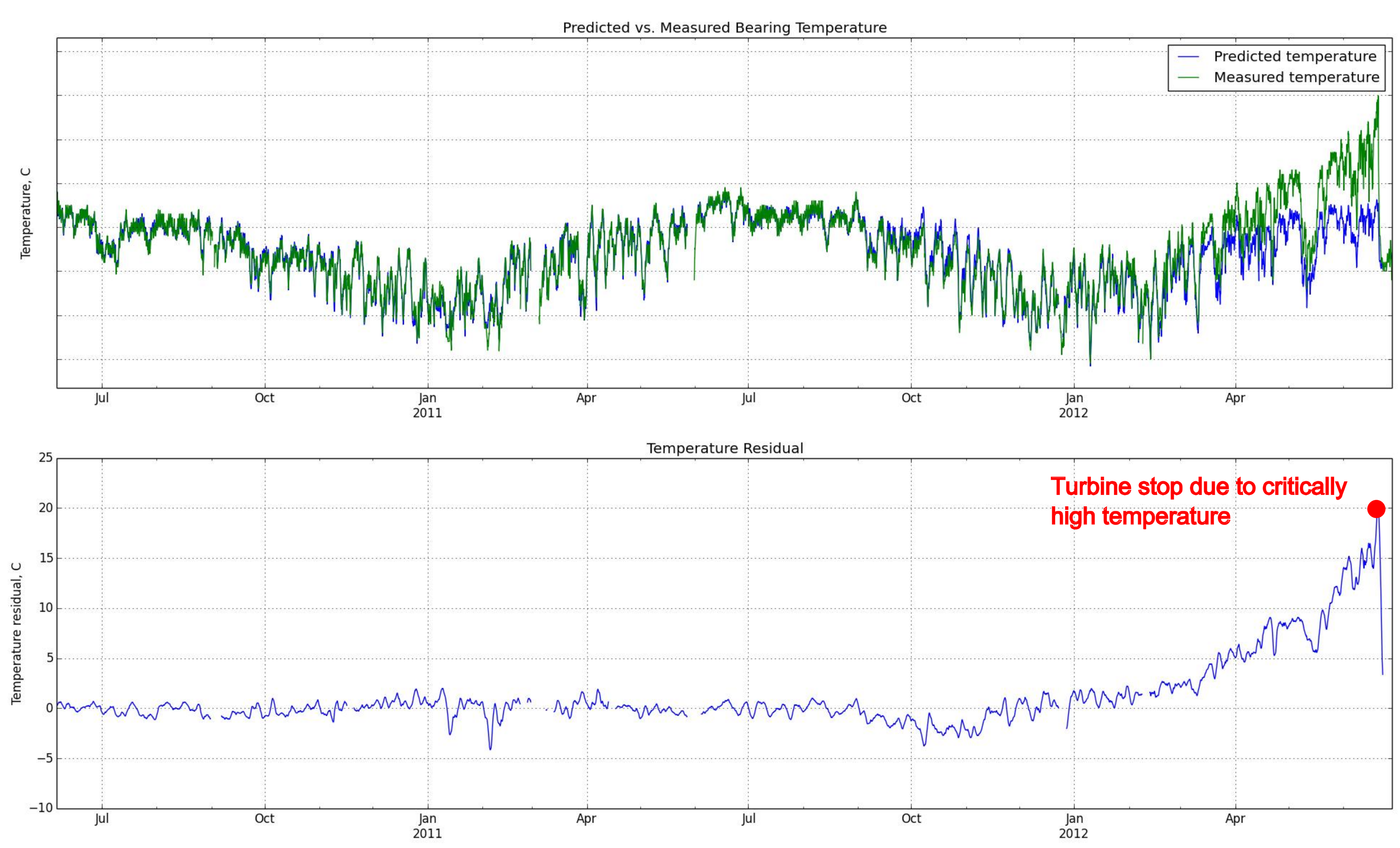
- Can the advanced diagnostic intelligence be fully automatized to provide accurate, up-to-date, diagnostics of the entire turbine fleet?



Initial study: Rotor bearing fault detection using a neural network based residual temperature model

- Component temperature increase is a typical sign of progressed damage. Challenge: The component temperatures are highly dependent on the operating conditions of the turbine and environmental variables.



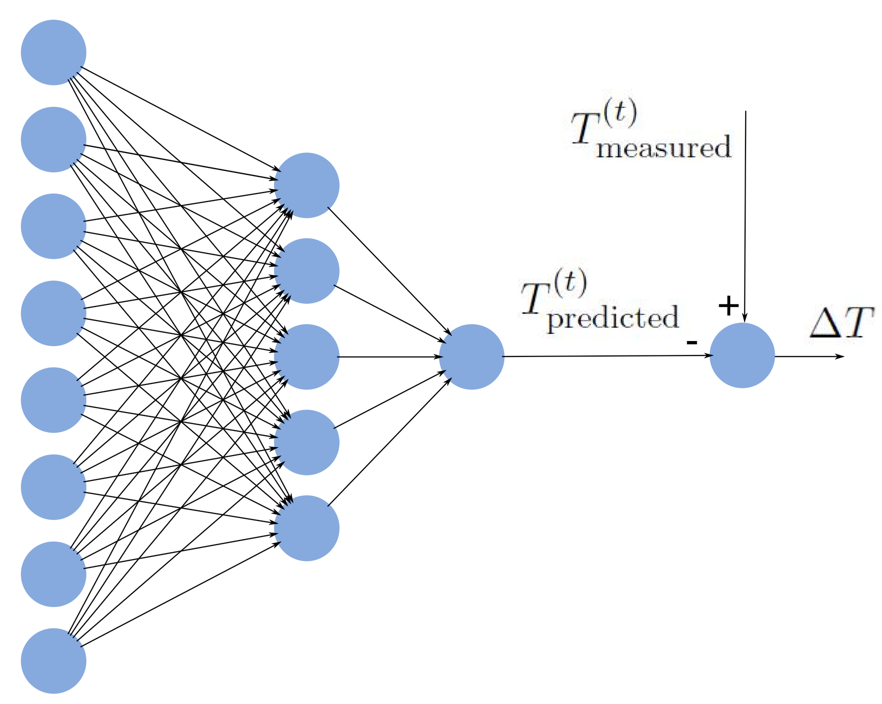


- Methodology: On the basis of a simple thermodynamic model, a two-layer feedforward neural network was trained to predict the bearing temperature during no-fault conditions. The residual between this prediction and the actual temperature is then used as a failure indicator.

$$f : \Theta^{(t,K)} \to T^{(t)}$$

$$\Theta^{(t,K)} = \begin{bmatrix} \theta_1^{(t)} & \theta_2^{(t)} & \cdots & \theta_N^{(t)} \\ \theta_1^{(t-1)} & \theta_2^{(t-1)} & \cdots & \theta_N^{(t-1)} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_1^{(t-K)} & \theta_2^{(t-K)} & \cdots & \theta_N^{(t-K)} \end{bmatrix}$$

Active power
Generator speed
Gear box temperature
Nacelle temperature
Ambient temperature



- A network (30 hidden units with tanh activation function and a linear output unit) was trained on a single turbine with a damaged rotor bearing using data from the first 14 months of operation. The temperature prediction is based on data from the last 48 hours (K=48 using 1 hour sampling intervals).
- The model predicts the bearing temperature accurately during no-fault conditions.
- From the temperature residual the progressing damage can be detected more than three months before critical failure.
- Current work: Quantify diagnostic performance of models from simulations on historic data across the entire fleet of turbines.

Deep learning perspectives

- As shown above, shallow architectures show promise for diagnostic systems based on deviations from a model of the no-fault condition. These models will typically rely on one or more engineered failure indicators and can be implemented without any prior failure data available.
- Is a purely data-driven approach feasible instead, where the diagnostic features are inferred from historic failure data, utilizing the full breadth of the data streams to achieve a diagnostic capability on par with, or superior to, human intelligence?
- Can deep learning architectures achieve this goal?

Example of a vibration frequency-time domain representation of a component failure mode.