AI for Civil Infrastructure

How AI can be applied to Civil Infrastructure with Case Studies

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The ARTS-Lab at USC

We use

foundational science

Day School

to develop essential tools

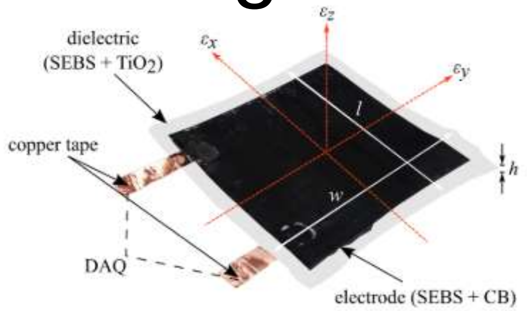
Dan Thompson

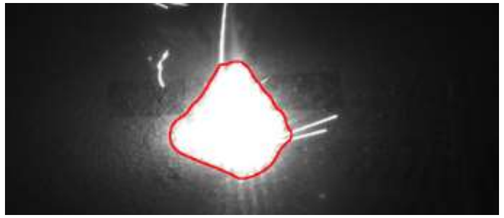
to solve real-world problems

public domain

We are Engineers (mostly)

Sensing





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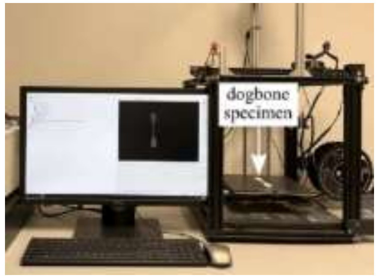
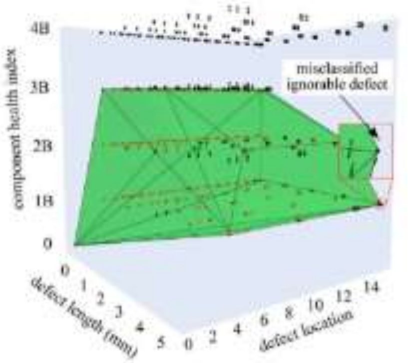
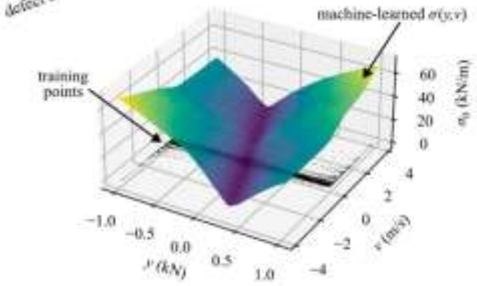
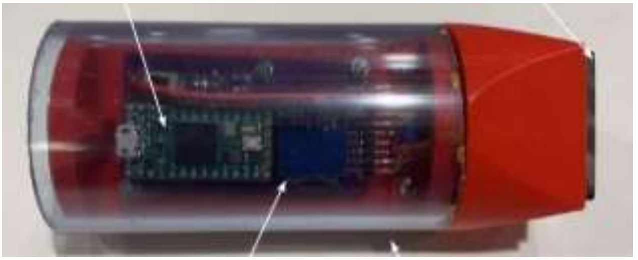


AI/ML





Embedded Systems



Civil Infrastructure

Introduction to Civil Infrastructure

- Civil infrastructure includes essential public systems and facilities:
  - Roads and highways
  - Bridges and tunnels
  - Water and sewage systems
  - Dams, levees, and flood control structures
  - Electrical grids, transportation networks, and more

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Infrastructure Maintenance and Upgrade

- Importance of Maintenance and Upgrades:
  - Critical for public safety and economic stability
  - Ensures infrastructure longevity and reliability
  - Necessary to handle increasing demand and urbanization
  - Key to reducing the risk of catastrophic failures, like bridge collapses or dam breaches

Infrastructure Challenges

Traditional Challenges:

- Aging infrastructure and limited budgets for repairs
- Manual inspection processes are labor-intensive and time-consuming
- Delayed detection of structural issues leads to reactive maintenance
- Difficulty in predicting failures due to the complexity of infrastructure systems

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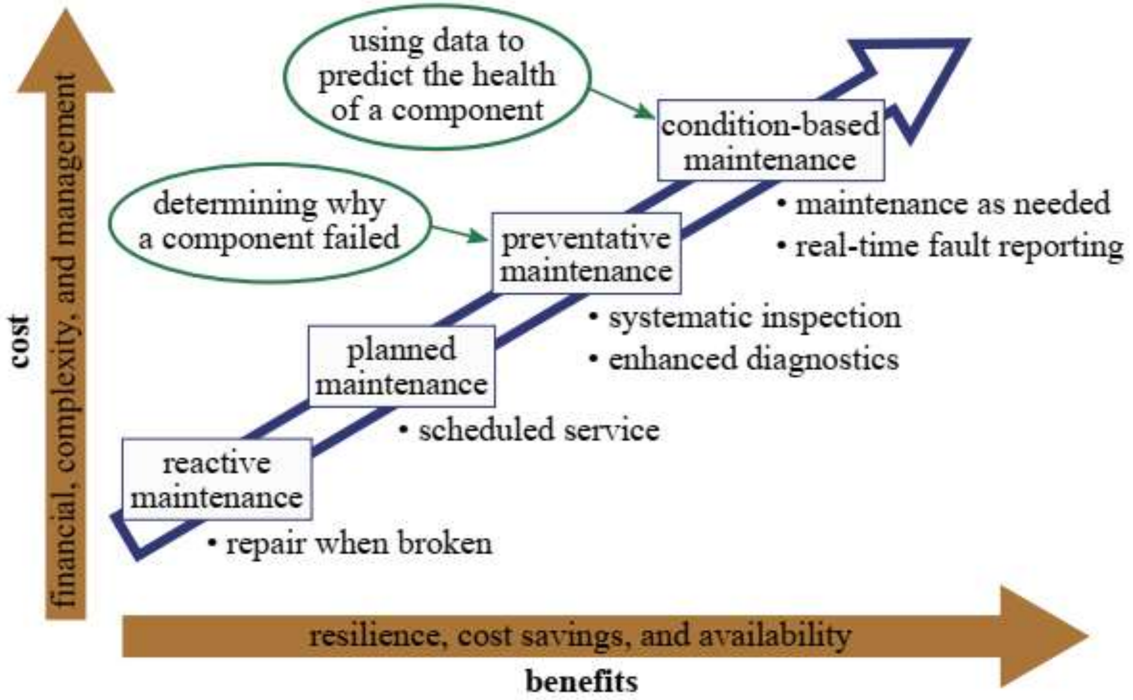
Arlington Memorial Bridge Repair & Reconstruction. National Park Service and Federal Lands Transportation Program. U.S. Department of the Interior. 2013, p. 2., Public domain, via Wikimedia Commons

Role of AI in Civil Infrastructure

AI Use Cases in Infrastructure:

- **Predictive Maintenance:** Machine learning models predict wear and tear, allowing for timely repairs before critical failures occur
- **Safety Monitoring:** AI-driven sensors detect anomalies (e.g., cracks, pressure changes) in structures like bridges and levees
- **Optimization:** AI optimizes traffic flow, energy usage, and resource allocation in urban systems



Austin Downey. Sensing skin for the structural health monitoring of mesoscale structures. Iowa State University, 2018, Iowa State University Graduate Theses and Dissertations. 16571

The Intersection of Civil Engineering and AI

Civil Engineering and AI include:

- **Data-Driven Decision Making:** AI uses data from sensors, satellites, and simulations to inform civil engineering decisions.
- **Smart Infrastructure:** Integration of AI into civil systems creates smart infrastructure that can self-monitor and report potential failures.
- **Automation in Civil Engineering:** AI automates time-consuming tasks like structural inspections and material testing.
- **Leveraging IoT:** The Internet of Things (IoT) combined with AI allows for real-time data collection from infrastructure.
- **Current Trends in Smart Cities:** AI-driven infrastructure is key to enabling smart cities.

Photos of the flood gate by Austin Downey in Örebro Sweden, Creative Commons BY-SA 4.0. 3D view taken from Google Maps in October 2024; copyright held by Google.

Applications and Case Studies

Application 1: Structural Health Monitoring

AI in Structural Health Monitoring

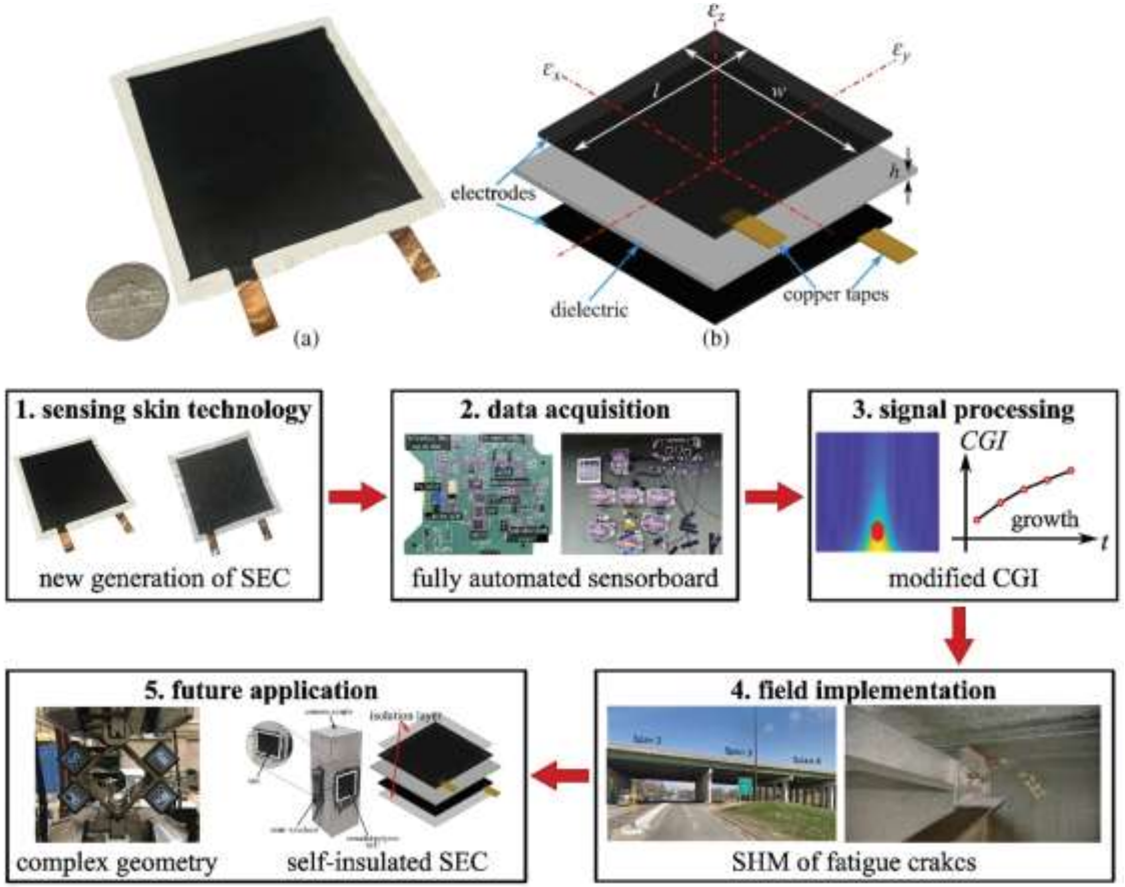
- **Real-Time Monitoring:** AI enables continuous monitoring of structures like bridges, dams, and buildings.
- **Early Anomaly Detection:** AI models identify small defects before they become serious issues.
- **Predictive Maintenance:** Machine learning predicts when repairs are needed, reducing downtime.
- **Data-Driven Decisions:** AI uses sensor data to evaluate the structural health of infrastructure.
- **Improved Safety:** AI increases safety and extends the life of structures with proactive interventions.

VTrans Rail Bridge Inspection Public Domain

Case Study 1.1: Bridge Monitoring

Key Benefits of AI in Bridge Monitoring

- **Fatigue Crack Detection:** Sensing skin technology (SEC) detects and monitors fatigue cracks in steel bridges.
- **Large-Area Monitoring:** Soft elastomeric capacitors (SECs) provide coverage over large bridge surfaces for crack detection.
- **Improved Signal Processing:** AI algorithms process noisy field data for more accurate fatigue monitoring under traffic loads.
- **Field Validation:** The system was successfully deployed on a highway bridge in Kansas, providing real-world validation for the SEC.



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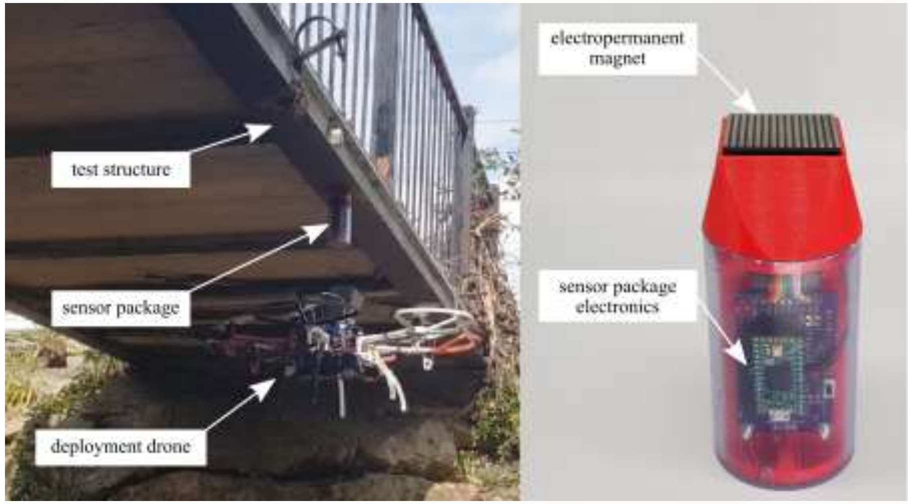
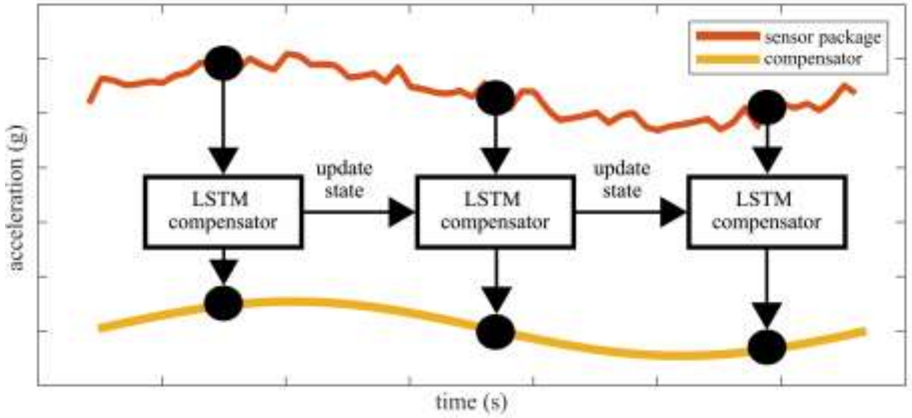
Case Study 1.2: Edge Computing

Key Benefits of Edge Computing in Structural Health Monitoring

- **Real-Time Data Processing:** Edge computing enables immediate analysis of UAV vibration data, reducing latency.
- **AI Error Compensation:** AI models correct vibration signal errors, improving quality without cloud processing.
- **Autonomous Deployment:** Edge devices deploy and process sensor data directly on-site.
- **Efficient Resource Use:** Reduces power and bandwidth for real-time monitoring in remote areas.
- **Predictive Maintenance:** AI-driven edge devices predict failures, enabling proactive maintenance.





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Application 2: Water Quality Monitoring

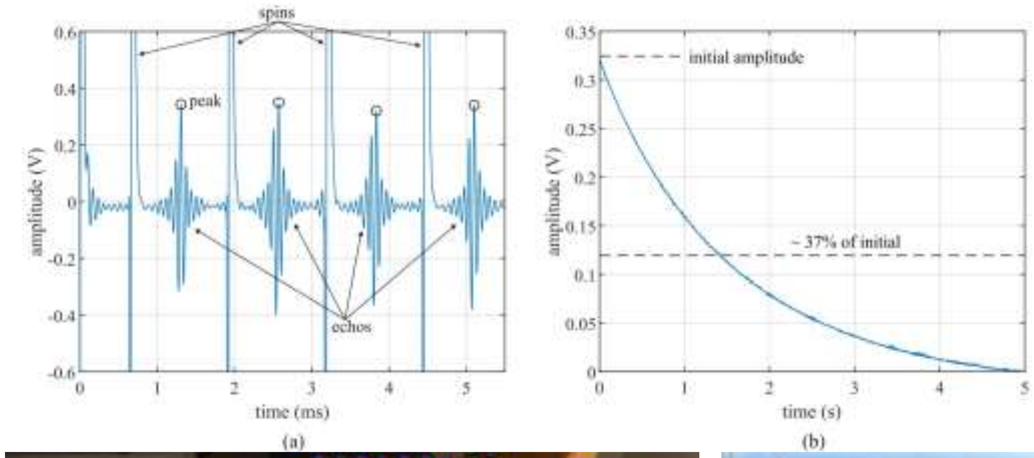
AI in Water Quality Monitoring

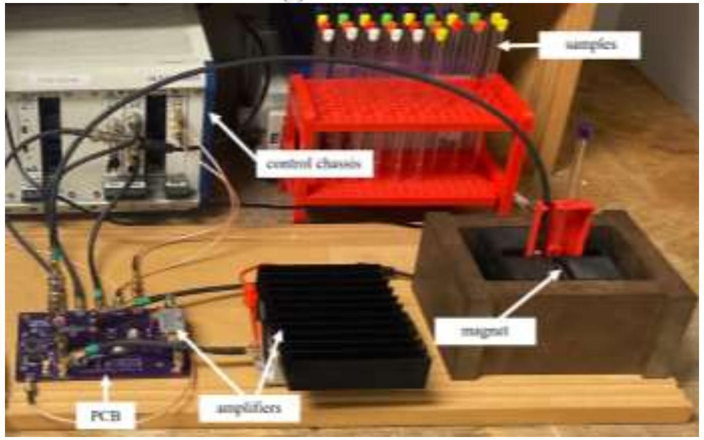
- **Real-Time Monitoring:** AI enables continuous, real-time tracking of water quality parameters (e.g., pH, turbidity, contaminants).
- **Early Detection of Contaminants:** Machine learning models identify harmful substances in water early, improving response times.
- **Predictive Analysis:** AI predicts potential water quality issues based on environmental and historical data trends.
- **Automated Alerts:** AI systems provide automatic alerts when water quality thresholds are breached.
- **Cost Efficiency:** AI reduces the need for manual sampling and testing, optimizing resource use and lowering operational costs.

Case Study 2.1: NMR-based Water Quality Monitoring with online learning

NMR-Based Water Quality Monitoring

- **Real-Time Monitoring:** Compact TD-NMR systems continuously monitor water quality parameters in real-time.
- **Detection of Heavy Elements:** The system detects magnetic particles (MPs) in water, helping to monitor contaminants.
- **AI-Based Relaxation Analysis:** Machine learning models analyze T2 relaxation data to assess water quality and detect harmful algae or pollutants.
- **Adaptive Learning:** Online learning adapt to changing environmental conditions, improving detection accuracy over time.





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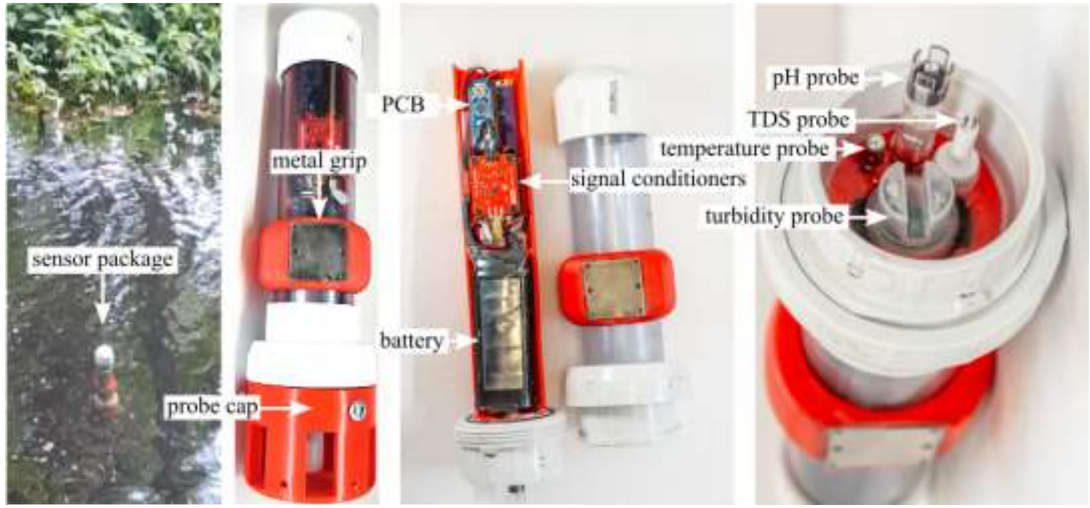
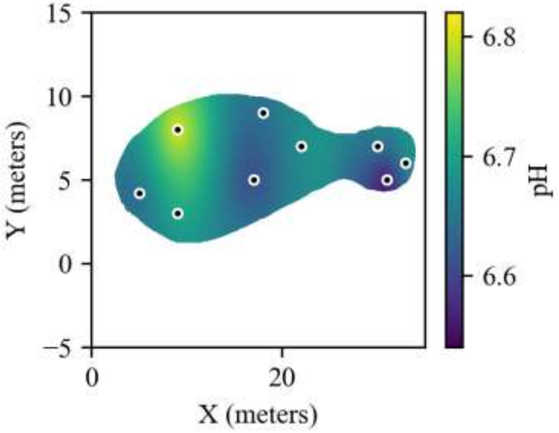
Case Study 2.2: UAV-deployable in situ Water Quality Sensors

Key Benefits of in situ Sensors

- **Real-Time Monitoring:** UAVs deploy water quality sensors to provide continuous, real-time data on key parameters like pH, turbidity, and temperature.
- **Rapid Deployment:** UAVs allow fast, efficient sensor deployment in remote or hazardous locations, making monitoring more accessible.
- **Spatial and Temporal Analysis:** AI-driven spatial interpolation techniques, such as Kriging, map water quality over time and across different locations.
- **Cost-Effective Solution:** Affordable, open-source sensors provide reliable water quality data, reducing the need for costly manual sampling.





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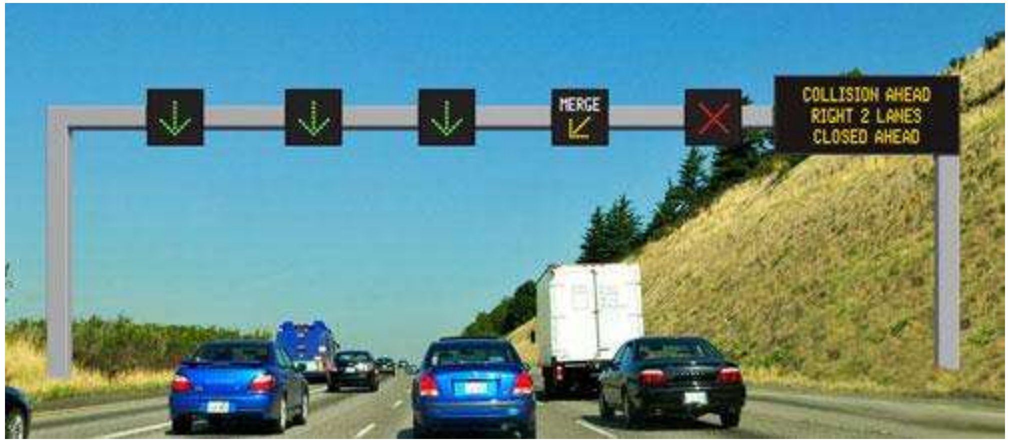
Application 3: Traffic and Transportation

Key Benefits of AI in Transportation

- **Traffic Flow Optimization:** AI helps manage and optimize traffic flow in real-time, reducing congestion.
- **Predictive Traffic Management:** Machine learning algorithms forecast traffic patterns, allowing cities to adjust signals and infrastructure accordingly.
- **Autonomous Vehicle Integration:** AI plays a crucial role in the development and management of autonomous vehicles, enhancing safety and efficiency.
- **Smart Public Transportation:** AI enables efficient routing, scheduling, and capacity management for public transport systems.
- **Environmental Benefits:** AI optimizes traffic systems to reduce fuel consumption and minimize emissions, contributing to greener cities.



Washington State Department of Transportation: Public Domain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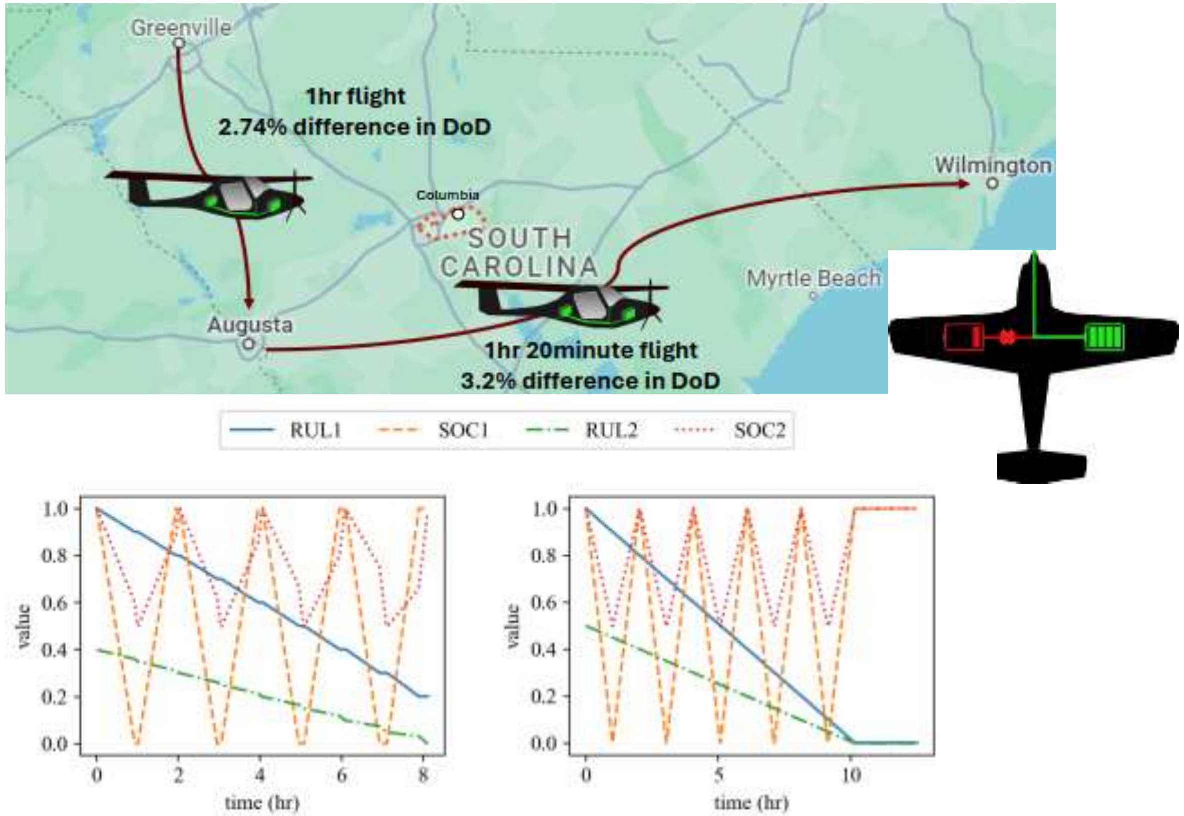
Case Study 3.1: Electric Aircraft Optimization

AI in Electric Aircraft Optimization

- **Load Sharing for Battery Life:** Load-sharing systems adjust power distribution across multiple batteries to extend lifespan.
- **Predictive Maintenance:** Predict battery degradation and optimize flight plans, ensuring efficient maintenance.
- **Battery Degradation Prediction:** Models forecast the remaining useful life (RUL) of batteries, adjusting power loads for optimal performance.
- **Flight Route Optimization:** AI analyzes flight routes to minimize battery degradation, improving the sustainability of electric aircraft.



George Anthony, Nathaniel Cooper, Jarrett Peskar, Austin R. Downey, and Kristen Booth. Extending battery life via load sharing in electric aircraft. In AIAA SCITECH 2024 Forum. American Institute of Aeronautics and Astronautics, January 2024. doi:10.2514/6.2024-2154

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Application 4: Flood Modeling and Forecasting

AI in Flood Modeling and Forecasting

- **Real-Time Data Analysis:** AI processes sensor and weather data in real-time to predict flood risks.
- **Improved Forecast Accuracy:** Machine learning models enhance the accuracy of flood forecasts.
- **Early Warning Systems:** AI-driven models provide early flood warnings, improving disaster preparedness.
- **Risk Mapping:** AI generates flood risk maps to identify vulnerable areas and inform urban planning.
- **Emergency Response:** AI helps optimize resource allocation during flood events for efficient response.

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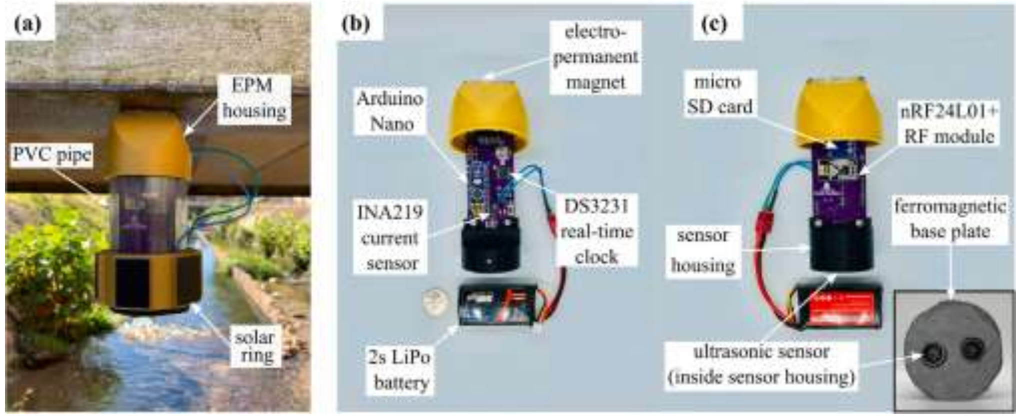
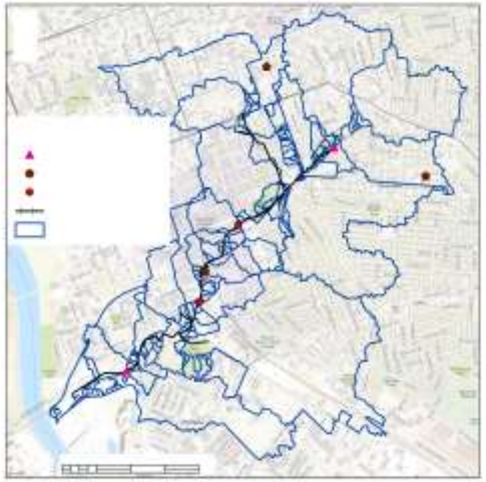
Case Study 4.1: Low-cost Height Sensors

Flood Modeling and Forecasting

- **Real-Time Monitoring:** Sensors deployed by UAVs collect real-time water height data, providing real-time information during floods.
- **Bayesian Optimization:** AI-based tools optimize flood model parameters in real-time, improving prediction accuracy.
- **Uncertainty Reduction:** AI reduces uncertainty in flood forecasts by continuously updating models with real-time data.
- **IoT Integration:** AI integrates with IoT-enabled sensors for seamless data transmission and faster model updates, improving flood response times.
- **Predictive Forecasting:** AI enhances flood prediction by processing large data sets and optimizing forecasts for urban watersheds.





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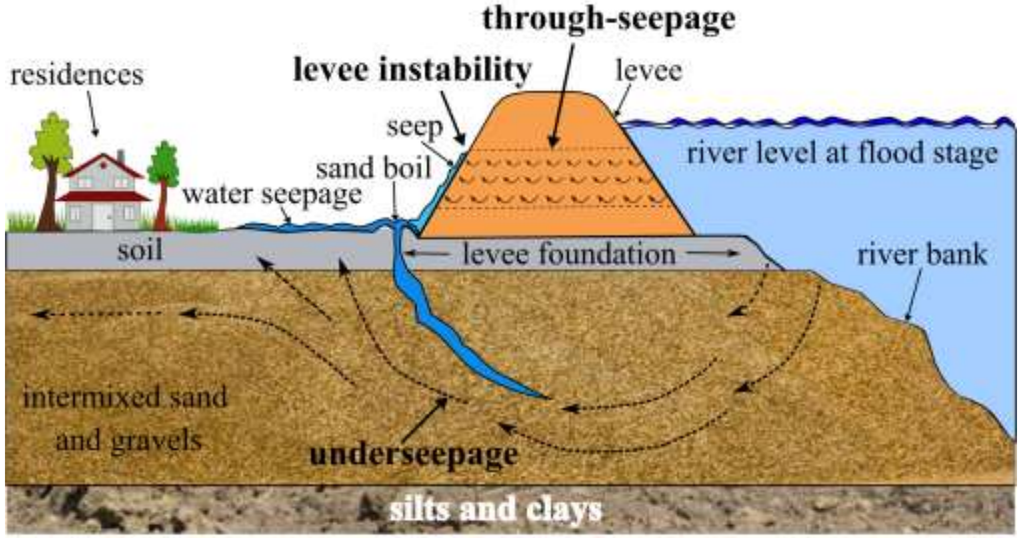
Application 5: Geotechnical Monitoring

AI in Geotechnical Monitoring

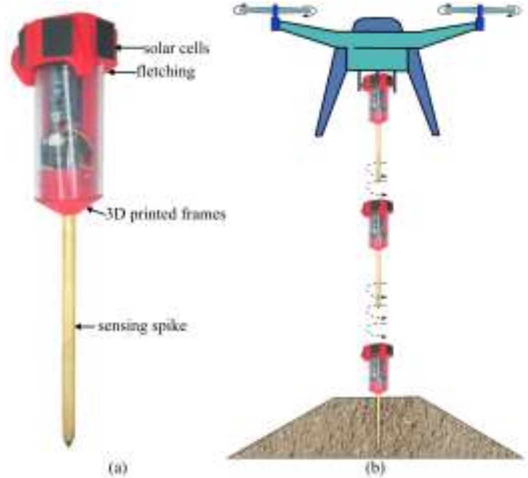
- **Real-Time Monitoring:** AI processes sensor data to monitor soil movement and stability in real time.
- **Early Detection of Failures:** Machine learning detects early signs of slope instability, landslides, and foundation settlement.
- **Predictive Maintenance:** AI forecasts potential geotechnical issues, allowing for timely interventions.
- **Risk Assessment:** AI evaluates geotechnical risks and informs decision-makers for better infrastructure planning.
- **Cost Reduction:** AI-driven monitoring reduces the need for frequent manual inspections and prevents costly failures.

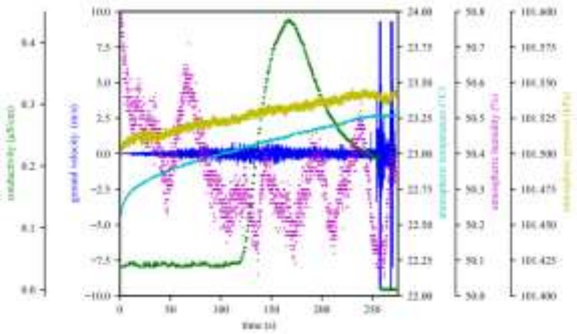


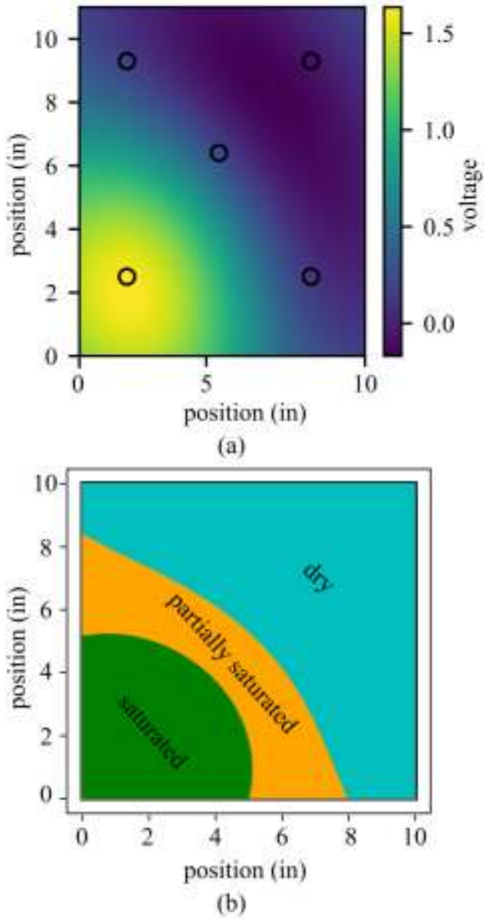
Case Study 5.1: UAV-Deployable Soil Saturation Sensors

Soil Saturation Monitoring

- **Real-Time Monitoring:** UAV-deployed smart sensing spikes provide continuous soil moisture monitoring across levees.
- **Kriging for Data Expansion:** Gaussian process regression (kriging) to generate continuous moisture maps from discrete sensor data.
- **Automated Classification:** Categorize soil conditions into dry, partially saturated, and saturated zones using k-means clustering.
- **Early Detection:** The system predicts areas at risk of levee failure by monitoring soil saturation and detecting seepage.
- **Cost-Effective Deployment:** UAV deployed of sensors reduces the need for wired systems and manual inspections.







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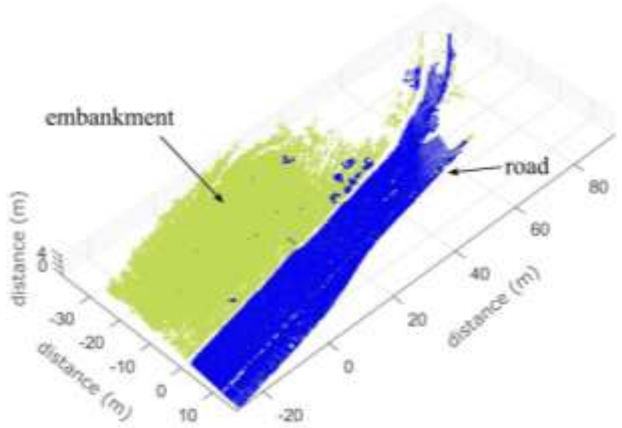
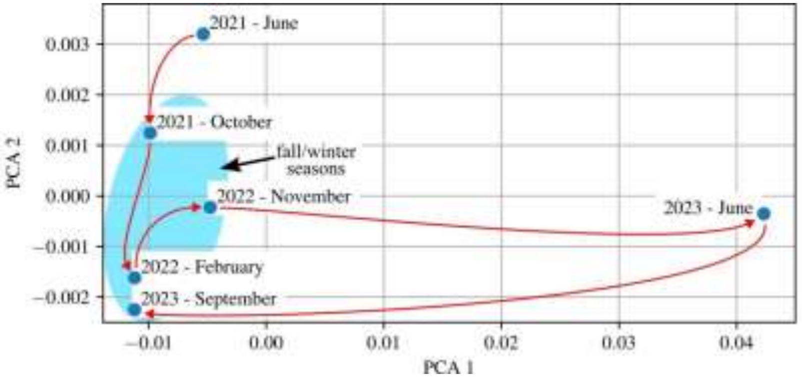
Case Study 5.2: LIDAR-based Monitoring

Key Benefits of AI in LIDAR-Based Monitoring for Slope Stability

- **High-Resolution Data Collection:** LiDAR captures 3D topography for precise monitoring of slopes and embankments.
- **Seasonal Monitoring:** AI analyzes LiDAR data to track moisture variations and their impact on soils.
- **Risk Assessment:** LiDAR scans identify potential failures, offering early warnings for slope instability.
- **Efficient Processing:** Advanced algorithms speed up point cloud data analysis for real-time monitoring.
- **Open-Source Datasets:** The SLidE dataset promotes collaboration on slope stability and geotechnical risk management.





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Current Challenges in AI for Infrastructure

Current AI/Infrastructure Challenges:

- **Data Quality and Availability:** Limited access to high-quality, labeled training data.
- **Model Interpretability:** Difficulty in understanding and trusting AI decisions in critical infrastructure applications.
- **Integration with Legacy Systems:** Challenges in integrating AI with existing, often outdated, infrastructure systems.
- **Scalability:** Ensuring models can scale across large, diverse infrastructure networks.
- **Regulatory and Ethical Concerns:** Navigating regulations, privacy concerns, and ethical issues surrounding AI deployment in public systems.

Volvo Cars Data Collection Video, Austin Downey CC BY-SA 2.0

Opportunities for Computer Scientists

Opportunities for Computer Scientists

- **AI in Smart Cities:** Contribute to the development of smart cities, optimizing transportation, energy, and urban planning.
- **Big Data Analytics:** Process and analyze vast amounts of sensor and environmental data for infrastructure management.
- **Automation and Optimization:** Develop automated systems for real-time monitoring, traffic control, and resource management.
- **IoT Integration:** Design systems that connect infrastructure to the Internet of Things (IoT) for seamless data collection and communication.

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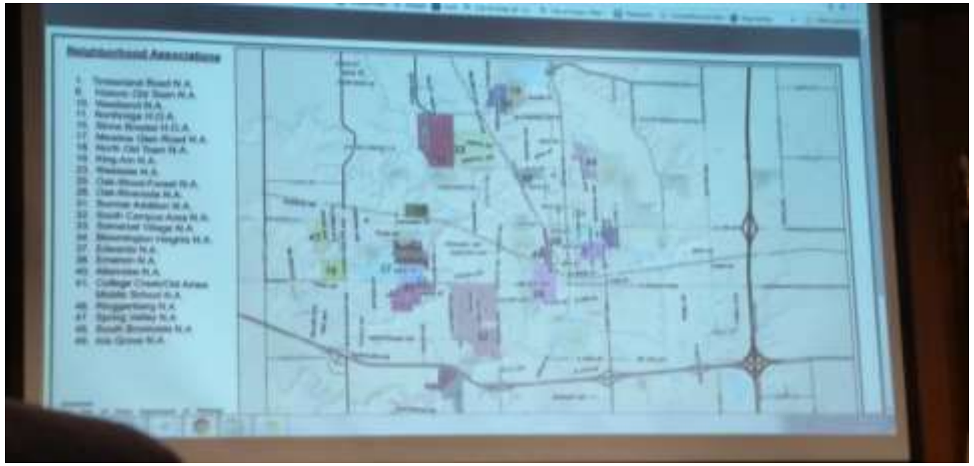
Conclusion

Final Thoughts:

- **Collaborate for Success:** Working with civil engineers is essential to solving infrastructure challenges using AI.
- **Co-Generated Knowledge:** Engage with communities to create solutions that are inclusive and culturally sensitive.
- **Design for All:** Consider diverse societal needs—age, physical abilities, and culture—when developing AI systems.
- **Shaping the Future:** AI's potential in infrastructure depends on interdisciplinary teamwork and ethical design.



Ames City Council Meeting, Austin Downey,

Questions and Discussion

This material is based upon work supported by the Air Force Office of Scientific Research (AFOSR) through award no. FA9550-21-1-0083. This work is also partly supported by the National Science Foundation Grant numbers 1850012, 1956071, 2152896, 2344357, and 2237696. as well at the Departments of Transportation of Iowa, Kansas, South Carolina, and North Carolina, through the Transportation Pooled Fund Study TPF-5(449). The support of these agencies is gratefully acknowledged. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors, and they do not necessarily reflect the views of the National Science Foundation, the United States Air Force, or the state DOTs.