Austin Downey[1], Simon Laflamme[1], Filippo Ubertini[2]

[1]Department of Civil, Construction and Environmental Engineering, Iowa State University, USA
[2]Department of Civil and Environmental Engineering, University of Perugia, Italy

Data Fusion of Dense Senor Networks for Damage Detection in Wind Turbine Blades

Research Objectives

- Propose an integrated soft elastomeric capacitor (SEC) based dense sensor network for the real-time structural health monitoring of wind turbine blades.
- Demonstrate the capability of the SECs to operate in the electromagnetically noisy environment of a wind tunnel, showing that the SEC would be capable of operating inside the similarly noisy environment of a wind turbine blade.
- Evaluate a data fusion data algorithm that fuses the data from a dense sensor network into a single damage detection feature and show that the SEC-based dense sensor network is capable of detecting and tracking damage that is not directly monitored by an SEC.

Abstract

Damage in wind turbine blades frequently manifests in the form of strain-field anomalies. However, local detection of damage over the global surface of a blade is difficult due to the lack of scalability of existing sensing methods. A solution to this local-global problem is the deployment of dense sensor arrays fabricated from inexpensive materials capable of discretely monitoring local conditions over a global area. The authors have previously proposed a large area electronic consisting of a soft elastomeric capacitor (SEC). The SEC is highly scalable due to its low cost and ease of fabrication, and can, therefore, be used for monitoring large-scale components. A single SEC is a strain sensor that measures the additive strain over a surface. Recently, its application in a dense sensor network configuration has been studied, where a network of SECs is augmented with a few off-the-shelf strain gauges to measure boundary conditions and decompose the additive strain to obtain unidirectional surface strain maps. These maps can be analyzed to detect, localize, and quantify faults. Here, we study the performance of the proposed SEC-based dense sensor network at conducting condition evaluation of a wind turbine blade model in an operational environment. Damage in the form of changing boundary conditions is induced into the blade. An dense sensor network is deployed onto the interior surface of the substrate, and the blade is excited in a wind tunnel. Results demonstrate the capability of the dense sensor network and associated algorithms to detect and quantify damage. These results show promise for the future deployment of a fully integrated SEC-based dense sensor network deployed inside wind turbine blades for condition evaluation.

SEC-based Dense Sensor Network

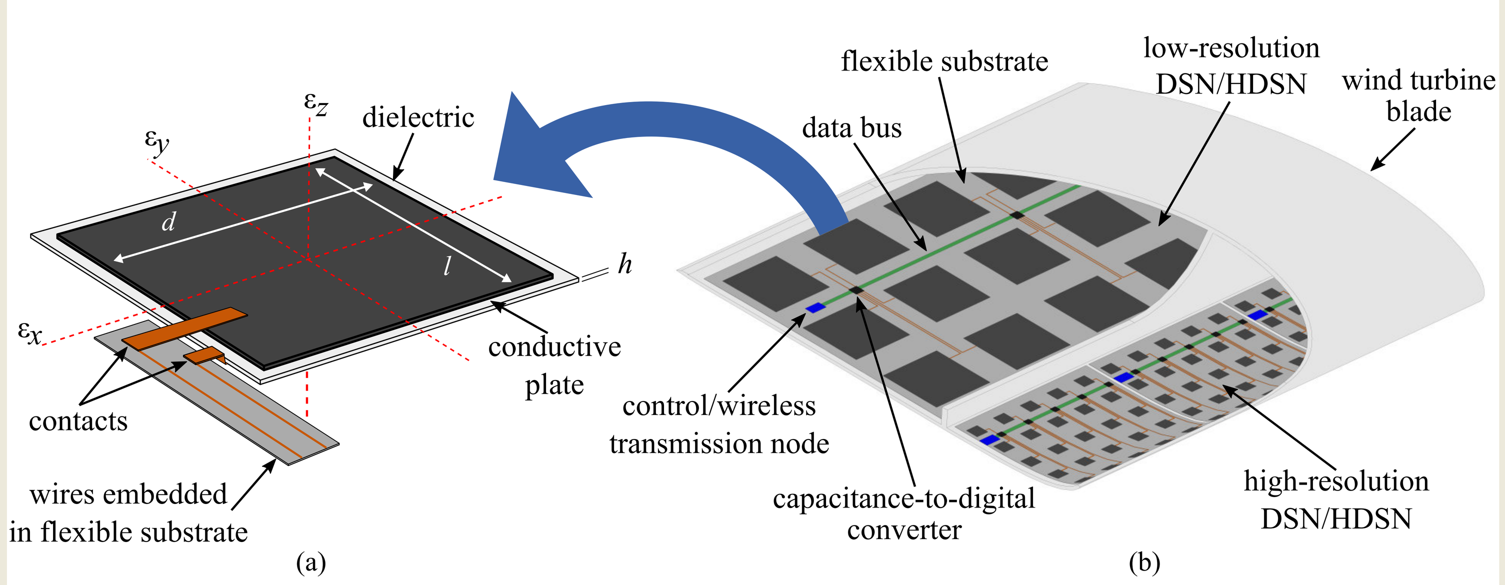

Figure 1. Conceptual layout of a fully integrated SEC-based dense sensor network for a wind turbine blade: (a) SEC with connectors and annotated axis; and (b) proposed deployment.

The SEC, presented in Figure 1(a), transduces a change in a monitored substrate's strain into a measurable change in capacitance. It is modeled as a capacitor with capacitance C defined by $C = e_0 e_r (d \cdot l)/h$ where $e_0 = 8.854$ pF/m is the vacuum permittivity, e_r is the polymer relative permittivity, d and l are the sensor's width and length, respectively, and h is the thickness of the dielectric [1]. Figure 1(b) presents a fully integrated SEC-based dense sensor network with the required electronics for power management, data acquisition, data processing, and communications, all mounted onto a flexible substrate (e.g. Kapton).

Strain Decomposition and Damage Detection

When deployed in a network configuration the SEC's additive strain measurement can be decomposed into unidirectional strains using an assumed shape function, enforced boundary conditions and the least squares estimator (LSE) [2]. The strain decomposition algorithm assumes a p^{th} order polynomial shape function with deflection in the x-y plane written as:

$$w(x,y) = \sum_{i=1,j=1}^{p} b_{ij} x^i y^j \tag{1}$$

here $b_{i,j}$ are regression coefficients. Considering a dense sensor network with m sensors, the displacement values at sensor locations can be collected in a displacement vector, $\mathbf{W}$, such that:

$$\mathbf{W} = \begin{bmatrix} w_1 & \cdots & w_m \end{bmatrix}^T = \mathbf{HB} \tag{2}$$

where matrix $\mathbf{H}$ contains sensor location information and is defined as $\mathbf{H} = [\mathbf{H}_x|\mathbf{H}_y]$ where $\mathbf{H}_x$ and $\mathbf{H}_y$ account for the SEC's additive strain measurements. $\mathbf{B}$ contains the f regression coefficients $\mathbf{B} = \begin{bmatrix} b_1 & \cdots & b_f \end{bmatrix}^T$. The components of matrix $\mathbf{H}$ can be developed from the previously defined polynomial equation, for each sensor location k, as:

$$\mathbf{H}_x = \mathbf{H}_y = \begin{bmatrix} y_1^n & x_1 y_1^{n-1} & \cdots & x_1^{n-1} y_1 & x_1^n \\ y_k^n & x_k y_k^{n-1} & \cdots & x_k^{n-1} y_k & x_k^n \\ y_m^n & x_m y_m^{n-1} & \cdots & x_m^{n-1} y_m & x_m^n \end{bmatrix} \tag{3}$$

Using Kirchhoff's plate theory, unidirectional strain functions for ε_x and ε_y are obtained:

$$\varepsilon_x(x,y) = -\frac{c}{2}\frac{\partial^2 w(x,y)}{\partial x^2} = \mathbf{H}_x \mathbf{B}_x \qquad \varepsilon_y(x,y) = -\frac{c}{2}\frac{\partial^2 w(x,y)}{\partial y^2} = \mathbf{H}_y \mathbf{B}_y \tag{4}$$

where c is the thickness of the plate and $\mathbf{B} = [\mathbf{B}_x|\mathbf{B}_y]^T$. Here, $\mathbf{B}_x$ and $\mathbf{B}_y$ hold the regression coefficients for strain components in the x and y directions, respectively. A vector $\mathbf{S} = \begin{bmatrix} s_1 & \cdots\cdots & s_m \end{bmatrix}^T$ containing the signal for each sensor in the dense sensor network is constructed. The regression coefficient matrix $\mathbf{B}$ is estimated using an LSE such that $\hat{\mathbf{B}} = (\mathbf{H}^T\mathbf{H})^{-1}\mathbf{H}^T\mathbf{S}$ where the hat denotes an estimation. Therefore:

$$\hat{\mathbf{E}}_x = \mathbf{H}_x \hat{\mathbf{B}}_x \qquad \hat{\mathbf{E}}_y = \mathbf{H}_y \hat{\mathbf{B}}_y \tag{5}$$

where $\hat{\mathbf{E}}_x$ and $\hat{\mathbf{E}}_y$ are vectors containing the estimated strain in the x and y directions for sensors transducing $\varepsilon_x(x,y)$ and $\varepsilon_y(x,y)$, respectively. A damage detection algorithm has been developed that produces trackable features, providing a method for damage detection and quantification for the SEC-based dense sensor networks [3]. It works through comparing the signal measured by an individual sensor with the estimated strain map (Equation (5)). An error function defined as the mean square error (MSE) between a sensor's measured and estimated strains can be used to associate a feature value with a given increase in the strain map's complexity. The error between the sensors' measured the LSE derived strains can be calculated as:

$$V = \frac{1}{m}\sum_{k=1}^{m}(S_k - S'_k)^2 \tag{6}$$

where V is a scalar. For a given sensor location k, S_k is the sensor signal, and S'_k is the estimated sensor signal using the reconstructed strain maps. Changes in V, defined for a given shape function complexity, can be combined to form a feature distance (with units of ε^2). Temporal changes in this feature distance can be tracked to detect and localize damage not directly monitored by an SEC sensor.

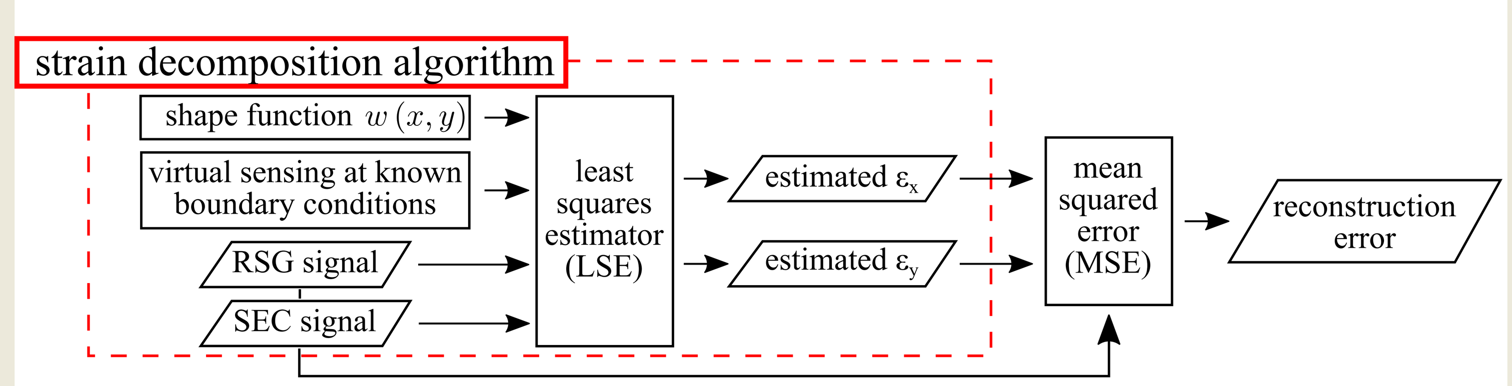

Figure 2. Flow chart for the damage detection algorithm with the strain decomposition algorithm enclosed inside the dashed red box.

Experimental Methodology

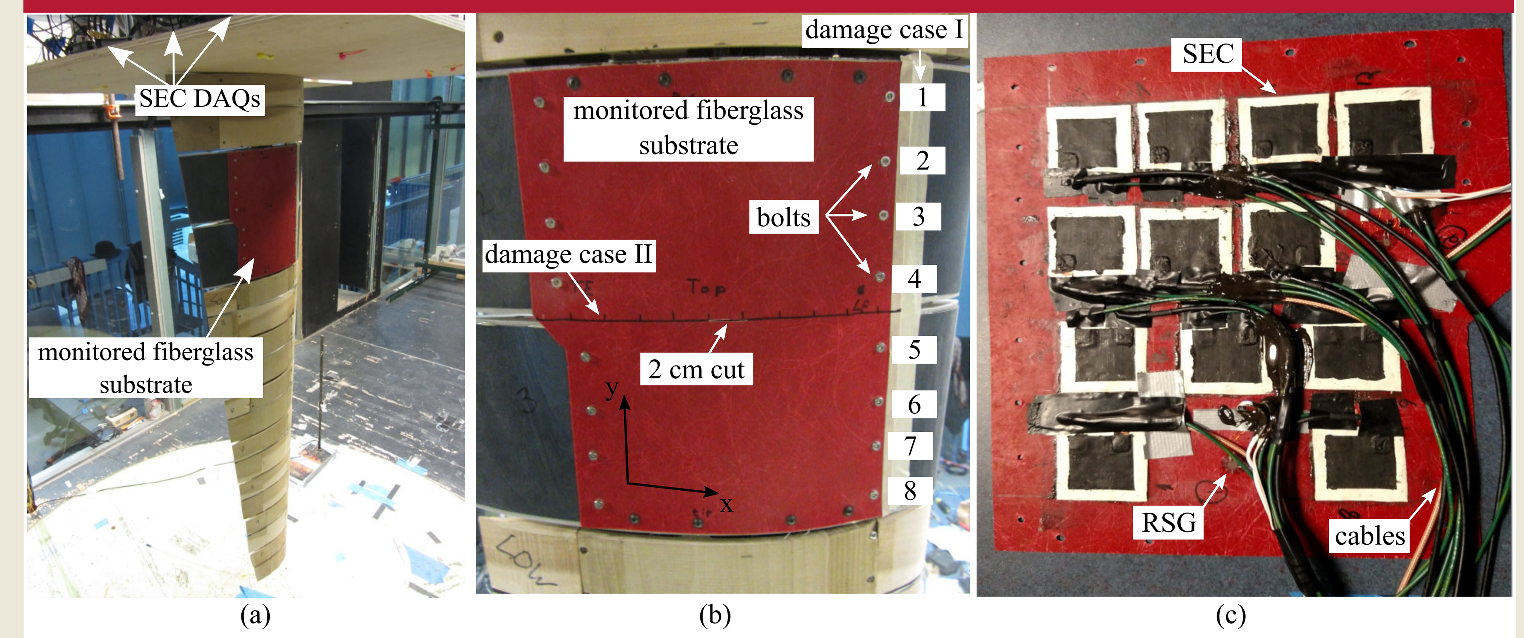

Figure 3. Experimental setup: (a) wind turbine blade model mounted in the wind tunnel showing the model's monitored fiberglass substrate; (b) monitored fiberglass substrate with labeled bolts along the leading edge (righthand side) of the substrate to be removed; (c) interior surface view of the SEC-based dense sensor network.

Experimental Validation

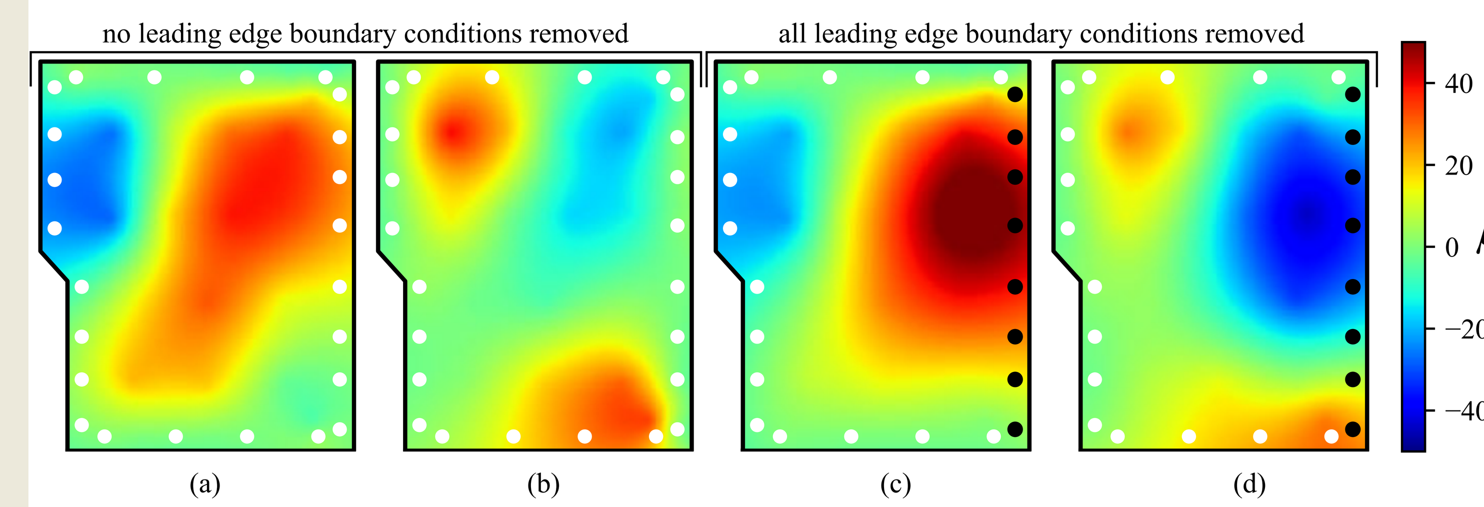

Figure 4. Reconstructed strain maps: (a) healthy condition ε_x; (b) healthy condition ε_y; (c) damage case ε_x; (d) damage case ε_y.

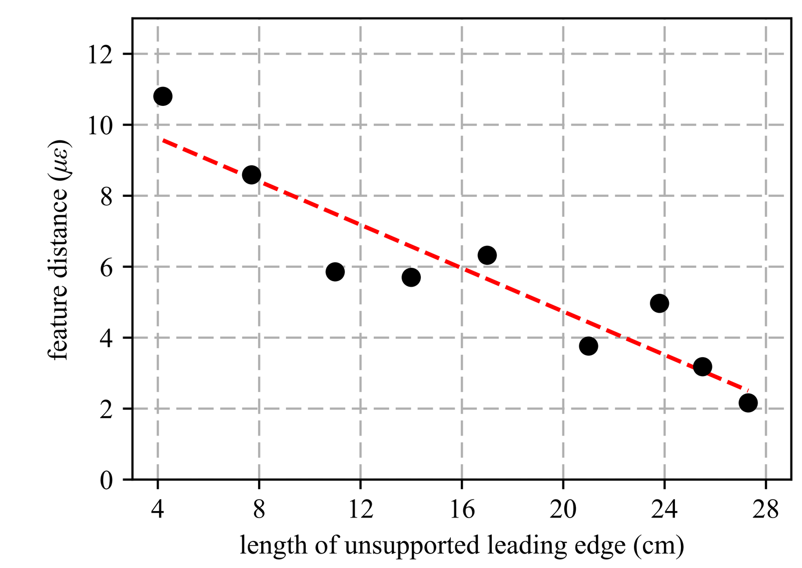

Figure 5. Damage detection algorithm results for the changing boundary conditions on the leading edge of the monitored substrate

Conclusion

- A novel dense sensor network was experimentally investigated for the condition evaluation of a wind turbine blades. The critical advantage of the soft elastomeric capacitor is its high scalability, low cost, simple fabrication and ease of installation.
- Results demonstrated that the SEC-based dense sensor network could be used to detect and track damage through the use of a proposed damage detection algorithm. Here, a damage case consisting of sequential bolt removal was successfully tracked.
- The high level of data fusion provided by the damage detection algorithm enhances the potential of the SEC-based dense sensor network through reducing the amount of data stored for operations and maintenance.

Acknowledgments

References

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