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Showcase #5

# Condition-Based Monitoring as a Robust Strategy Towards Sustainable and Resilient Multi-Energy Infrastructure Systems

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## Background

As climate and disruption risk increases, extreme weather conditions that cause energy systems disturbances have also significantly increased over the past years. To mitigate the impacts of any unwanted disruptive events on the energy supply, the energy infrastructure systems need to be disaster resilient. The resilience capability in energy infrastructures can be realized through effective planning decisions and maintenance strategies. Maintenance activity has been proven to minimize the total completion time of restoration, and timely restorations of critically damaged components are essential for energy infrastructure resilience. This showcase examines how condition-based monitoring (CBM) can be used as a robust strategy to achieve sustainable and resilient multi-energy systems.

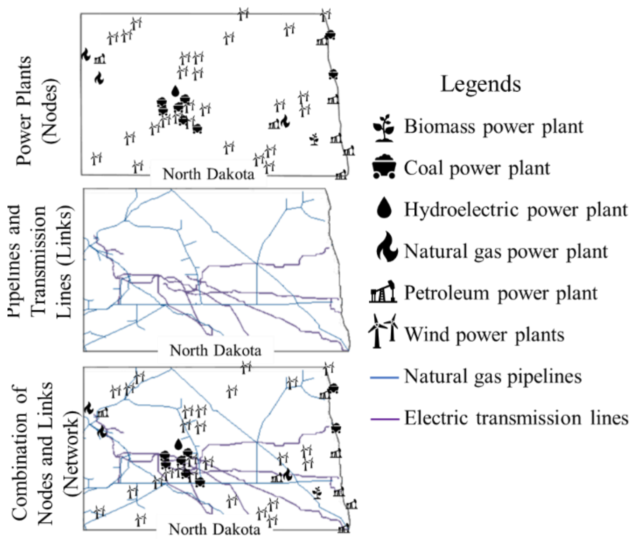


Figure 1 – Partial representative of North Dakota's energy infrastructure network

## Approach

Condition-based monitoring (CBM) is a widely practiced predictive maintenance approach in operation and maintenance. CBM minimizes the unplanned downtime of a system by monitoring the system's health status in real time and predicting upcoming failures. Being an essential part of predictive maintenance strategy, CBM aims to perform maintenance only when specific performance measures reach the thresholds indicating signs of deteriorating performance or upcoming potential failure. The three critical steps of CBM include data acquisition, data/signal processing, and feature extraction (Figure 2). There are many types of data that can be collected in energy infrastructure systems. Data collected through the sensors can be processed using different data processing algorithms. Additionally, data collected through inspections, testing, and coring can be inferred from various graphical representations and statistical analysis methods. From these processed data, parameter values are retrieved through the feature extraction process to establish the monitored system's current operating condition status and to detect any anomaly in the system. Fault detection and prediction, also known as diagnostic and prognostic, can be obtained after the data is processed. Further, depending on the failure conditions obtained, the decision-makers should make an effective decision accordingly.

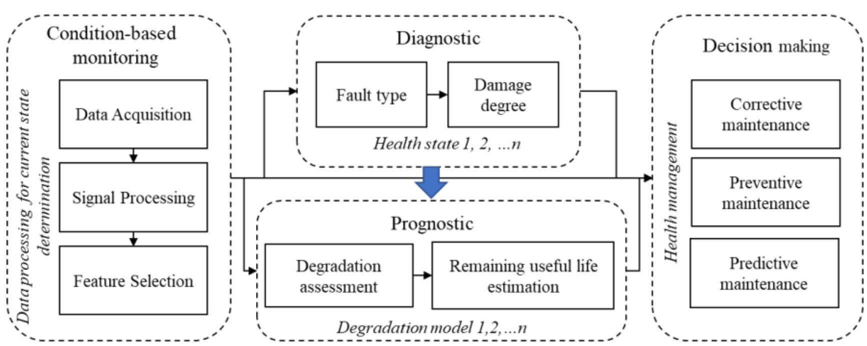


Figure 2 – An overview of condition-based monitoring (CBM)

## Results and Discussion

CBM offers two fundamental advantages towards improving overall resilience: (1) monitoring for fault prediction and detection allows for early detection of the potential fault type, potential occurrence time, and potential damage degree imposed. Therefore, (2) allowing more time for decision-making to determine the effective fault mitigation or restoration plan. Decision-makers also can draft additional contingency plans if the main plan does not turn out as expected due to implementation uncertainty. Thus, CBM is best implemented in the preventive state as a preventive strategy before the actual failure occurs. CBM also can be implemented during the restoration state to monitor restoration progress to ensure successful restoration is achieved. The best-case scenario of CBM in improving overall resilience is presented in Figure 3, where early detection influences immediate restoration. The overall system resilience can be enhanced by minimizing the potential performance loss.

The time between early detection by CBM ($t_{p(CBM)}$) and actual occurrence ($t_p$) is the fault mitigation window. Depending on the severity of the actual failure, minor-degree failure may be resolved entirely, and the system can operate as usual without any disturbances. For a medium-degree loss, which may be inevitable, the decision makers can use the fault mitigation window to minimize the negative impact of the failure occurrence with preplanned restoration planning. Thus, performance loss can be minimized from $P(t_d)$ to $P_{CBM}(t_d)$ with an early restoration executed at time $t_{d(CBM)}$ instead of at time $t_d$ to subside further performance loss. With the early restoration plan in place, the restoration time required can be minimized from $t_r$ to $t_{r(CBM)}$, and restoration state $P_{CBM}(t_r)$ can be completed in advance. For more severe failure losses that are often inevitable, for example, those included by a natural disaster, CBM implementation still allows for longer mitigation planning time from $t_{p(CBM)}$ to $t_d$, and shorter restoration time from $t_d$ to $t_{r(CBM)}$.

The potential for the CBM approach to be employed in a larger-scale energy infrastructure application has grown in recent years with the advancement of artificial intelligence and data-driven algorithms such as machine learning or deep learning approach. These algorithms can minimize data processing efforts to obtain faster and more accurate prognosis and diagnosis results. With advances in data-driven, CBM is believed to be able to improve and realize the energy infrastructure resilience against future extreme weather events.

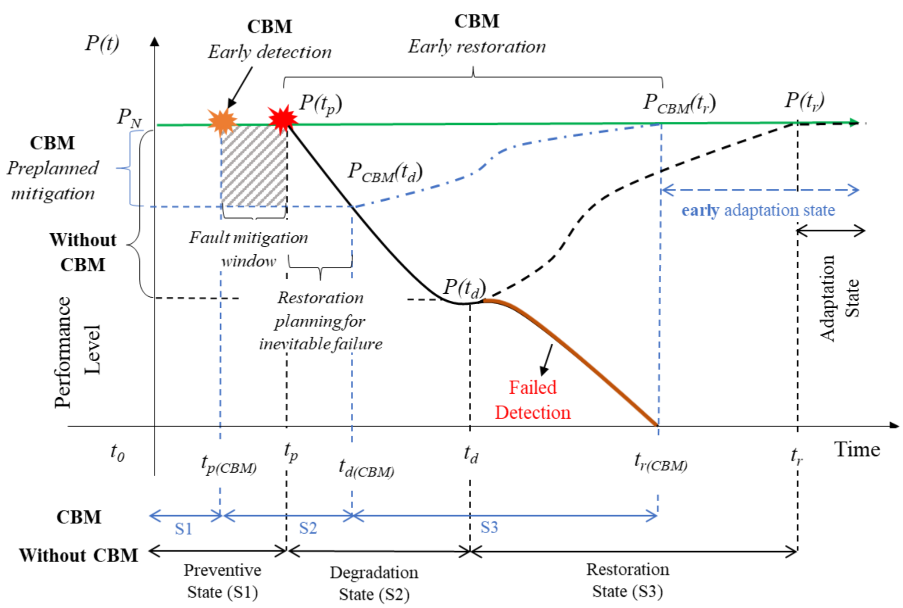


Figure 3 – Best-case scenario of CBM impact on resilience

For more information, please refer to: [Full article: Condition-based monitoring as a robust strategy towards sustainable and resilient multi-energy infrastructure systems (tandfonline.com)]