A Deep Learning Surrogate Model for Rapid Prediction of Atmospheric Radioisotope Dispersion

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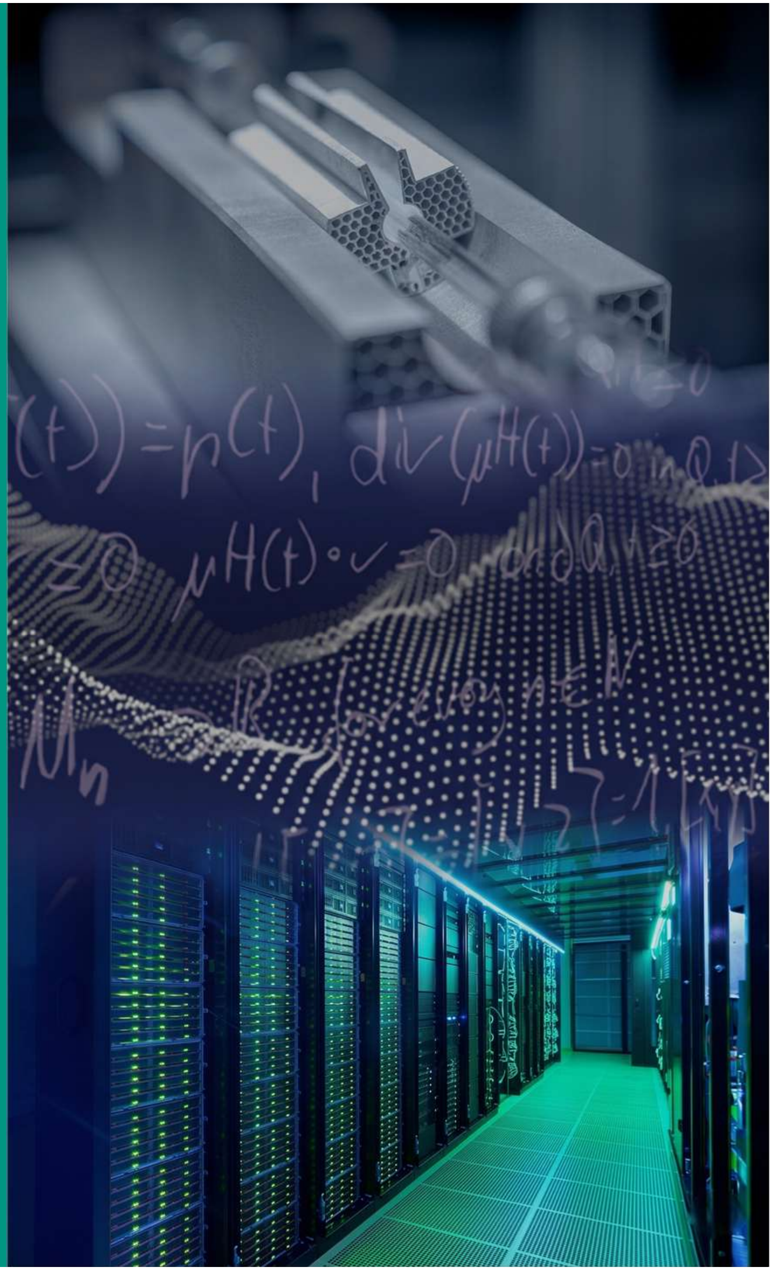

Onur Murat, Fabrizio Gabrielli, Victor Hugo Sanchez Espinoza

Karlsruhe Institute of Technology
Institute for Neutron Physics and Reactor Technology
Reactor Physics and Dynamic Group
Hermann-von-Helmholtz Platz 1, 76344 Eggenstein-Leopoldshafen

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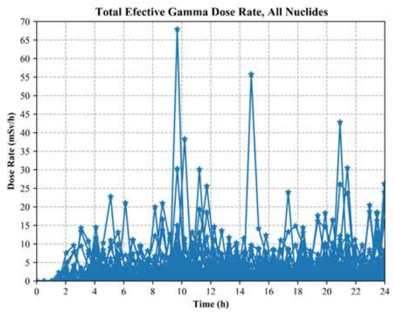
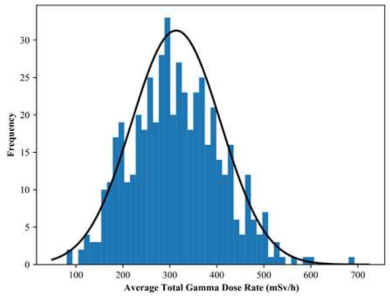
Motivation

- In the event of a severe accident, emergency response authorities require fast and accurate predictions of radionuclides.
  - Emergency Management Guidelines
  - Identification of Emergency Planning Zones
- Comprehensive risk assessments covering multiple calendar years and thousands of weather scenarios are computationally prohibitive.



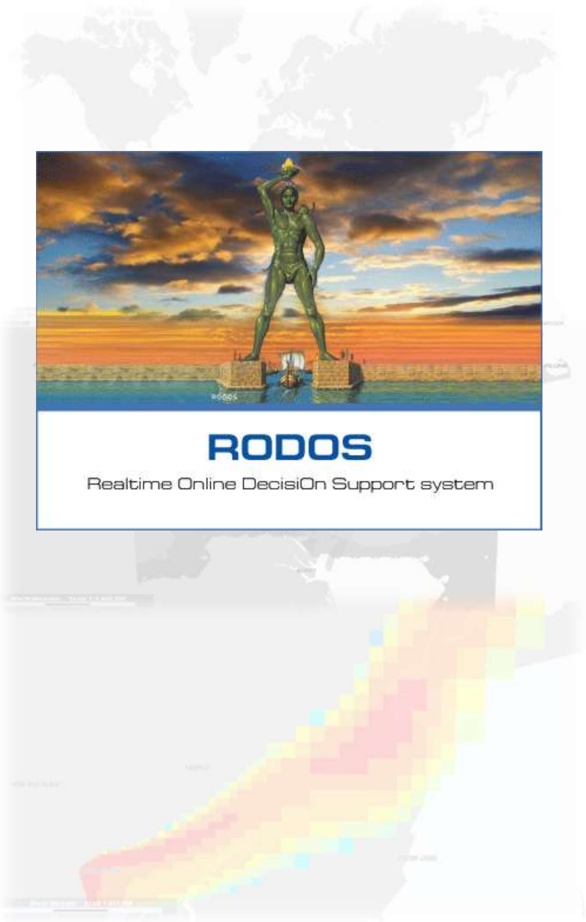


JRODOS Simulation of large batches requires years of CPU time

60,000 simulation + Central Limit Theorem 25 days CPU time

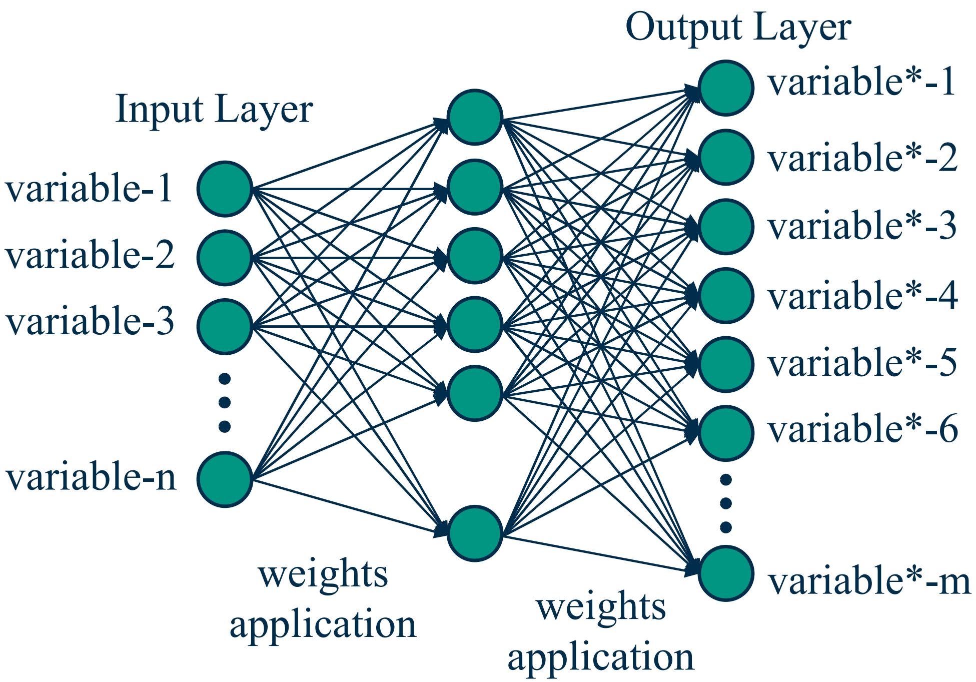
- A surrogate model is needed that can reproduce the Code (JRODOS) quality dispersion maps in a fraction of the time.

What is JRODOS?

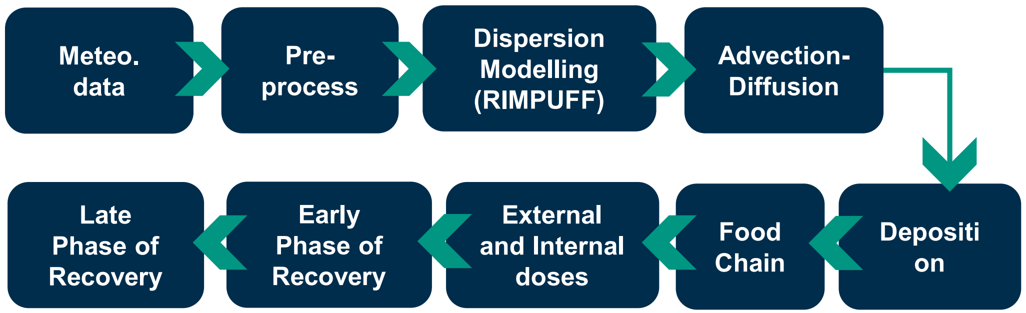


- JRODOS (Java-based Real-time Online Decision Support) System is the European standard tool for radiological emergency management, currently operational in regulatory bodies across many countries.
- The system integrates meteorological forecast data with user-defined source terms and advanced atmospheric dispersion models to calculate radionuclide transport and deposition over any region on the globe.
- Simulation outputs guide protective actions such as population sheltering, evacuation zone definition, and iodine tablet distribution.
- JRODOS relies on physically rigorous Gaussian puff and Lagrangian particle models, which accurately capture plume behavior and topographic interactions but at significant computational cost.

Artificial Neural Network (ANN) Surrogate Approach



- JRODOS or any other dispersion tool deals with differential equations, wrappers and libraries.



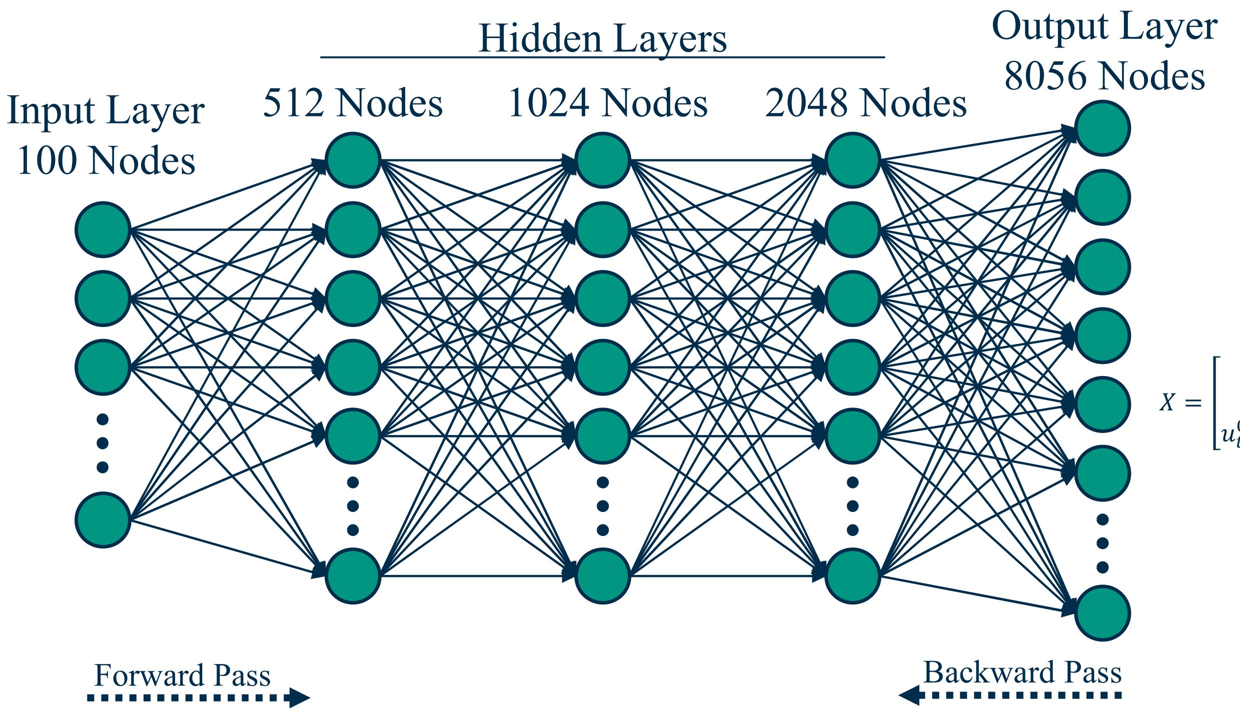
- An Artificial Neural Network (ANN) can be trained on a large database of pre-computed JRODOS simulations.
  - No equations are solved at runtime, only a series of fast matrix multiplications
- This acceleration makes it feasible to evaluate dispersion consequences across thousands of weather scenarios and multiple calendar years

Database and Setup

Isotope	Activity (Bq)	Isotope	Activity (Bq)
Cs-134	1.1E+15	**Kr-87**	9.0E+15
Cs-136	4.7E+14	**Kr-88**	1.8E+17
Cs-137	6.5E+14	**Sr-90**	4.7E+13
I-131	9.5E+15	**Sr-91**	6.4E+14
I-132	1.3E+16	**Te-131m**	1.1E+15
I-133	1.5E+16	**Te-132**	1.3E+16
I-135	7.0E+15	**Xe133**	4.6E+18
Kr-85	2.4E+16	**Xe-135**	2.1E+18
Kr-85m	1.5E+17		

- 1,000 JRODOS simulations was generated using a fictitious NPP location at KIT Campus North.
  - 100 km radius
  - 30 minutes time-steps over 24 hours simulation windows
- Radionuclides discharged into the atmosphere within a single 30-minute interval from a stack height of 150 meters.
- Weather data from U.S. NOAA NOMADS servers in GRIB format at 0.5-degree spatial resolution.
  - Random sampling of analysis starting time in year 2021
- 4 atmospheric parameters were extracted over a 5×5 grid centered on the plant.
  - U, V component of wind
  - Temperature
  - Surface pressure
- The dataset was divided into **90% for training** and **10% for testing.**

ANN Architecture and Training 1/2

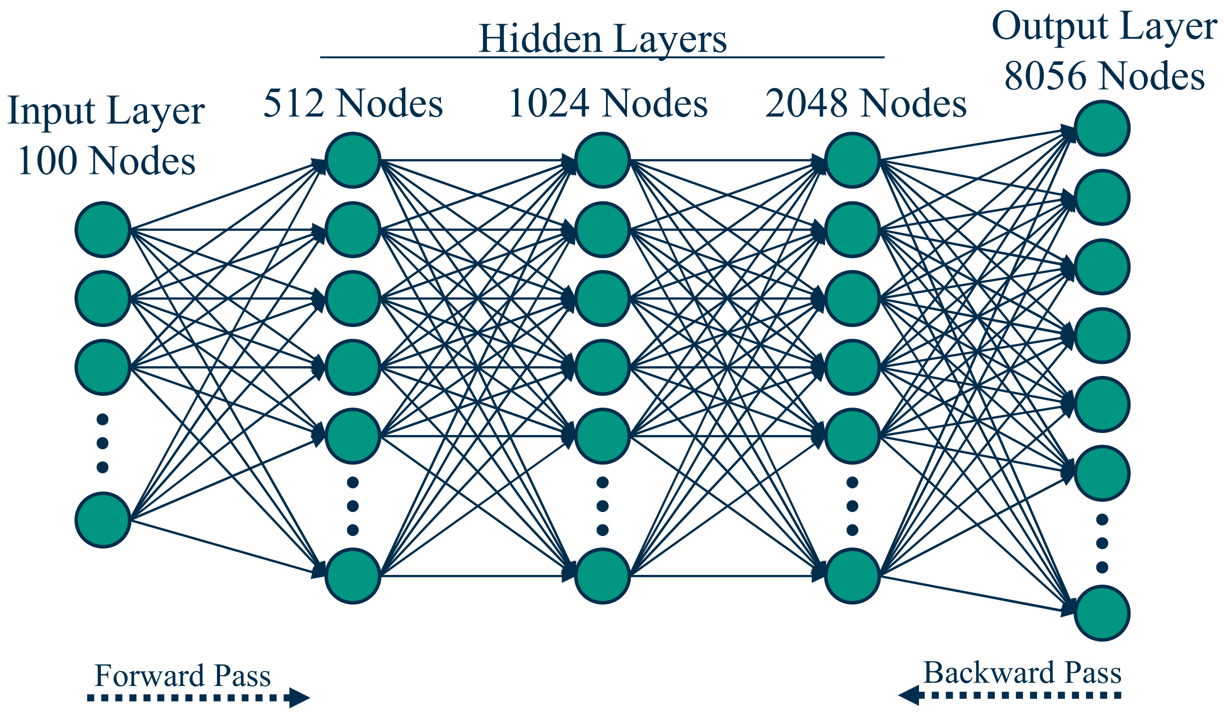


- Multilayer Perceptron (MLP) regressor with around 19 millions trainable parameters.
  - 100 nodes for meteorological input.
  - 8,056 output nodes for dose rate values corresponding to every mesh.

$$X = \begin{bmatrix} u_{t\_0}^{0} \dots u_{t\_0}^{24} & v_{t\_0}^{0} \dots v_{t\_0}^{24} & T_{t\_0}^{0} \dots T_{t\_0}^{24} & P_{t\_0}^{0} \dots P_{t\_0}^{24} \\ \vdots & \vdots & \vdots & \vdots \\ u_{t\_47999}^{0} \dots u_{t\_47999}^{24} & v_{t\_47999}^{0} \dots v_{t\_47999}^{24} & T_{t\_47999}^{0} \dots T_{t\_47999}^{24} & P_{t\_47999}^{0} \dots P_{t\_47999}^{24} \end{bmatrix}$$

$$y = \begin{bmatrix} dose_{t\_0}^{mesh\_0} & \dots & dose_{t\_0}^{mesh\_8055} \\ \vdots & \vdots & \vdots \\ dose_{t\_47999}^{mesh\_0} & \dots & dose_{t\_47999}^{mesh\_8055} \end{bmatrix}$$

ANN Architecture and Training 2/2

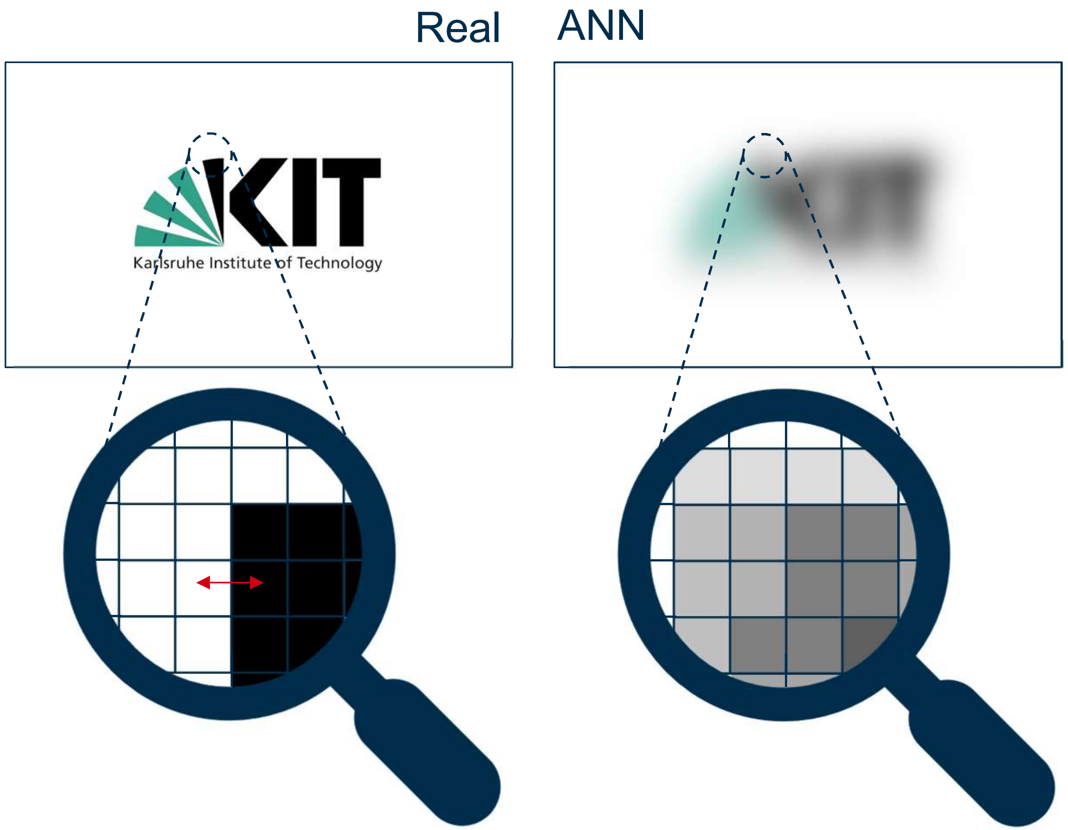


- ReLU activation functions are applied throughout the hidden layers to capture the non-linear behavior of the dispersion physics.
- Input parameters are normalized to prevent large-magnitude values like surface pressure from dominating gradient updates.
- Overfitting prevention: early stopping based on validation loss.

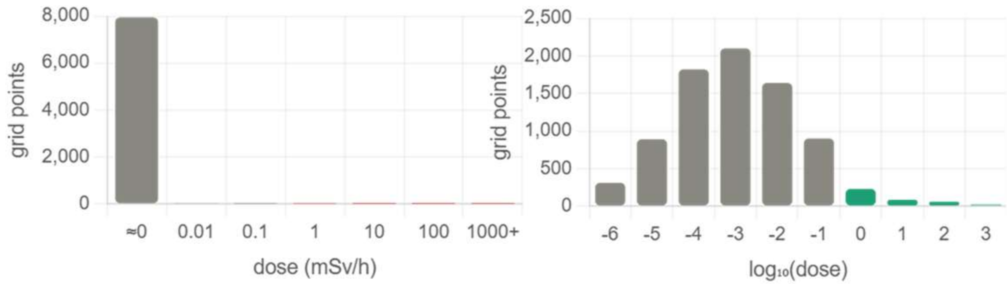
intel ~20 hours

NVIDIA ~15 minutes

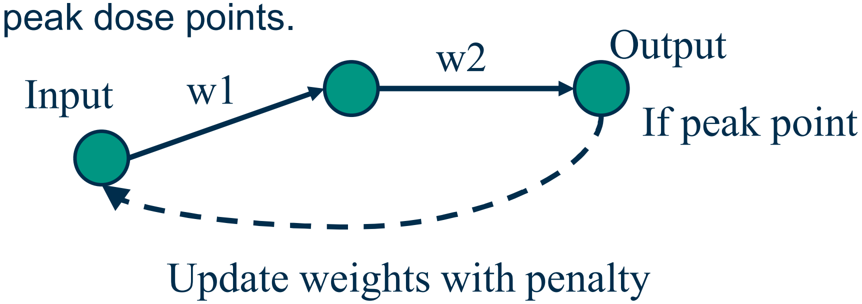
Training Challenges and Solutions



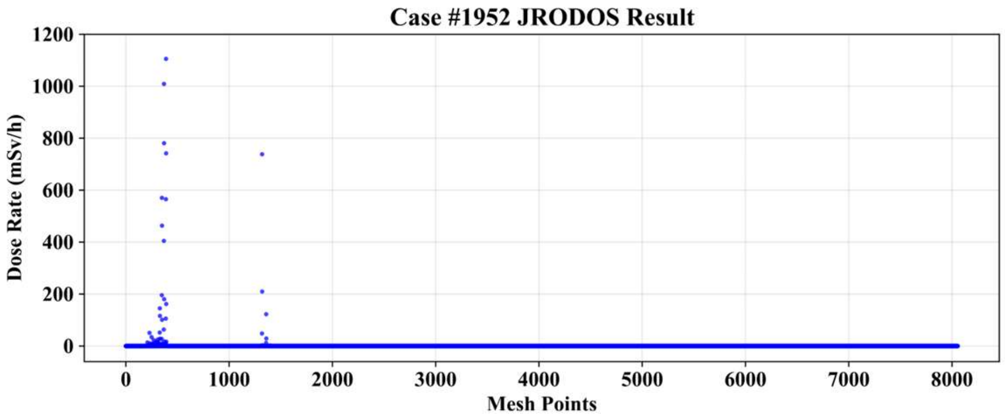
- Radioactive dispersion affects only a small fraction of the grid at any time.
  - Most grid points have near-zero dose → model learns to predict zeros.
- **Logarithmic scaling:** compressing the dynamic range and allowing the network to learn the shape.

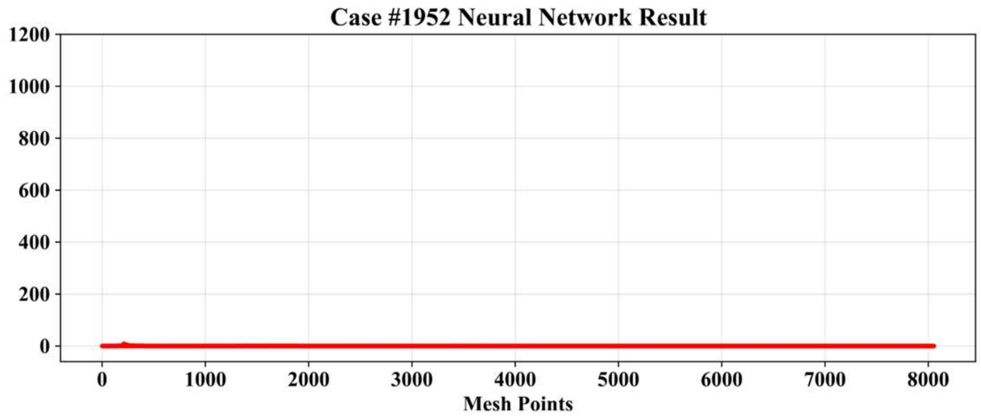


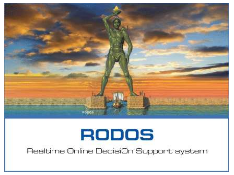
- **Penalty weighting:** penalty for underestimation of peak dose points.



Results: JRODOS vs ANN Prediction







~135 seconds

ANN

~0.08 seconds

- The ANN model successfully identifies the spatial location and general footprint of the radioactive plume across the majority of test cases.
- For most test cases, dose rate predictions show good agreement with JRODOS results, with some tendency to overestimate peak values which is consequence of the penalty weighting.
- Model currently fails to capture cases where the plume remains close to the release point and does not travel far result in very high localized dose readings.

Why is it important? Climate Change

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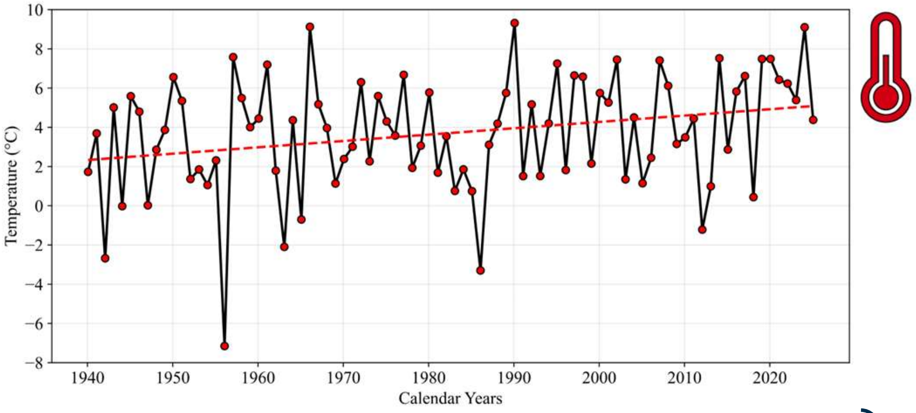

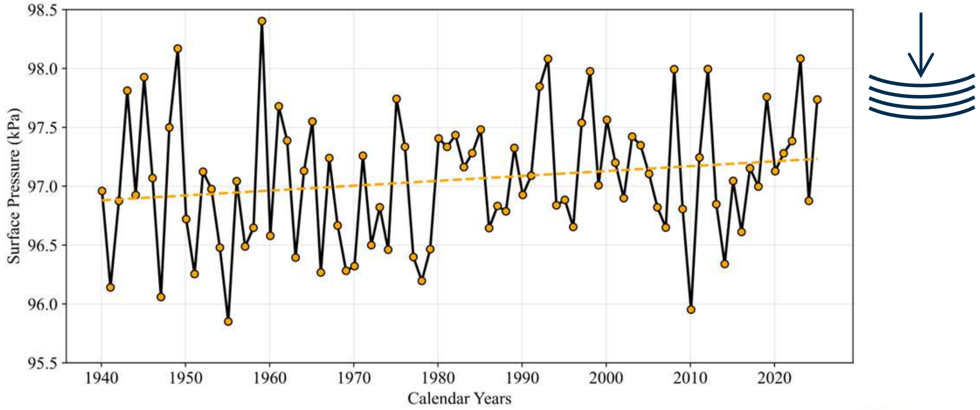

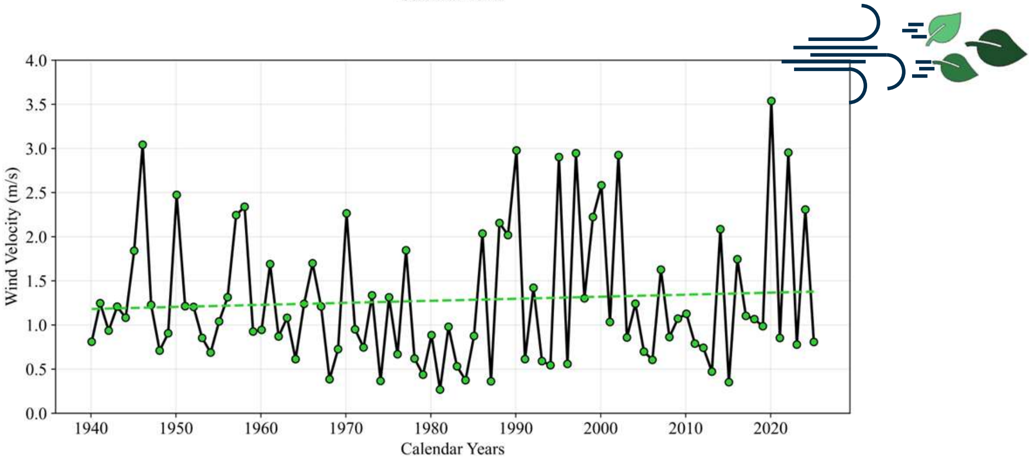

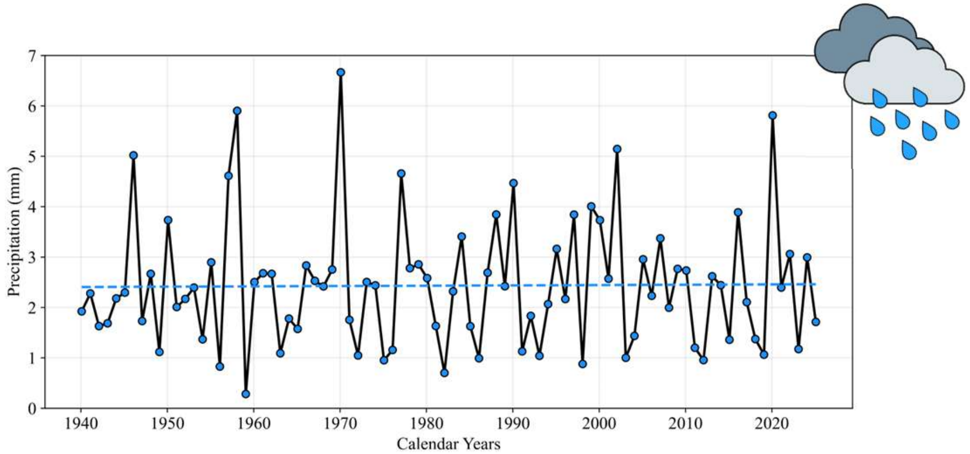

KIT

Conclusion

- A deep learning surrogate model was successfully developed and validated against JRODOS, reducing dispersion prediction time from over 2 minutes to less than 0.1 seconds.
- The ANN accurately captures plume location and footprint across a wide range of meteorological conditions, demonstrating the viability of data-driven surrogate models as a complement to physics-based dispersion codes.
- The speed advantage opens the door to comprehensive multi-year, multi-scenario statistical assessments that significantly strengthen nuclear emergency preparedness and planning.
- The model will be extended for variable source terms derived from severe accident simulation codes. Scenario-specific dose predictions for different accident progressions is going to be considered.
- Investigation of application to Small Modular Reactor (SMR) siting studies, Environmental Impact Assessments, and Emergency Planning Zone definition is in agenda.
- The model accuracy will be improved iteratively for high-consequence, low-probability dispersion events through targeted data augmentation and advanced loss function design.

Thank you for your attention

Onur Murat

onur.murat@kit.edu