
Artificial Intelligence in Internal Dosimetry: Mechanisms, Models, and Multiscale Applications

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George W. Woodruff School of Mechanical Engineering

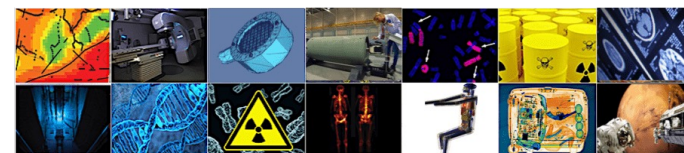
Nuclear and Radiological Engineering and Medical Physics Programs

shaheen.dewji@gatech.edu

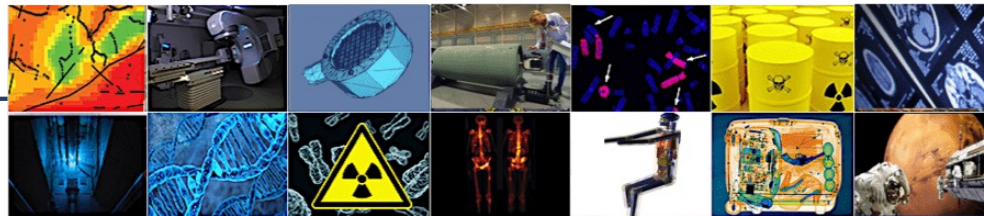
February 19th, 2026

EURADOS Annual Meeting

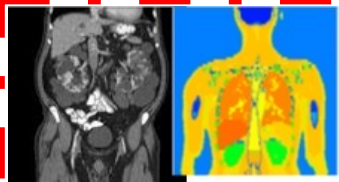
Helsinki, Finland



Annual Meeting 2026, Helsinki



Mission: The **Radiological Engineering, Detection, and Dosimetry (RED²) Laboratory**, led by **Dr. Shaheen Dewji**, conducts innovative, interdisciplinary research focusing on harnessing **both computational capabilities** in Monte Carlo radiation transport modeling and **experimental measurements** for applications in **radiation detection**, **radiation protection and shielding**, **dosimetry**, **health physics**, and **nuclear materials accounting**.

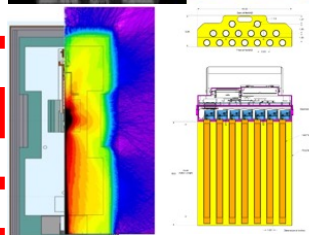
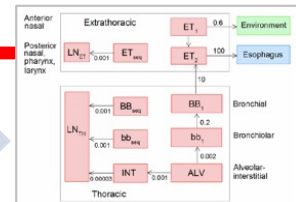


Computational Dosimetry and Shielding

Development of dose coefficients and shielding design using Monte Carlo radiation transport codes

Age/sex-specific anthropomorphic computational phantoms

Radionuclide biokinetic models for emergency response, nuclear medicine, and occupational

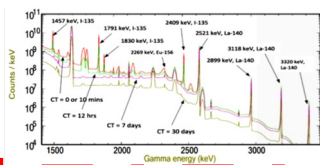
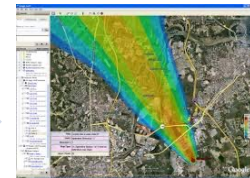


Radiation Detection

Employment of validation and verification of gamma-ray spectroscopic detector responses

Contaminated environmental media for environmental assessment and decommissioning

Field triage of uptake during nuclear, radiological, and fission product release events



Nuclear Nonproliferation and 3S (Safety, Security & Safeguards)

Nuclear materials control, accounting, and safeguards of SNM

Gamma-ray spectroscopic analysis for safeguards by design of advanced non-LWR reactors

Neutron multiplicity counting for field search/detection and criticality safety



AI + Multiphysics Modeling and Measurements

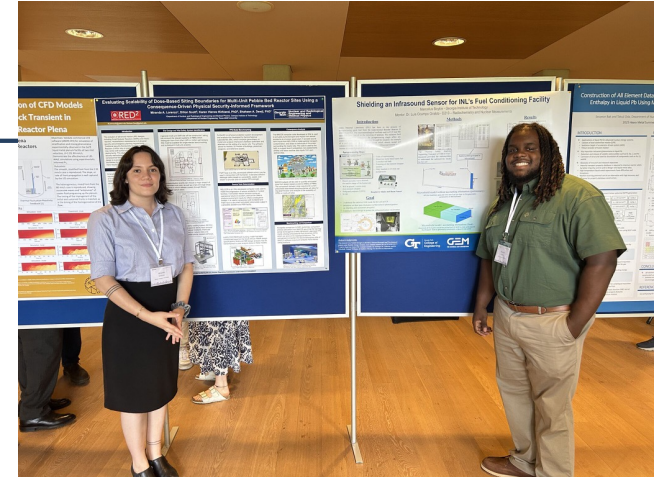
RED² Laboratory Status and Outlook

Spring 2026 Research Group

- 12 Ph.D. students
- 1+2 M.S. students
- 8 undergraduate students
- 1 Post-doctoral Fellow
- 1 Research Engineer

Laboratory Capabilities

- 8 Mirion NAIS 2x2 NaI and LaBr3 detectors with digital base
- Male CIRS Atom Phantom
- Sources (Gamma check, point, area; AmBe, PuBe)
- ADVACAM AdvaPIX Timepix3 hybrid pixelated detector
- PHDS GeGI Compton Imaging System
- PACE High Performance Computing
- RSEL Systems (DD/DT neutron generator, OGS, BSS)



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Introduction: Evolutions in Radiation Dosimetry

Breakthroughs driven by medicine in radiation sciences

- “Digital twins”
- “Personalized medicine”



Computational capabilities in anatomical modeling

- Anthropomorphic phantoms
- Age/Sex
- Non-reference: Height/ Weight
- Pregnancy



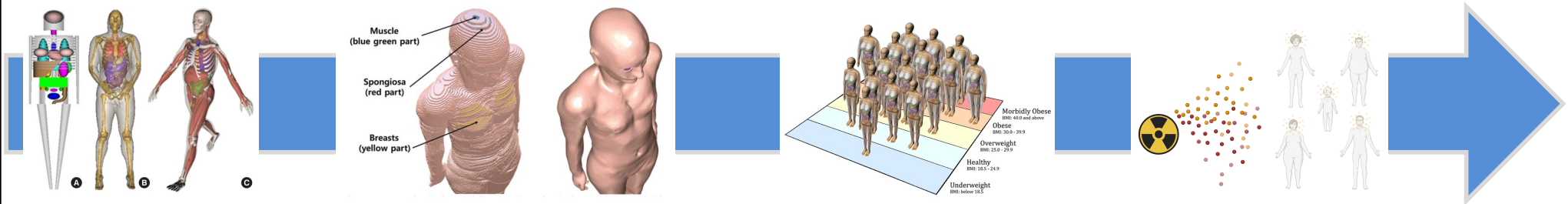
Modeling **physiological behavior** represents the **greatest** source of variability in dose assessment

- Physiologically-based (i.e. **spatio-temporal**) models of radiation behavior can harness advanced **multiphysics** and **artificial intelligence**



Radiological incidents may expose **large, diverse populations**

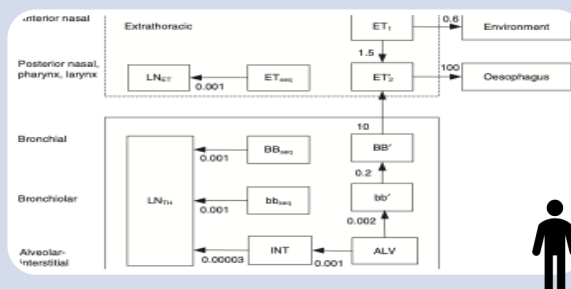
- **Triage** and **medical countermeasures** require models that reflect physiological variation in inhalation and excretion



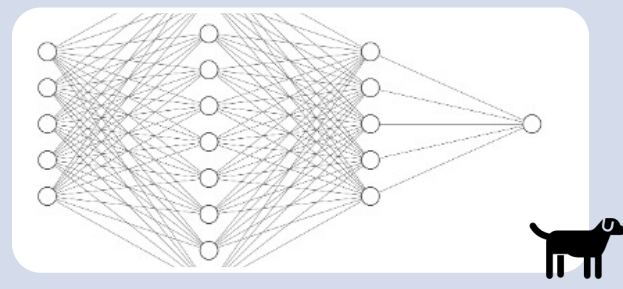
Case Overview: Pathways for Internal Exposure via Human Respiratory Tract (HRT)



Case 1: Predict aerosol deposition in the airway and clearance to blood from inhaled radionuclide contaminants in the human respiratory tract (HRT) for an exposed population using **multiphysics models and artificial intelligence**.



Case 2: Develop stochastic biokinetic models for **uncertainty quantification** that are representative of breadth of exposed population (*non-reference adults, children*) for radiological/nuclear inhalation and using **artificial intelligence**.



Case 3: Develop inverse biokinetic models from simulated in-vitro data to reconstruct radionuclide uptake from time-dependent radionuclide biodistribution using **reconstructive historical data with artificial intelligence**.

Increase in mechanistic scale

Preamble: Setting the Stage

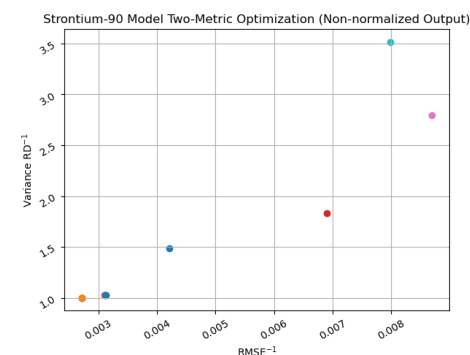
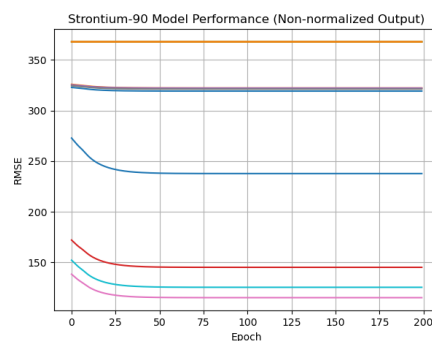
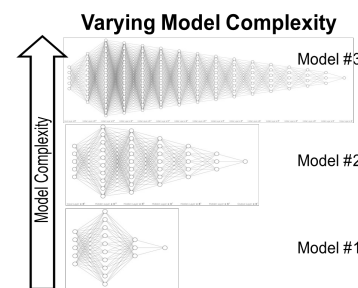
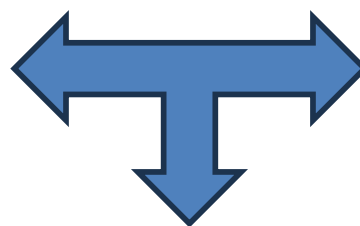
MACHINE LEARNING FOR ANIMAL-TO-HUMAN SCALING AND DOSE RECONSTRUCTION EXAMPLE INTAKE RECONSTRUCTION OF STRONTIUM-90 EXPOSURE – BEAGLE DOGS

Table 1 Parameters of Multi-Component Exponential Retention Equations With 2, 3, or 4 Component Fits for ⁹⁰ Sr Longevity Dogs*			
Parameters	Number of Components Used to Fit Retention Curve		
	2 Components	3 Components	4 Components
a ₁ (fraction)	.58 (±.03)	.64 (±.08)	.57 (±.09)
λ ₁ (day ⁻¹)	1.4 (±.3)	2.5 (±.8)	2.0 (±.5)
a ₂ (fraction)	.42 (±.03)	.16 (±.04)	.15 (±.06)
λ ₂ (day ⁻¹)	.015 (±.006)	.031 (±.04)	.11 (±.05)
a ₃ (fraction)		.20 (±.04)	.11 (±.03)
λ ₃ (day ⁻¹)		.00063 (±.0002)	.0074 (±.004)
a ₄ (fraction)			.16 (±.07)
λ ₄ (day ⁻¹)			.00036 (±.0002)

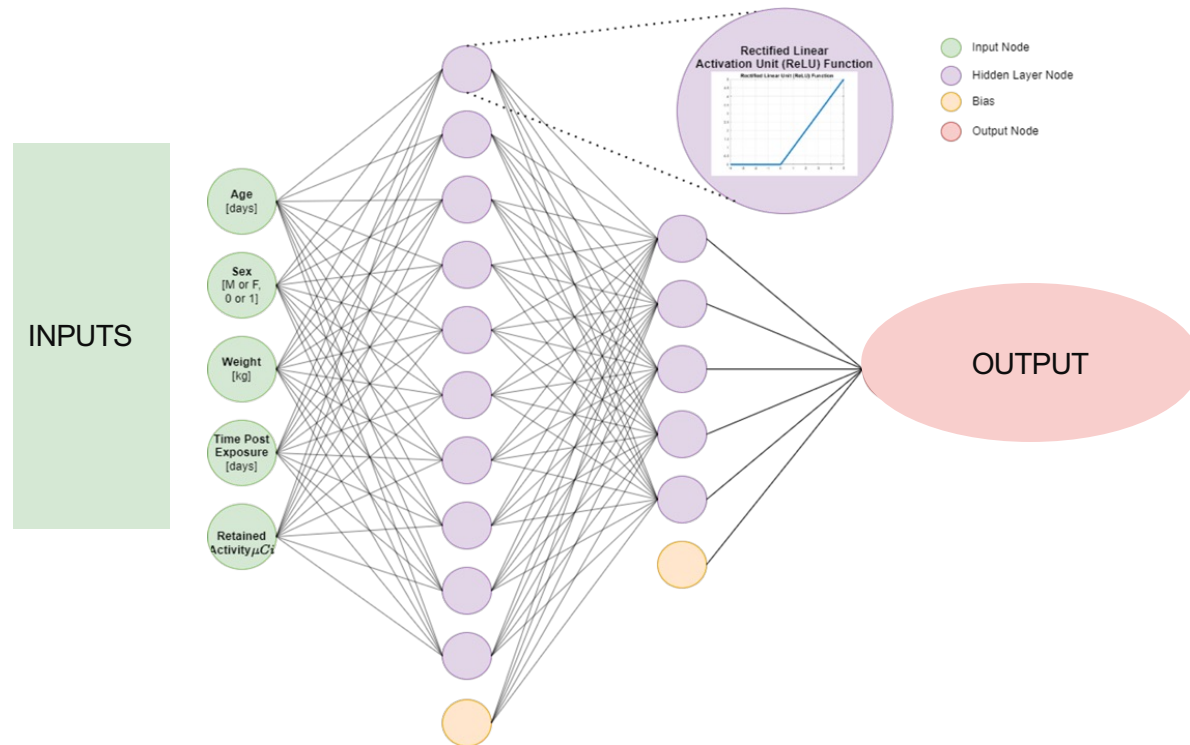
* Average (± 1 standard deviation)

Inhalation Toxicology Research Institute (ITRI)
Annual Reports

Estimated dose is used to
reconstruct the long
termed retained burden.

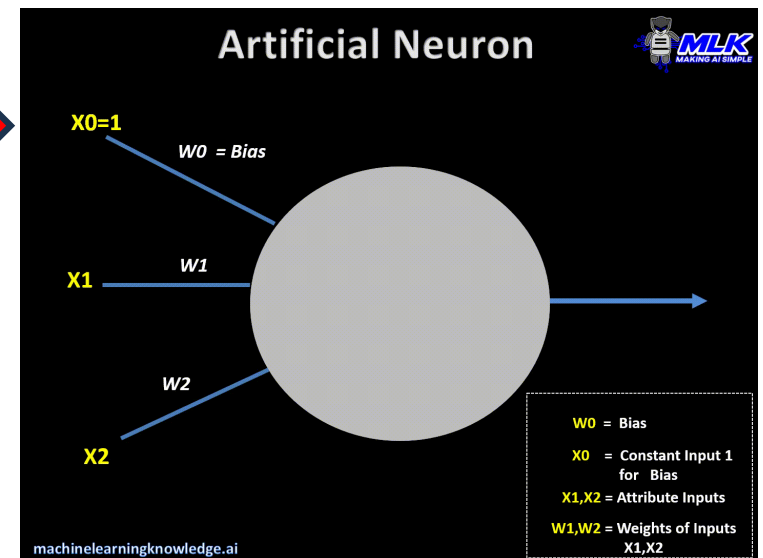
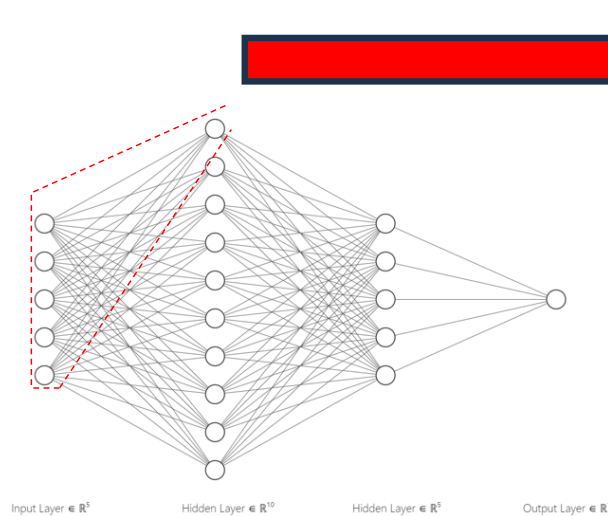


Preamble: AI Basis of Neural Networks



Preamble: AI Supervised Learning: Deep-Learning based Dose Estimation

- The prediction (or reconstruction) of an acute inhaled intake of a radionuclide may be modelled as a regression problem informed by:
- **Input:** Age, Sex, Weight, Bioassay (i.e., measured activity), and time post exposure
- In a 5-10-5-1 network architecture:



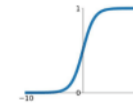
Preamble: AI Supervised Learning: Deep-Learning based Dose Estimation

- **Network Manipulation - Hyperparameters:**
Number of layers and nodes (**Architecture, Complexity**): 5-10-5-1
- **Activation Function:** ReLU
- **Train/Test Split:** 70/30
- **Loss Function:** MSE
- **Optimization Function:** ADAM
- **Data Manipulation – Preprocessing Techniques**
- Normalization is a powerful tool to reconcile the magnitude of the input features with that of the output

Activation Functions

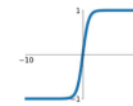
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



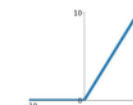
tanh

$$\tanh(x)$$



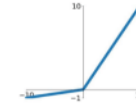
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

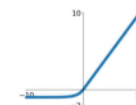


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



For each Parameter w^j

(j subscript dropped for clarity)

$$\nu_t = \beta_1 * \nu_{t-1} - (1 - \beta_1) * g_t$$

$$s_t = \beta_2 * s_{t-1} - (1 - \beta_2) * g_t^2$$

$$\Delta\omega_t = -\eta \frac{\nu_t}{\sqrt{s_t + \epsilon}} * g_t$$

$$\omega_{t+1} = \omega_t + \Delta\omega_t$$

η : Initial Learning rate

g_t : Gradient at time t along ω^j

ν_t : Exponential Average of gradients along ω_j

s_t : Exponential Average of squares of gradients along ω_j

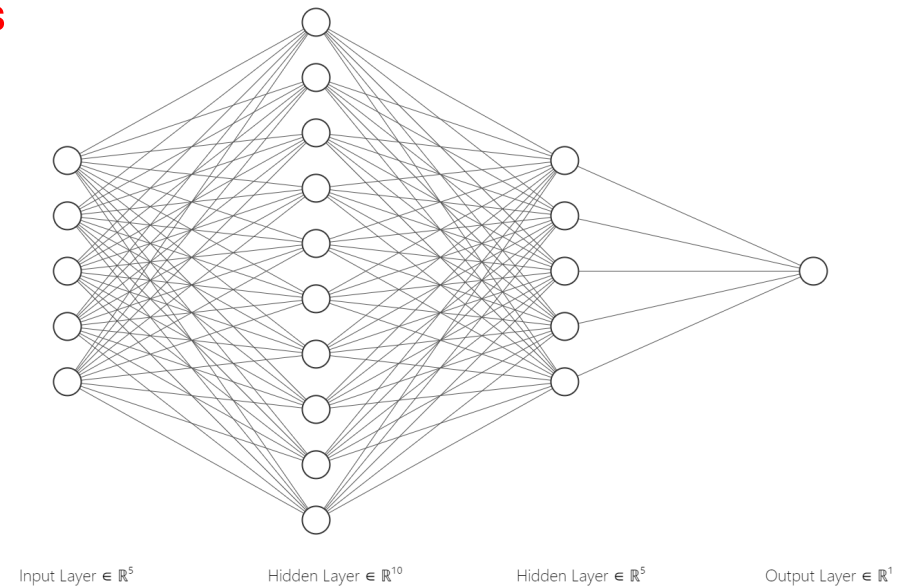
β_1, β_2 : Hyperparameters

Preamble: Supervised Learning: Deep-Learning based Dose Estimation

Network Manipulation - Hyperparameters:

Number of layers and nodes: 5-10-5-1

- Architecture complexity
- Construction of boundaries and limits



Preamble: Supervised Learning: Deep-Learning based Dose Estimation

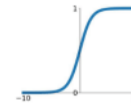
Network Manipulation - Hyperparameters:

- Number of layers and nodes: 5-10-5-1
- **Activation Function: ReLU non-linear function** to transform the dot product from the input nodes into an output for the current node
- **Rectified Linear Unit function (ReLU):** RELU activated if output layer (e.g., pixel) is above threshold.

Activation Functions

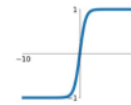
Sigmoid

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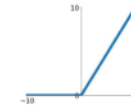
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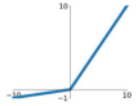


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Leaky ReLU
 $\max(0.1x, x)$

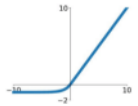


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Preamble: Supervised Learning: Deep-Learning based Dose Estimation

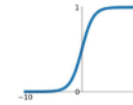
Network Manipulation - Hyperparameters:

- Number of layers and nodes: 5-10-5-1
- Activation Function: ReLU
- **Train/Test Split: 70/30**
- **Optimize limited data.**

Activation Functions

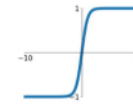
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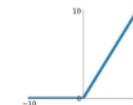
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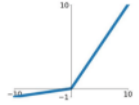
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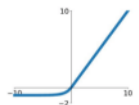


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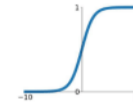
Network Manipulation - Hyperparameters:

- Number of layers and nodes: 5-10-5-1
- Activation Function: ReLU
- Train/Test Split: 70/30
- **Loss Function: MSE**
- Once data has reached the output layer, the performance of the system is analyzed using a **loss function**.
- How well a particular iteration (or **epoch**) performs in its predictive goal through the loss function.
- Compares the values or class labels **predicted** by the network to the **true** values associated with the inputs that yield said predicted output.

Activation Functions

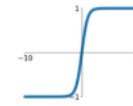
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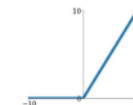
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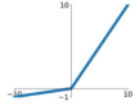
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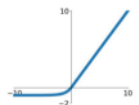


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Mean Squared Error: measures the average proximity of a single estimation generated from a set of test inputs to their respective, true, test output.

Preamble: Supervised Learning: Deep-Learning based Dose Estimation

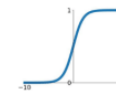
Network Manipulation - Hyperparameters:

- Number of layers and nodes: 5-10-5-1
- Activation Function: ReLU
- Train/Test Split: 70/30
- Loss Function: MSE
- **Optimization Function: ADAM**
 - Dictates by what amount/direction the weights of synapses are altered.
 - Decide how to adjust the weights of the synapses that connect nodes, (learnable parameters of the network.
 - **Adaptive Moment Estimation (ADAM)** - common and relatively complex
 - Gradient descent - find minimum of the loss function according to a varying/adapted first and second moment of the respective gradient.
 - Adopts parameter learning rates real-time based on avg.

Activation Functions

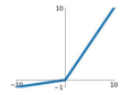
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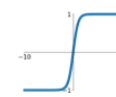
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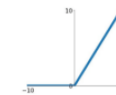


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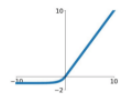
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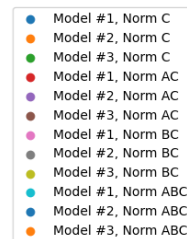
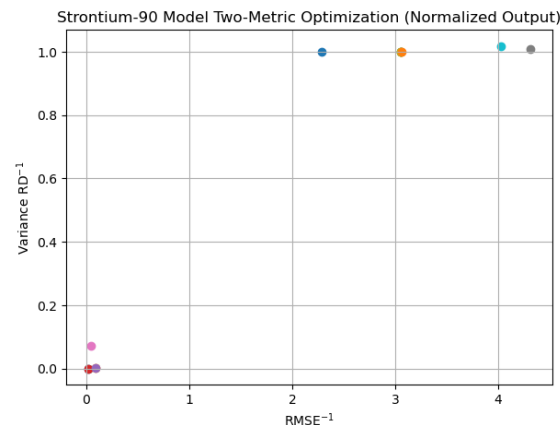
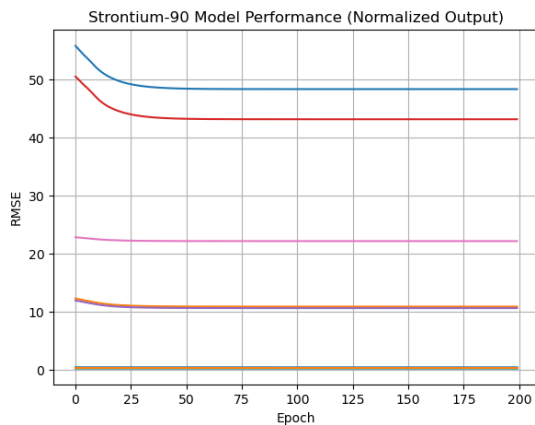
s_t : Exponential Average of squares of gradients along ω_j

β_1, β_2 : Hyperparameters

Initial
Learning
Rate

Preamble: Supervised Learning: Deep-Learning based Dose Estimation Results

Complexity: Model 1 < Model 2 < Model 3



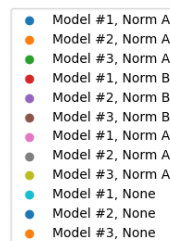
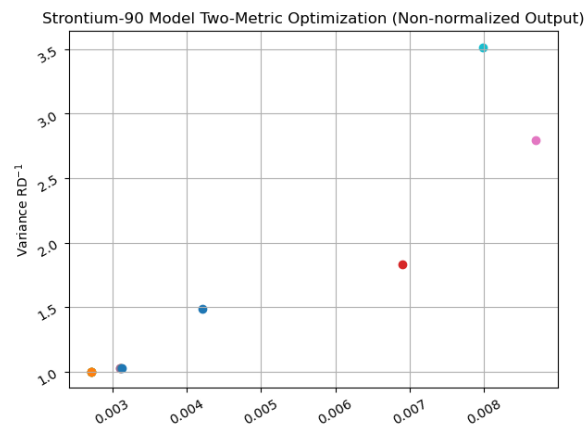
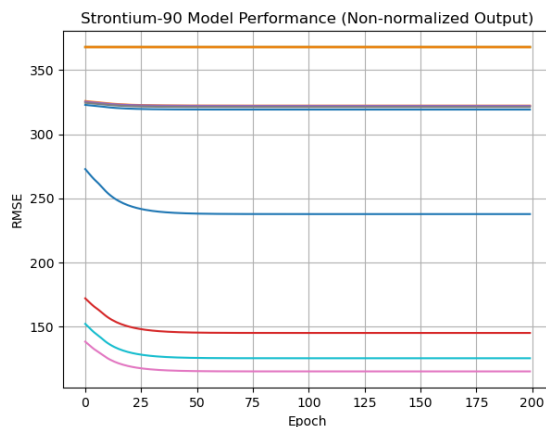
Normalization Groups:

Group A: {Age, Weight} → Physiological parameters defining the exposed individual

Group B: {Time Post Exposure} → Chronological parameters defining the progression of the acute exposure

Group C: {Initial Burden, Retained Burden, Dose} → Values arising from whole body counting

Total Models: 8 normalization combinations
X 3 models = 24



➡ RMSE: 114.964 μCi
Variance RD: -35.81%

➡ RMSE: 125.23 μCi
Variance RD: -28.43%



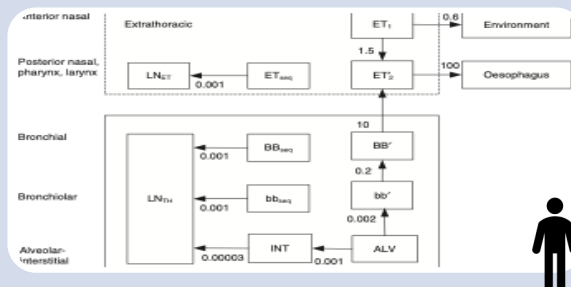
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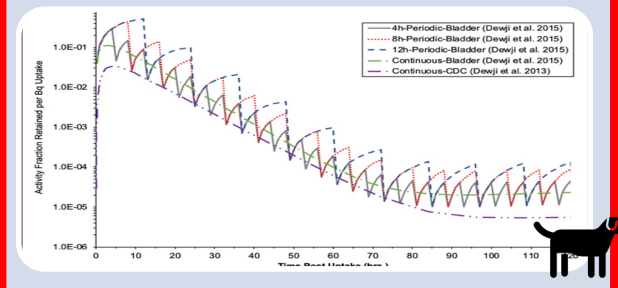
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Case 3: Develop inverse biokinetic models from simulated in-vitro data to reconstruct radionuclide uptake from time-dependent radionuclide biodistribution using **reconstructive historical data with artificial intelligence.**

Case 3: ITRI ^{90}Sr Beagle Dose Reconstruction

IOP Publishing

J. Radiol. Prot. 45 (2025) 041512

<https://doi.org/10.1088/1361-6498/ae0e7f>

Journal of Radiological Protection



David Gonzalez,
Shaheen Dewji
(GT)
Alex Glasco,
Gayle Woloschak
(NU)



PAPER

Reconstructing strontium-90 intake in beagles using neural networks: a data-driven assessment of historical inhalation records

David Carpio Gonzalez¹ , Alexander D Glasco² , Gayle E Woloschak² and Shaheen Azim Dewji^{1,*}

¹ Nuclear and Radiological Engineering and Medical Physics Programs, George W. Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, GA, United States of America

² Department of Radiation Oncology, Feinberg School of Medicine, Northwestern University, Chicago, IL, United States of America

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E-mail: shaheen.dewji@gatech.edu

Keywords: internal dosimetry, artificial intelligence, machine learning, dose reconstruction, bioassay, ITRI, beagle dogs

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Annual Meeting 2026, Helsinki

Case 3: ITRI ⁹⁰Sr Beagle Dose Reconstruction

Primary Topic:

- Data needs and quality on acute, non-occupational inhalation of radionuclides with **accompanying bioassay data** (urinalysis/ biodistribution of particles)

Primary Data Source:

- Inhalation Toxicology Research Institute (ITRI)**
Beagle Dog Experiments with Sr, Pu, and Ce data augmented with simulations

$$I = \frac{q(t)}{F(t)}$$

1.) Can machine learning be used to reconstruct intake activity?

2.) If so, what quality of data is needed?

Table 1 Parameters of Multi-Component Exponential Retention Equations With 2, 3, or 4 Component Fits for ⁹⁰ Sr Longevity Dogs ^a			
Parameters	Number of Components Used to Fit Retention Curve		
	2 Components	3 Components	4 Components
a ₁ (fraction)	.58 (±.03)	.64 (±.08)	.57 (±.09)
λ ₁ (day ⁻¹)	1.4 (±.3)	2.5 (±.8)	2.0 (±.5)
a ₂ (fraction)	.42 (±.03)	.16 (±.04)	.15 (±.06)
λ ₂ (day ⁻¹)	.015 (±.006)	.031 (±.04)	.11 (±.05)
a ₃ (fraction)		.20 (±.04)	.11 (±.03)
λ ₃ (day ⁻¹)		.00063 (±.0002)	.0074 (±.004)
a ₄ (fraction)			.16 (±.07)
λ ₄ (day ⁻¹)			.00036 (±.0002)

^a Average (± 1 standard deviation)

Case 3: ITRI ^{90}Sr Beagle Dose Reconstruction

Inhalation Toxicology Research Institute (ITRI)

- Data for acute inhalation of soluble ^{90}Sr
- After inhalation, transferred to whole-body counting (**WBC**) facility
- Initial body burden (**IBB**) measured many times in first hour
- Brought back 14 days later for WBC measurement called “long-term retained burden” (**LTRB**)

Table 2. Initial Body Burdens and Long-Term Retained Burdens of the Beagle groups [7].

Experimental Group IBBs and LTRBs					
Experimental Group	Number of Dogs	IBB [$\mu\text{Cu/kg}$]		LTRB [$\mu\text{Cu/kg}$]	
		Mean	SD	Mean	SD
Longevity	12	226.67	40.28	99.25	16.41
Longevity	12	103.5	17.01	42	10.36
Longevity	12	23.42	5.42	7.83	1.21
Longevity	12	4.03	1.08	1.75	0.6
Longevity	15	0	0	0	0
Sacrifice	24	88.75	29.07	37.82	13.74
Sacrifice	10	0	0	0	0

Case 3: ITRI ^{90}Sr Beagle Dose Reconstruction

- WBC conducted ~3 months and non-linear regression used to fit individual-level retention equations
- Individual WBC measurements beyond IBB and LTRB not available

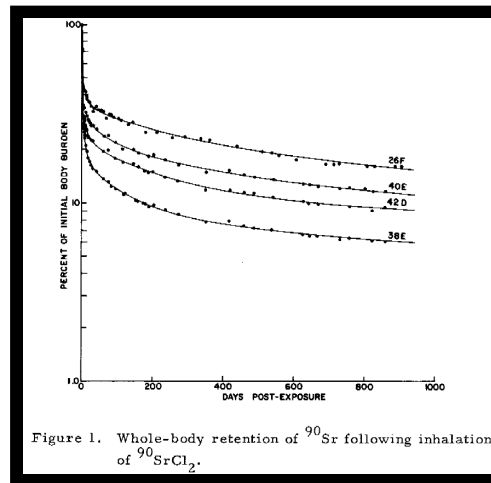


Figure 3. Retention of ^{90}Sr following inhalation based on WBC measurements made for four individual dogs.

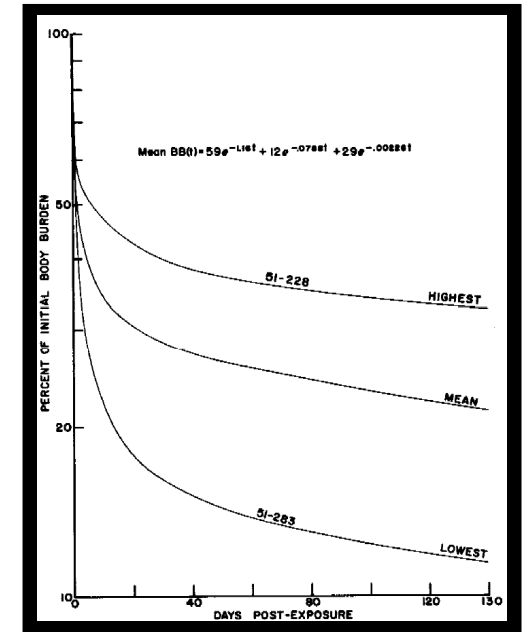


Figure 2. Mean and range of whole-body retention of ^{90}Sr inhaled as $^{90}\text{SrCl}_2$ by [first] 36 longevity dogs with initial body burdens of 2.6 to 127 $\mu\text{Ci/kg}$. (ITRI Annual Report LF-38, 1966-1967)

Case 3: ITRI ⁹⁰Sr Beagle Dose Reconstruction

Table 3. Summary statistics of major features used in ML from historical data of ⁹⁰Sr acute inhalation exposure in beagles.

Parameter	Mean	Standard Deviation	Minimum	Maximum
Age [days]	401.5	15.282	377	438
Sex [0-Male, 1-Female]	48 M, 47 F	N/A	N/A	N/A
Weight [kg]	8.7	1.232	5.7	11.9
IBB [μ Ci]	592.7	740.592	0	3000
Days Post Exposure [days]	14	0	14	14
LTRB [μ Ci/kg]	27.8	33.534	0	120
Dose at 730 days [rad]	4572.6	4566.471	140	18,000
Dose at Death [rad]	8217.2	5984.718	420	22,000
Dose at 5000 days [rad]	16886.7	17617.561	430	73,000

Case 3: ITRI ⁹⁰Sr Beagle Dose Reconstruction

$$\text{Absorbed } \beta \text{ dose (rad)} = \frac{0.457 A_0}{W} \int_0^t SB(t) dt$$

Where:

A_0 = initial body burden of ⁹⁰Sr in μCi

W = total body weight in kg

$SB(t)$ = average skeletal burden at time t expressed as a fraction of the initial body burden

Assumptions:

Skeletal weight = $0.1W$

W remained constant throughout the observation period

$SB(t)$ could be adequately expressed as the whole-body retention minus the first or early clearance component

$$BB(t) = \sum_{i=1}^k a_i e^{-\lambda_i t} \quad SB(t) = \sum_{i=2}^k a_i e^{-\lambda_i t}$$

Table 4. Mean and standard deviation of regression parameters for individual dog retention equations [10].

Parameters	Number of Components Used to Fit Retention Curve		
	2 Components	3 Components	4 Components
a_1 (fraction)	.58 ($\pm .03$)	.64 ($\pm .08$)	.57 ($\pm .09$)
λ_1 (day ⁻¹)	1.4 ($\pm .3$)	2.5 ($\pm .8$)	2.0 ($\pm .5$)
a_2 (fraction)	.42 ($\pm .03$)	.16 ($\pm .04$)	.15 ($\pm .06$)
λ_2 (day ⁻¹)	.015 ($\pm .006$)	.031 ($\pm .04$)	.11 ($\pm .05$)
a_3 (fraction)		.20 ($\pm .04$)	.11 ($\pm .03$)
λ_3 (day ⁻¹)		.00063 ($\pm .0002$)	.0074 ($\pm .004$)
a_4 (fraction)			.16 ($\pm .07$)
λ_4 (day ⁻¹)			.00036 ($\pm .0002$)
* Average (± 1 standard deviation)			

Case 3: ITRI ^{90}Sr Beagle Dose Reconstruction

ANNs versus pBNNs

Artificial Neural Networks (ANNs) versus Probabilistic Bayesian Neural Networks (pBNNs)

Bayesian: Synapses connected subsequent nodes are probability distribution functions, not scalars as in ANNs

Probabilistic: Output layer is two nodes, one for mean of the prediction and the other for the standard deviation

- Sequentially connected layers of nodes
- Node values are dot product of preceding node values and synapse weights
- **Activation Function** (ReLU or SoftPlus) – transforms dot product to introduce non-linearity in training
- **Loss Function** (MSE or negative log likelihood) - evaluates difference between prediction and ground truth
- **Optimizer Function (ADAM)** – adjusts synapse weights
 - Learning Rate: 0.0001-0.1
- **Train/Test Split:** 80/20 – 90/10

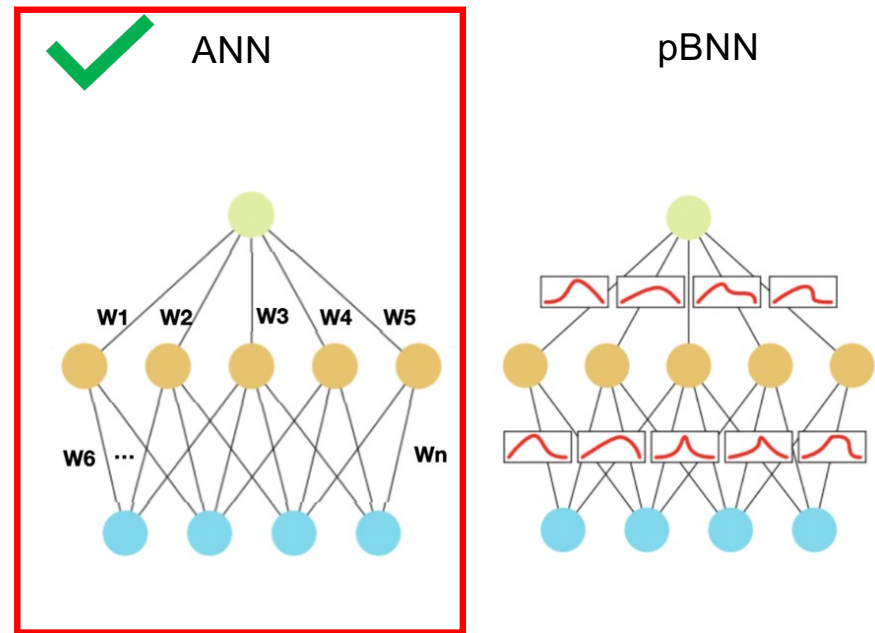


Figure 4. Differences between ANNs and pBNNs and associated loss functions.

Case 3: ITRI ⁹⁰Sr Beagle Dose Reconstruction – Model Architecture

Model Configurations (24)

- Complexities (3):
 - (Model #1) - Low Complexity: 5-10-3-1
 - (Model #2) - Moderate Complexity: 5-10-9-7-5-3-1
 - (Model #3) - High Complexity: 5-10-15-14-13-12-11-10-9-8-7-6-5-4-3-1
- Normalization Groups (8 Combinations):

Label	Description	Features
Group A	physiological features describing exposed dog	age, weight
Group B	chronological features	time post exposure, days to death
Group C	features involving WBC measurements or dose	IBB, LTRB, absorbed dose

Table 7. Reference table for linear normalization group labels and included features within each group.

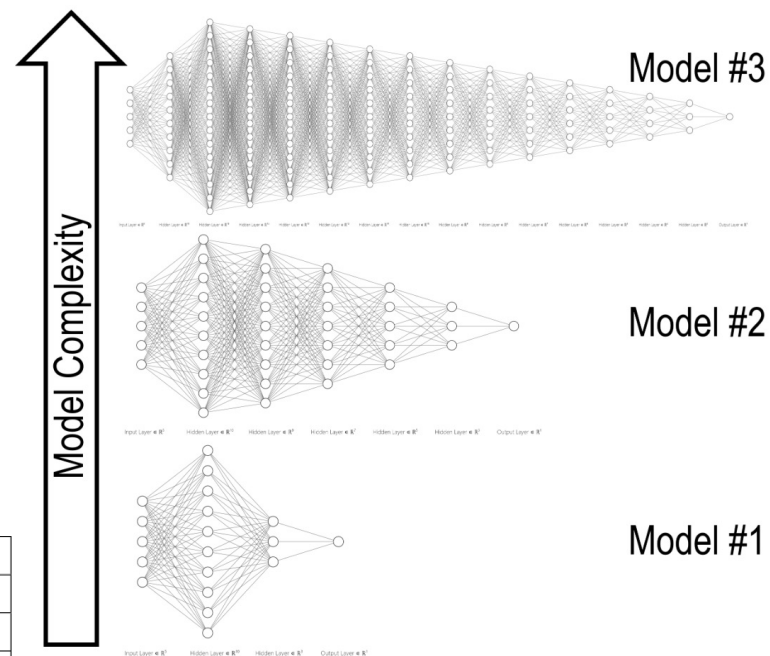


Figure 6. Architectures of the three model complexities used in the study, referred to by the enumeration on the right.

Case 3: ITRI ⁹⁰Sr Beagle Dose Reconstruction – Data Configurations

Regimen 1: Uncovering uncertainty or pattern in the rapidly clearing component of the intake

- Inputs:** Age, Sex, Weight, Long-Term Retained Burden (LTRB), Time Post Exposure
- Outputs:** Initial Body Burden (IBB)
- Observations:** 95

Regimen 2: Viability of simulated counting data for initial intake reconstruction

- Inputs:** Age, Sex, Weight, Simulated Activity Measurement, Time Post Exposure
- Outputs:** IBB
- Observations:** 288

Regimen 3: Reconstructing intake from Committed Dose to Skeleton from historical data

- Inputs:** Age, Sex, Weight, Dose to Skeleton, Time Post Exposure
- Outputs:** LTRB
- Observations:** 174

										BETA RADIATION DOSE TO SKELETON									
DOG IDENTIFICATION			INHALATION EXP.			I.B.B.			L.T.R.B.			DOSE RATE (RADS/DAY)			CUMULATIVE (RADS)			DEATH DATE	DAYS TO DEATH
			AGE	WT								730	POTENT. AT	AT	730	POTENT. TO	TO		
TATTOO	AN-EXPT	SEX	DATE	DAYS	KG	RANK	UCI/KG	UCI	RANK	UCI/KG	INITIAL	DAYS	5000 D	DEATH	DAYS	5000 D	DEATH		

Figure 7. Header of historical data file for ITRI ⁹⁰Sr inhalation Beagles.

Case 3: ITRI ⁹⁰Sr Beagle Dose Reconstruction – ANN Performance

Report of Individual Models

Scatterplot of training predictions versus true counterparts – how well the model “learns” the data

Scatterplot of relative error of test predictions – how well model may generalize pattern

Loss plot – ensure convergence of model

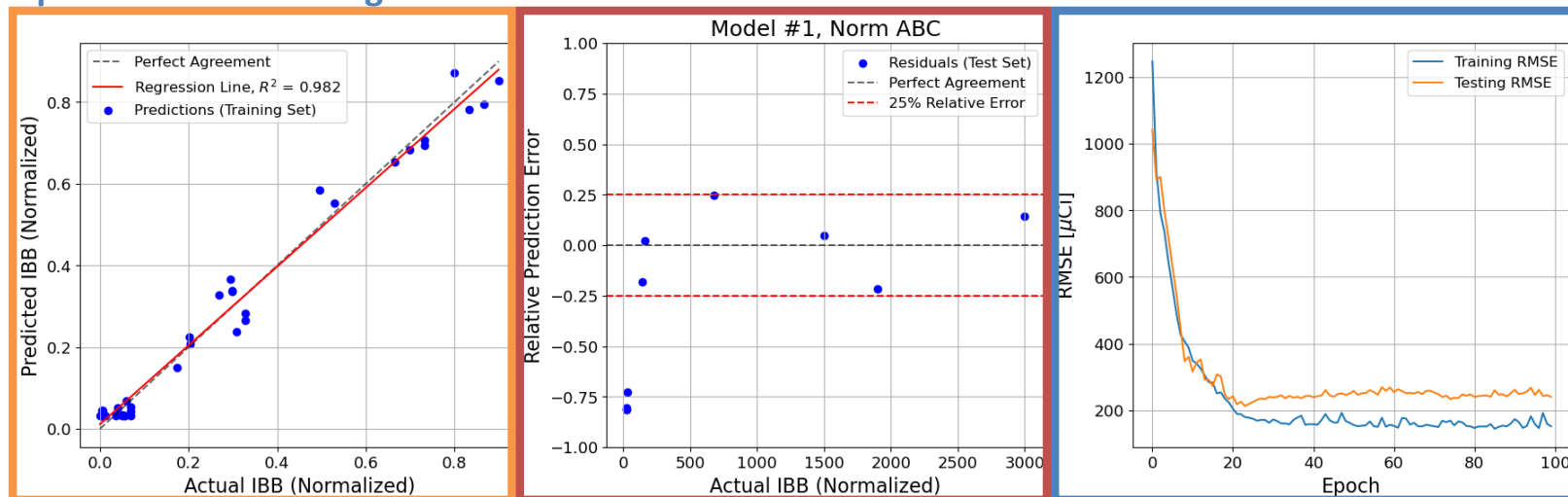
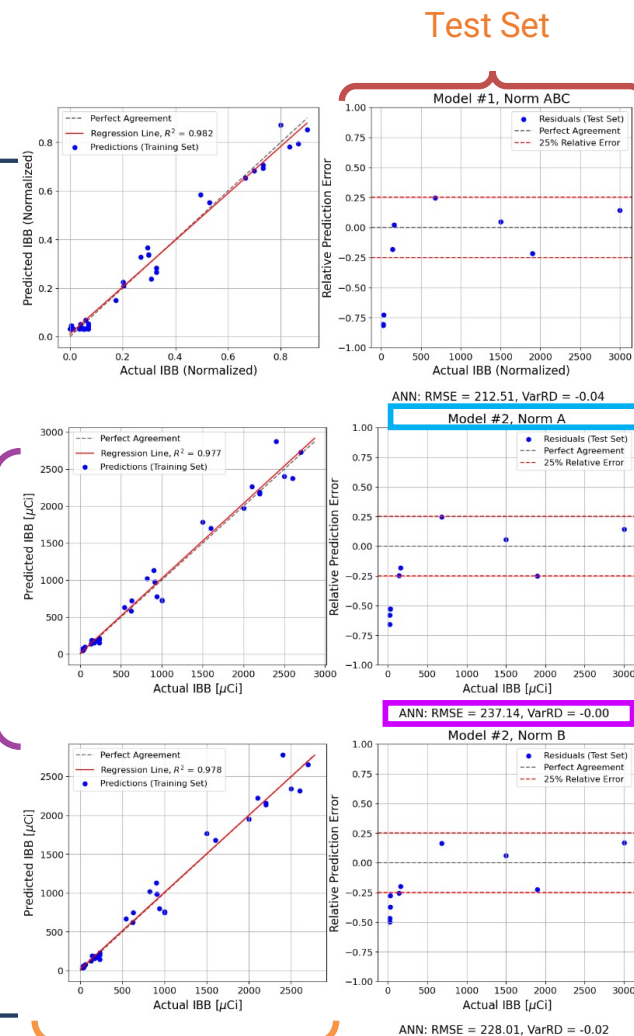
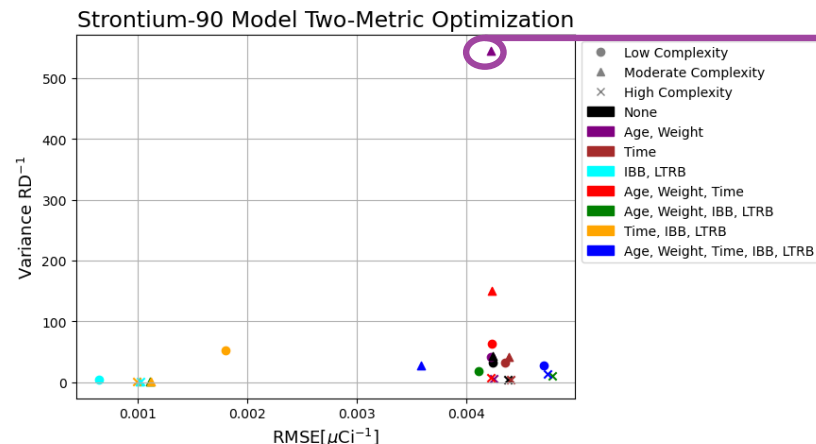


Figure 8. Example of graphical report for a regimen 1 trained ANN, specifically of lowest complexity (Model #1) and normalizing all features (Norm ABC).

Case 3: ITRI ^{90}Sr Beagle Dose Reconstruction

- Data Configurations: Designed to simultaneously investigate **historical data quality** and **capabilities of machine learning** to operate on the data
- **Regimen 1:** Uncovering uncertainty or pattern in the rapidly clearing component of the intake
- **Regimen 2:** Viability of simulated counting data for retained burden reconstruction
- **Regimen 3:** Reconstructing intake from Committed Dose to Skeleton from historical data



Complexity and Normalization

Performance Metrics
RMSE ~ Accuracy
VarRD ~ Bias

EURADOS

Annual Meeting Training Set ki

27

Case 3: ITRI ^{90}Sr Beagle Dose Reconstruction – Overall Takeaways

Regimen 1: Deep learning offers reliable way to predict initial activity soon after exposure

- Deep learning offers a reliable approach to reconstruct initial activity from sparse data shortly after exposure.
- The selected ANN, trained on non-normalized physical units, demonstrates strong test set accuracy and variance representation.
- A low-complexity deep neural network is sufficient for the inverse biokinetic problem under these conditions.

Regimen 2: The summarized regression parameters too uncertain to ascertain realistic historical measurements

- Augmenting sparse historical data with simulated values introduces modeling instability.
- The resulting model exhibits reduced predictive accuracy and uncertainty in reflecting realistic individual intake values.
- Regression behavior is inconsistent, limiting its applicability to real-world measurements.

Regimen 3: Historical dose estimates improves model performance compared to simulated measurements

- Providing known dose improves the model's ability to capture variability in intake across individuals.
- However, the ANN demonstrates a bias toward lower values—underpredicting high-magnitude long-term retention burdens (LTRBs).
- This reflects challenges in reverse-mapping from dose to intake in nonlinear regimes.

Case 3: ITRI ^{90}Sr Beagle Dose Reconstruction – Why this Matters



Modernizes historical data use: Demonstrates how supervised deep learning can extract value from sparse, decades-old bioassay records once considered too limited for modeling.



Enables intake reconstruction without full time-series data: Shows that accurate estimates of internal radionuclide intake can be made using only early and late measurements.



Reveals tradeoffs across modeling assumptions: Highlights how model performance varies depending on data structure—e.g., using dose as input improves spread prediction but introduces bias in point estimates.



Establishes a scalable framework for dose reconstruction: Introduces dual-metric optimization (RMSE and variance agreement) that captures both individual accuracy and population variability.



Guides future AI applications in dosimetry: Sets precedent for integrating deep learning into internal dosimetry, with relevance for retrospective exposure assessments and operational preparedness.



Enables next-phase investigations: Future work may explore time-series forecasting of retention, inter-individual variability modeling, or extension to human datasets for triage and health outcome correlation.

Takeaways

— AI-driven technologies aim to create more **precise, adaptive, and individualized** dosimetric models for **physiological/metabolic behavior**. —

Personalized Dosimetry: Tailoring treatments or countermeasures based on individual physiological characteristics.

Improved Treatment: Providing more effective radiological countermeasures administration by accounting for real-time variability.

Reduction of Uncertainties: Minimizing over- or under-exposure by reducing uncertainties in dose predictions, ultimately improving outcomes.

Acknowledgements



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Northwestern

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Alliance for Radiological Exposures and Mitigation
Science

<https://sites.northwestern.edu/allrems/>



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Resources (1) – ICRP + HPS Webinar

“INTRO TO INTELLIGENCE”: How AI and ML are Changing Radiation Protection
May 30, 2025



The graphic features a blue background with a network of glowing lines. On the left, there are four logos stacked vertically: HPS (Health Physics Society), ICRP (International Commission on Radiological Protection), the Georgia Institute of Technology seal, and RED² (Radiological Engineering, Detection, and Dosimetry). To the right of these logos are three portrait photos of the speakers, each with a corresponding text box to its right.

HPS
ICRP
International Commission
on Radiological Protection

Shaheen Azim Dewji, Ph.D. - Associate Professor, Nuclear and Radiological Engineering and Medical Physics Programs, Georgia Institute of Technology
Director - Radiological Engineering, Detection, and Dosimetry Laboratory

Martin Craffigna - Research Engineer, Nuclear and Radiological Engineering and Medical Physics Programs, Georgia Institute of Technology
Radiological Engineering, Detection, and Dosimetry Laboratory

David Gonzalez – Ph.D. Student – Medical Physics, Nuclear and Radiological Engineering and Medical Physics Programs, Georgia Institute of Technology
Radiological Engineering, Detection, and Dosimetry Laboratory



Resources (2) – U.S. National Academies

Webcast

Webcast

[DAY 1 MAIN SESSION](#) DAY 2 SESSION A DAY 2 SESSION B



https://www.nationalacademies.org/event/44039_03-2025_gilbert-w-beebe-symposium-on-ai-and-ml-applications-in-radiation-therapy-medical-diagnostics-and-radiation-occupational-health-and-safety

Report Proceedings



<https://nap.nationalacademies.org/catalog/29200/gilbert-w-beebe-symposium-ai-and-ml-applications-in-radiation>

Resources (3) – 2025 ICRP Symposium



Session:

<https://youtu.be/9qKs8aWxvho?list=PLvqQWSugM7UQqT9d72jij8zSRSCYjiiQS&t=25328>

My Presentation on Cases 1 and 2 (7:54:59):

<https://youtu.be/9qKs8aWxvho?list=PLvqQWSugM7UQqT9d72jij8zSRSCYjiiQS&t=25328>

Questions!



Follow us on LinkedIn!

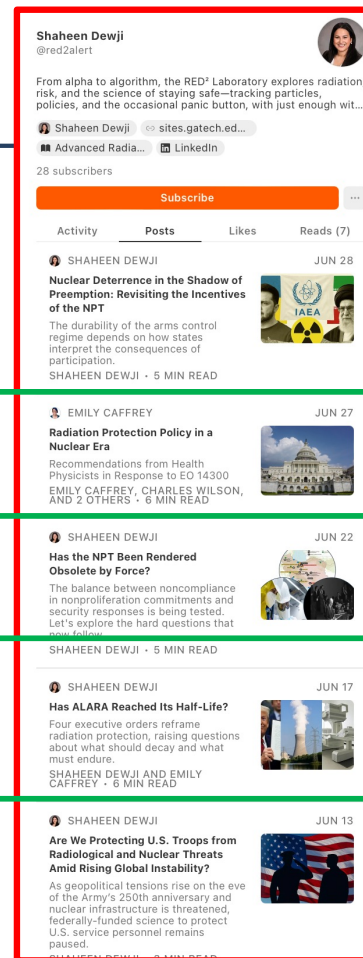


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Website



Substack:
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