Current and Planned AI Work at EPRI

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Consultancy Meeting on Safety Consideration on AI Neural Networks Design to Support Survey Results During Gamma Spectroscopy for Decommissioning and Site Remediation
IAEA, December 15th, 2025 (virtual)

ABOUT US

Founded in 1972, EPRI is the world's preeminent independent, non-profit energy research and development organization, with offices around the world. EPRI's trusted experts collaborate with more than 450 companies in 45 countries, driving innovation to ensure the public has clean, safe, reliable, affordable, and equitable access to electricity across the globe. Together, we are shaping the future of energy.

Data-Driven Decision Making (3DM)

Leverage data science for the Nuclear Power industry

Launch & support activities across the Nuclear Sector

General application areas

Insights: learning from the past

Prognostics: anticipating the future

Automation: increasing reliability

Optimization: increasing efficiency

More details on 3DM program page

Projects

Results

Applying Data Science in the Nuclear Power Industry

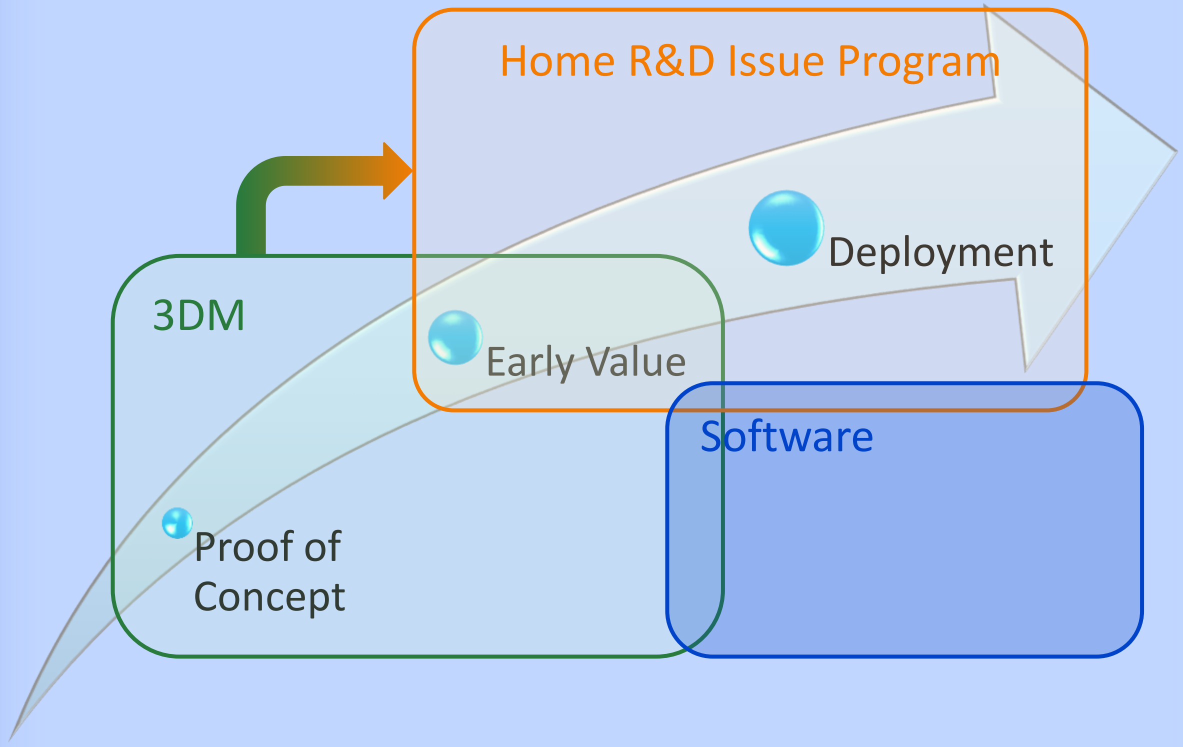
Overall Approach

Launch

- Initiate key proof of concepts
- Sponsor early implementation & tech transfer

Support

- AI projects across the R&D sectors
- Strategic initiatives



Current EPRI research: AI use cases

AI for Acoustic Emission NDE

- Current AE sensors are not robust against environmental noise.
- Could AE crack detection be improved with AI?
- As part of the project, data will be collected at the Charlotte Labs on various types of environmental noise, Pencil Lead Break tests, and real cracking.

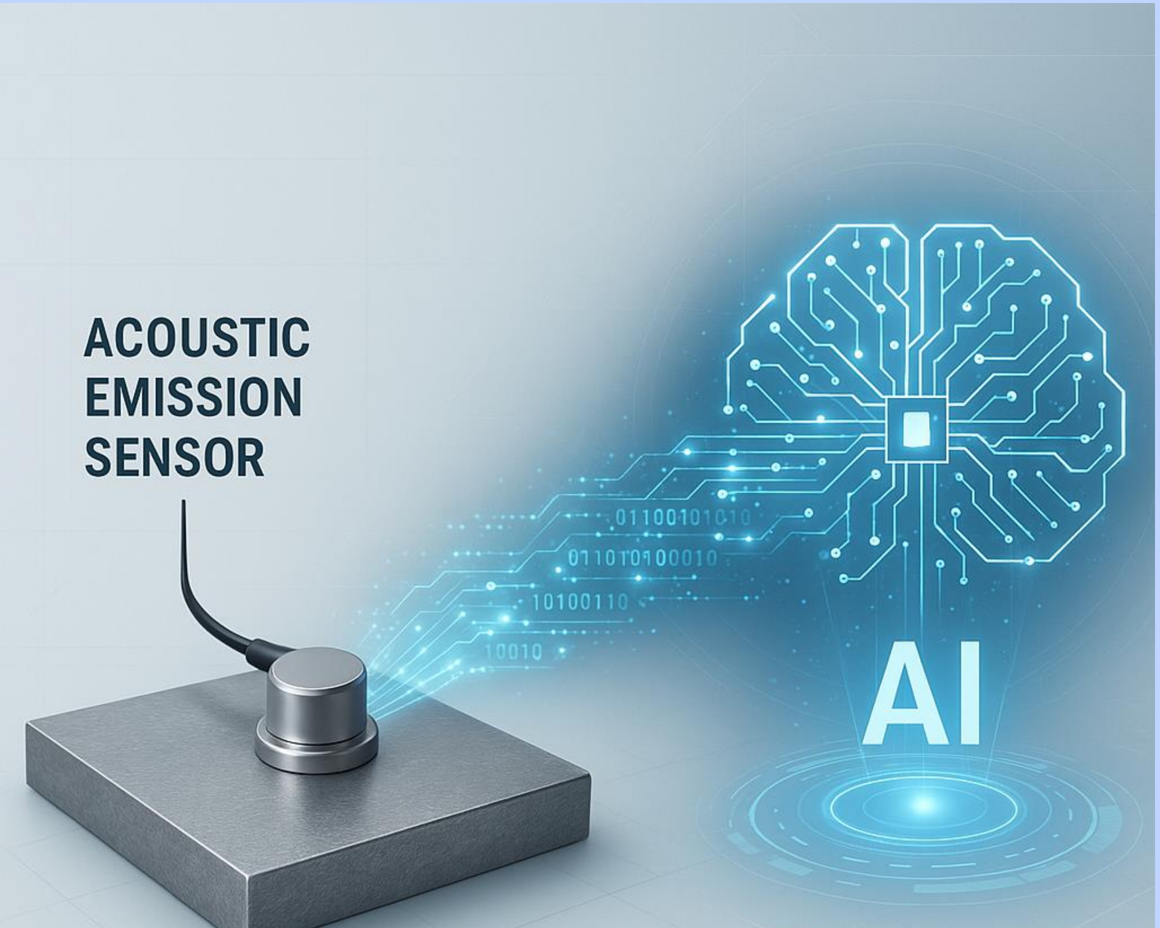


Image generated with Copilot

ALARA planner needs and AI model conceptual design

- Scope and objectives
  - Assess feasibility of using AI for ALARA task planning.
- Value
  - Enhance the efficiency and effectiveness of ALARA (As Low As Reasonably Achievable) planning by providing actionable insights and recommendations based on historical data analysis.
- Approach
  - Train a model to estimate dose based on operating conditions, work order, dose data, historical records, etc.

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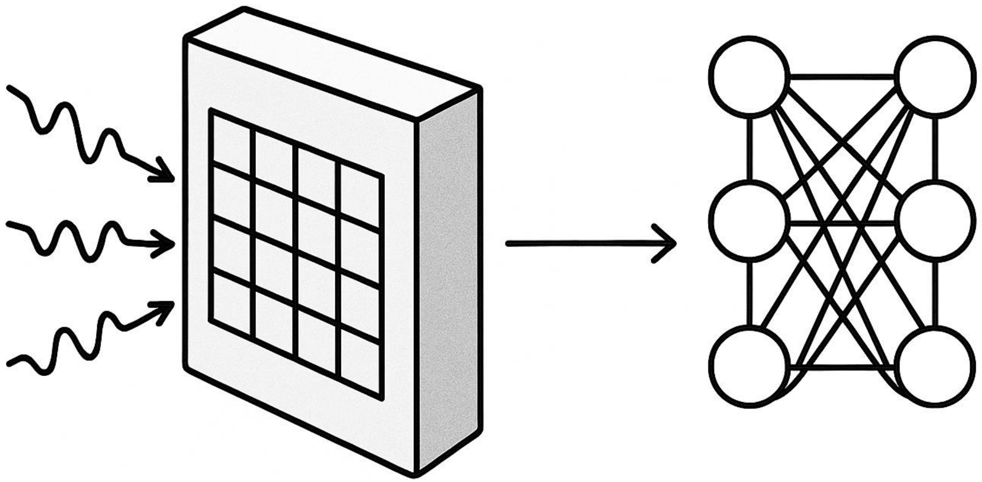
Empowering ALARA planning through AI

EPRI Project Proposal for 2026

Project Proposal

- Scoping project on use of Neural Networks in gamma spectroscopy for nuclear power plant operations
- Specifically focus on Physics-Informed Neural Networks and Bayesian Inference for uncertainty quantification



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Gamma Spectroscopy at NPP's

- Differentiating Man-made vs. Natural (avoid SCRAM, power uprates)
- Leak/Breach Detection: in the primary coolant or containment air, aids fuel failure identification and assessment
- Contaminant Tracing: targeted remediation
- More accurate dose assessment if nuclides are known – better ALARA planning
- Waste characterization
- Regulatory compliance

Enhancement in operations and safety

Challenges

- High Count Rate and Pile-Up (High Radiation Fields), dead time, pile-up
- Resolution and peak estimates
- Calibration drifts and detector damage
- Source geometry (i.e. pipes) and scattering effects – could be estimated more easily with NNs
- Uncertainty quantification

Deep Learning emerges as a promising improvement

Traditional Challenge	NN/DL Solution	How it Works
Pulse Pile-Up: Events overlap, creating false, high-energy sum peaks and spectrum distortion.	**Deep Learning (DL) for Signal Recovery:** Using Convolutional Neural Networks (CNNs) and specialized network architectures (like Attention U-Nets, or hybrid CNN-LSTMs) directly on the digitized **detector waveforms** (the electrical pulse shape).	The NN is trained on thousands of simulated and real pulses, including single events and highly piled-up events. It learns to **deconvolute** the superimposed waveforms, effectively identifying and restoring the original, individual pulses and their true amplitudes (energies). This is faster and more robust than traditional analytical signal processing.
Dead Time: The detector and electronics miss events at high rates, leading to undercounting.	**NNs for Activity Correction:** The NN can be trained to recognize the relationship between the measured spectral shape (which is distorted) and the true input activity (which is known from simulations).	The NN acts as a real-time calibration curve, automatically applying the necessary correction factor to the measured activity based on the current count rate and spectral distribution, overcoming the limitations of traditional, fixed dead-time formulas.

Traditional Challenge	NN/DL Solution	How it Works
Peak Overlap: Peaks from different nuclides (e.g., in a mixed waste sample) merge, especially with low-resolution detectors (like NaI).	**CNNs for Feature Extraction:** CNNs are excellent at automatically extracting and learning subtle features and patterns from the full spectral shape, rather than just relying on the peak maximum.	The NN is trained to classify the spectrum based on its entire shape, enabling it to accurately identify the presence and contribution of multiple nuclides even when their characteristic peaks are spectrally inseparable to a traditional analysis algorithm. This effectively **bridges the performance gap** between low-resolution and high-resolution detectors.
Nuclide Quantification (Activity): Accurately determining the *amount* of each nuclide from a complex, non-linear spectrum.	**Deep Regression Models:** Using networks to directly predict the concentration/activity of each nuclide from the spectrum's input channels.	The network learns the non-linear relationship between the intensity of spectral features (even non-peak features like the Compton background) and the true nuclide activity, providing a faster, more generalized solution than complex analytical fitting routines.

Traditional Challenge	NN/DL Solution	How it Works
Calibration and Geometry Effects: Detector efficiency changes with the sample's physical size, shape, and position (geometry), making lab calibration impossible for real-world, dynamic NPP monitoring.	**Physics-Informed Neural Networks (PINNs):** PINNs integrate the fundamental physical equations (like the law of radioactive decay, or equations for photon transport/attenuation) directly into the NN's loss function (the training objective).	The PINN is trained not only on measurement data but also on the *physics* of how gamma rays interact with matter. This forces the model to obey physical laws, allowing it to accurately predict detector efficiency and true activity for **any arbitrary geometry** or shielding condition it has not been explicitly trained on. This is a game-changer for field deployment.
Detector Drift and Environmental Variation: Changes in temperature, voltage, or background radiation cause the spectrum to shift or change.	**Adaptive Neural Networks:** NNs are inherently robust to noise and can be trained to be invariant to these environmental shifts.	The network is trained on a dataset that includes spectra acquired under various conditions (different temperatures, slight voltage drifts, different background rates). The network learns to normalize or correct the input spectrum for these drifts before classification or quantification, making the monitoring system far more robust and reliable in a real NPP environment.

Applications of developing expertise in NN, PINNs, Bayesian inference

- ALARA dose estimates
- Fuel failure
- Digital Twins
- Robotics/Edge AI for radiation detection
- Cross-domain applications

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