APPLICATION OF STOCHASTIC AND ARTIFICIAL INTELLIGENCE METHODS FOR NUCLEAR MATERIAL IDENTIFICATION

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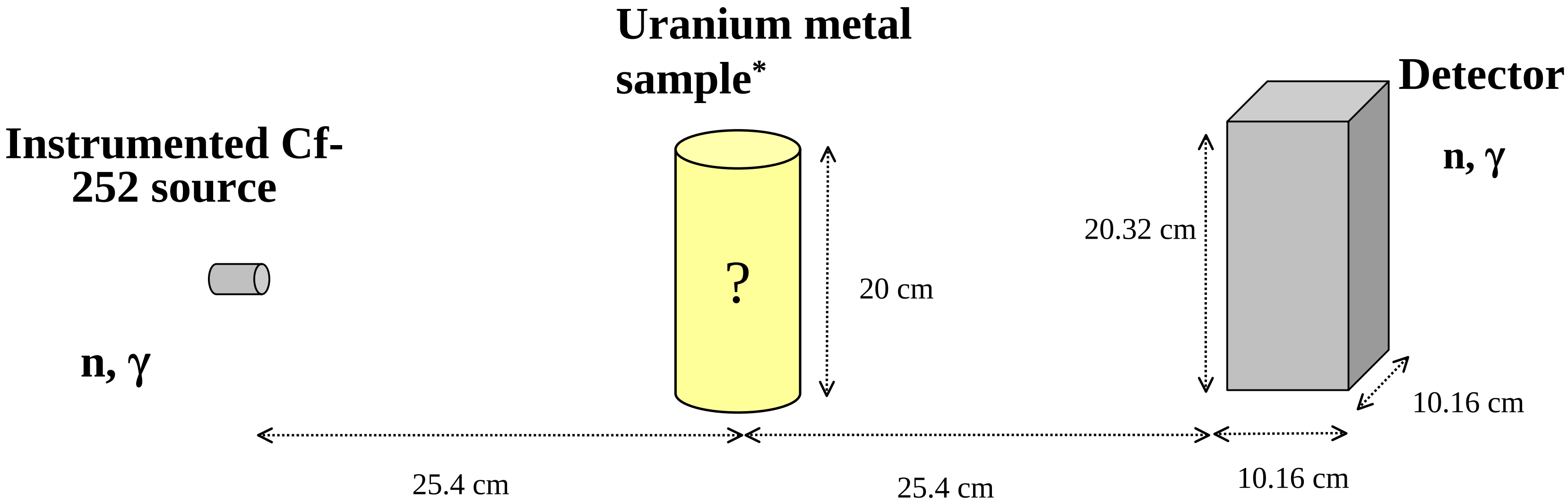


GOAL

Fissile sample attributes:

total mass

U-235 enrichment

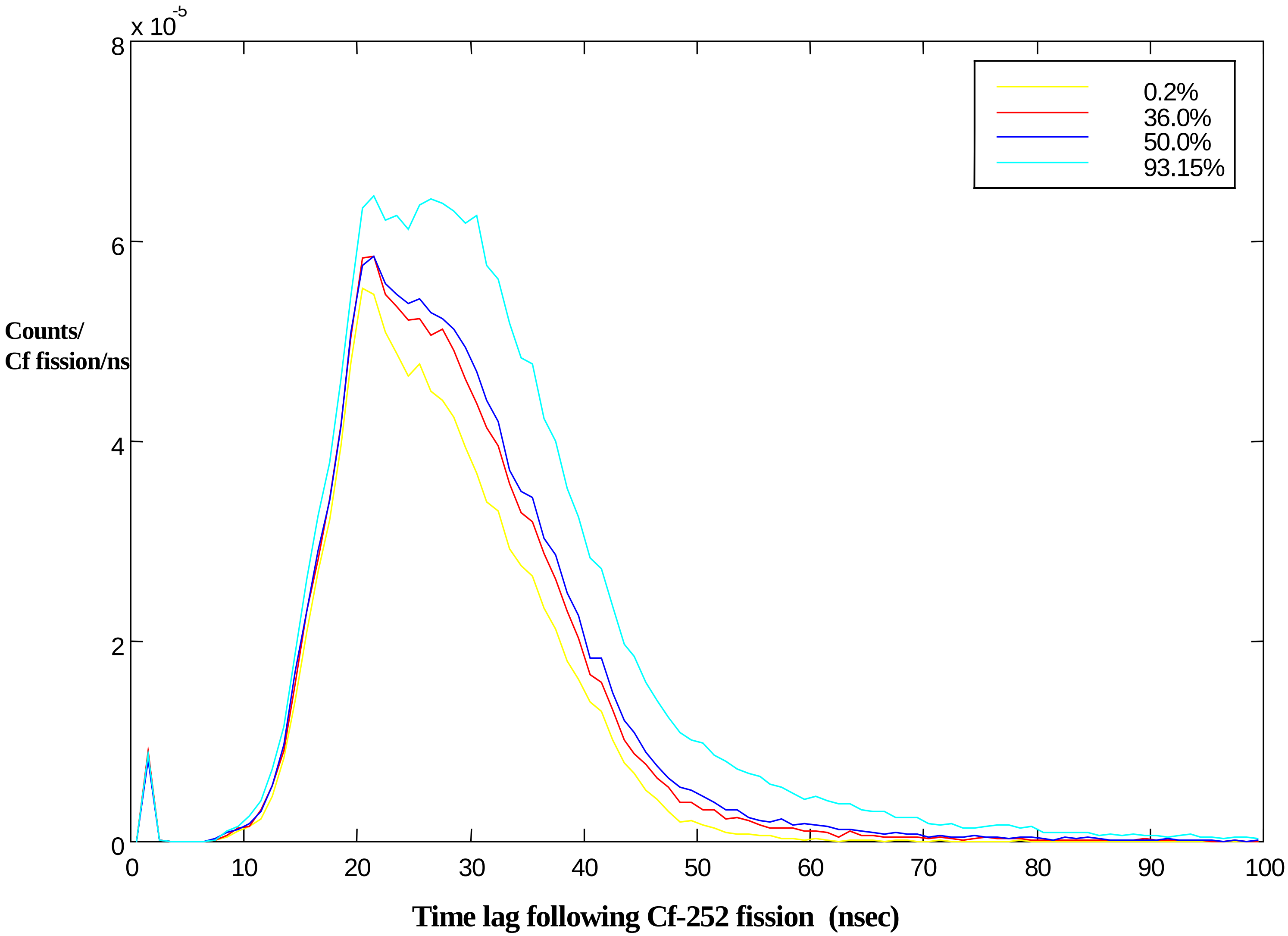
METHOD

Analysis of MCNP-DSP generated time dependent source-detector cross-correlation functions using

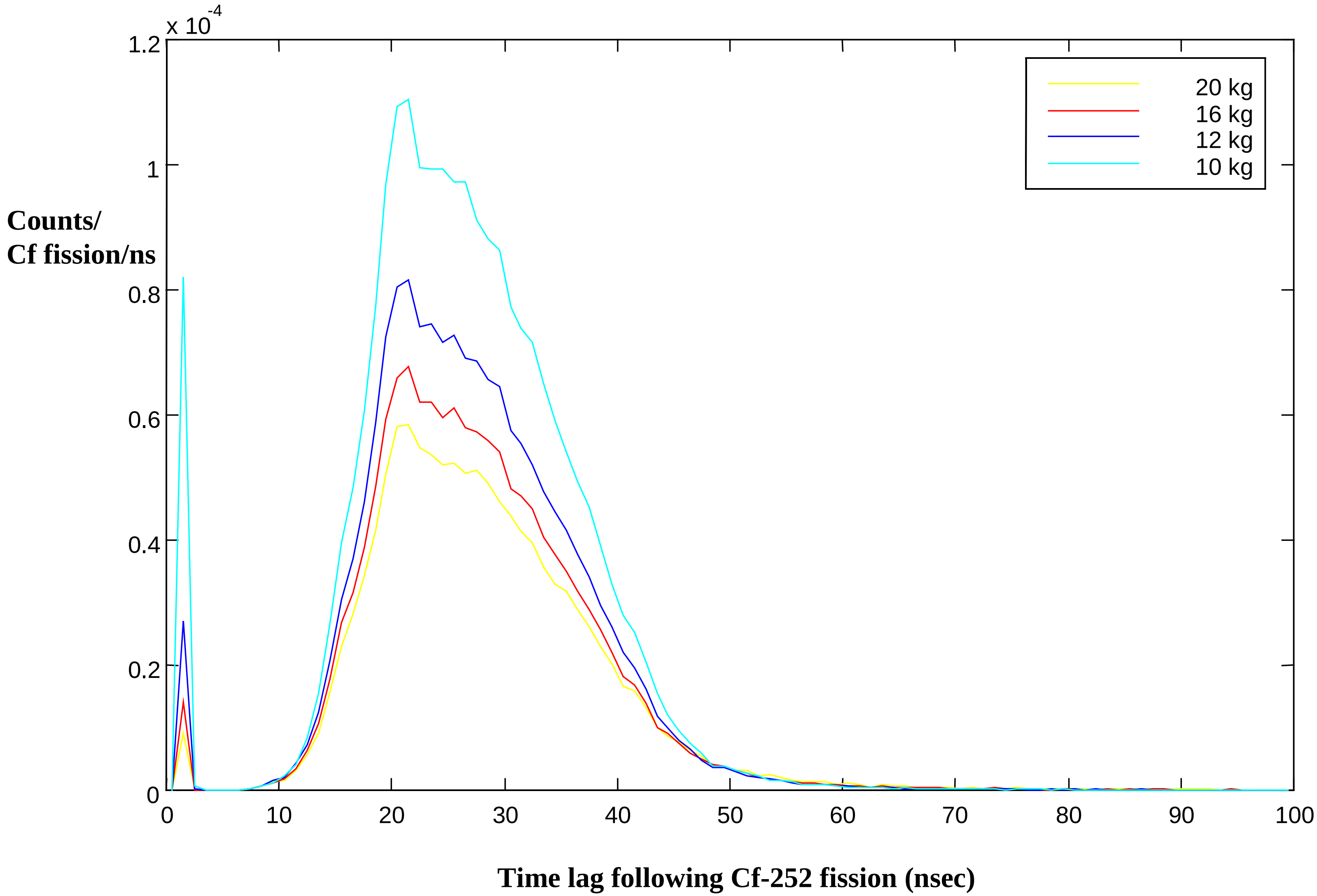
Artificial Neural Networks and Genetic Programming

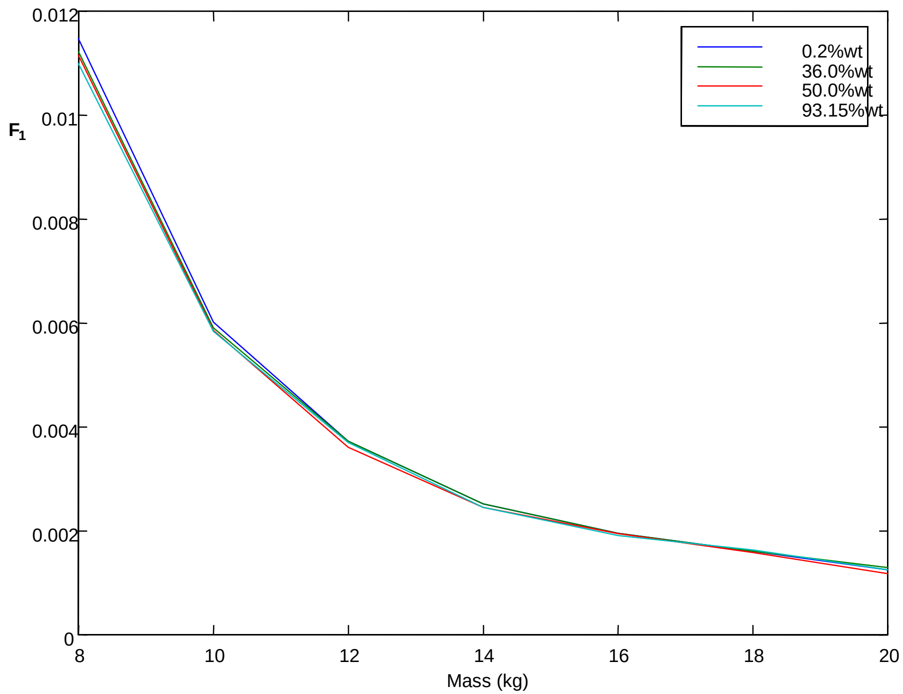
* *shapes: cylinders and spheres*
mass: 8, 10, 12, 14, 16, 18, 20 kg
enrichment: 0.2%, 36%, 50%, 93% wt ^{235}U

Source-Detector Cross-Correlation Functions for Uranium Cylinders of Different Enrichments and Fixed Mass (20 Kg)

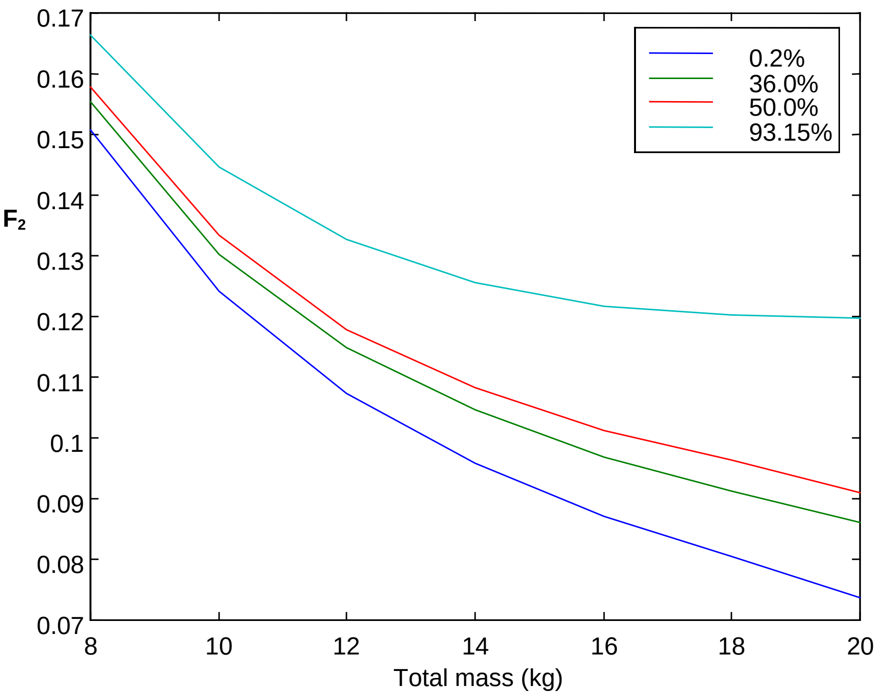


Source-Detector Cross Correlation Function (R_{12}) for Uranium Cylinders of Varying Masses and Fixed Enrichment (36 % wt ^{235}U).

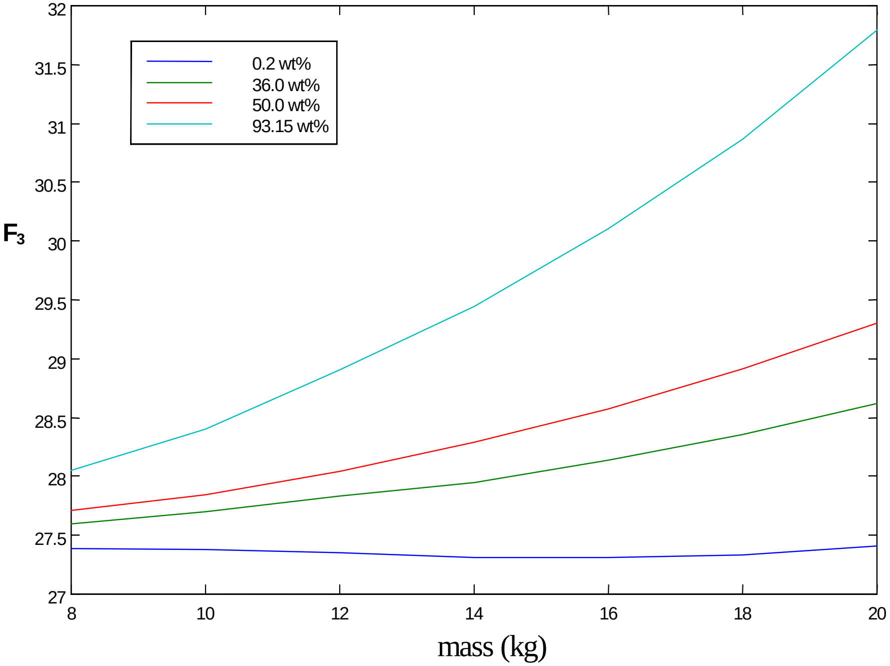




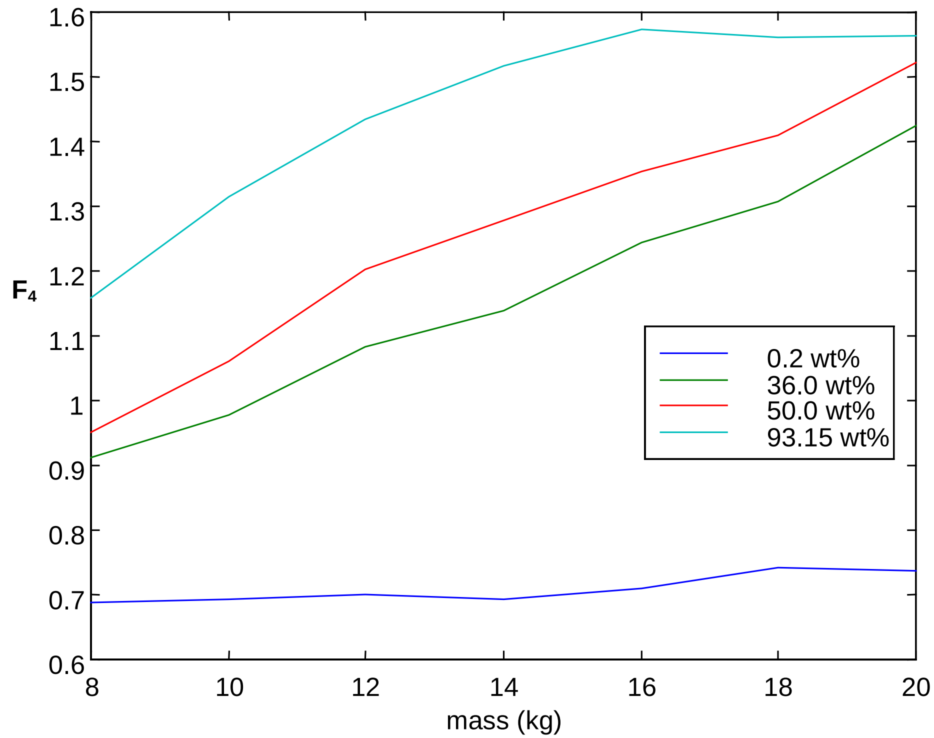
F_1 : area of the gamma peak



F_2 : total area



F_3 : mean delay after source fission



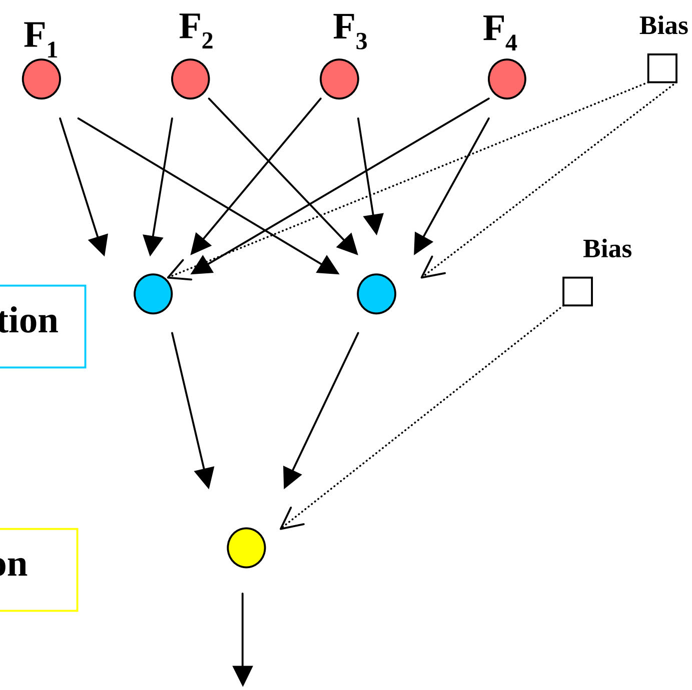
$$F_4 = \frac{\mu_3}{\sigma^3}$$ skewness

Artificial Neural Network

Input layer: features

Hidden layer: Sigmoidal activation function

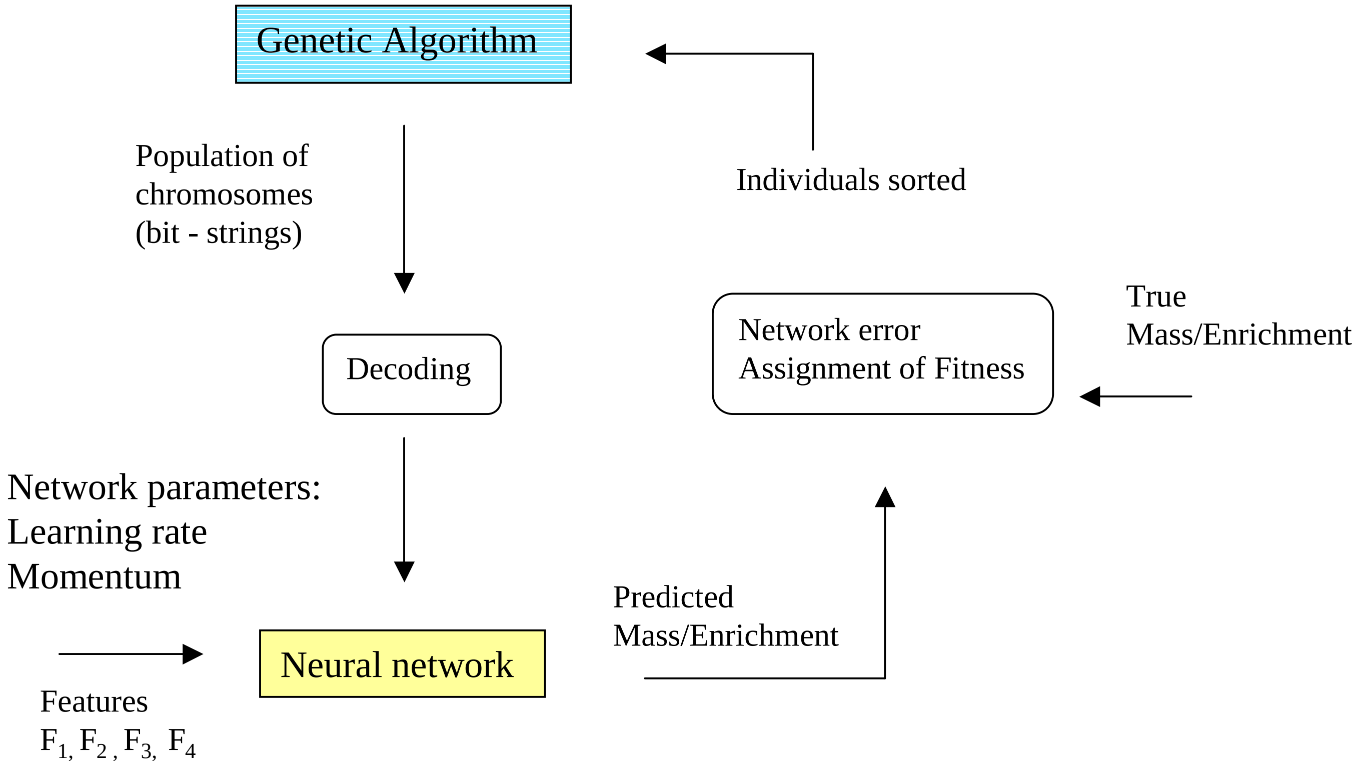
Output layer: Linear activation function



Sample mass
or
enrichment

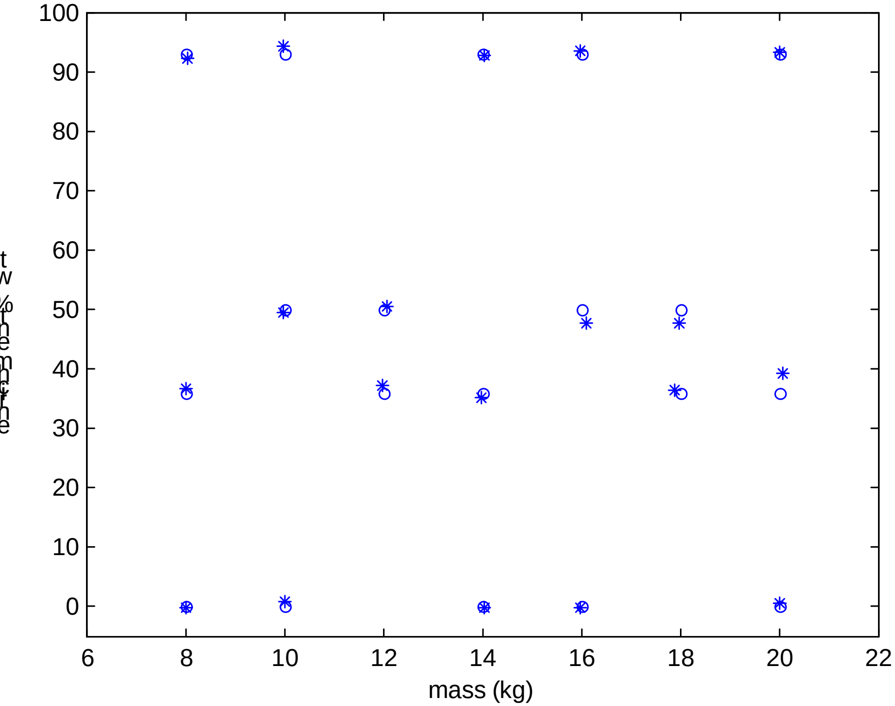
$$Output = \frac{a_1}{1+e^{-\left(\sum_{i=1\ldots4} b_i F_i + b_5\right)}} + \frac{a_2}{1+e^{-\left(\sum_{i=1\ldots4} c_i F_i + c_5\right)}} + a_3$$

Neural Network parameters optimized by a Genetic Algorithm

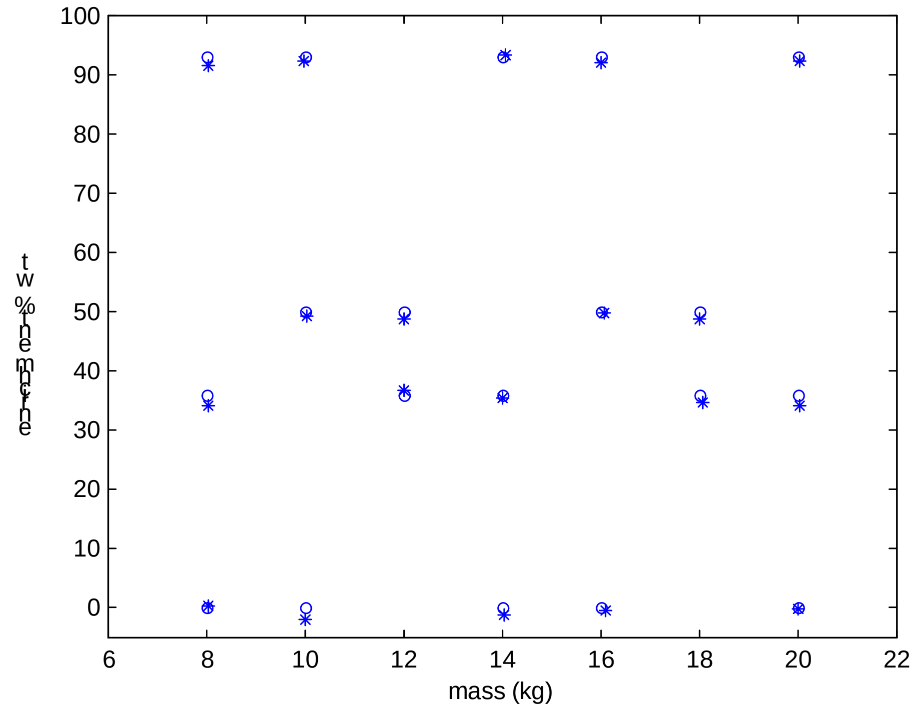


Results: training set of cylindrical and spherical samples

Uranium metal cylinders

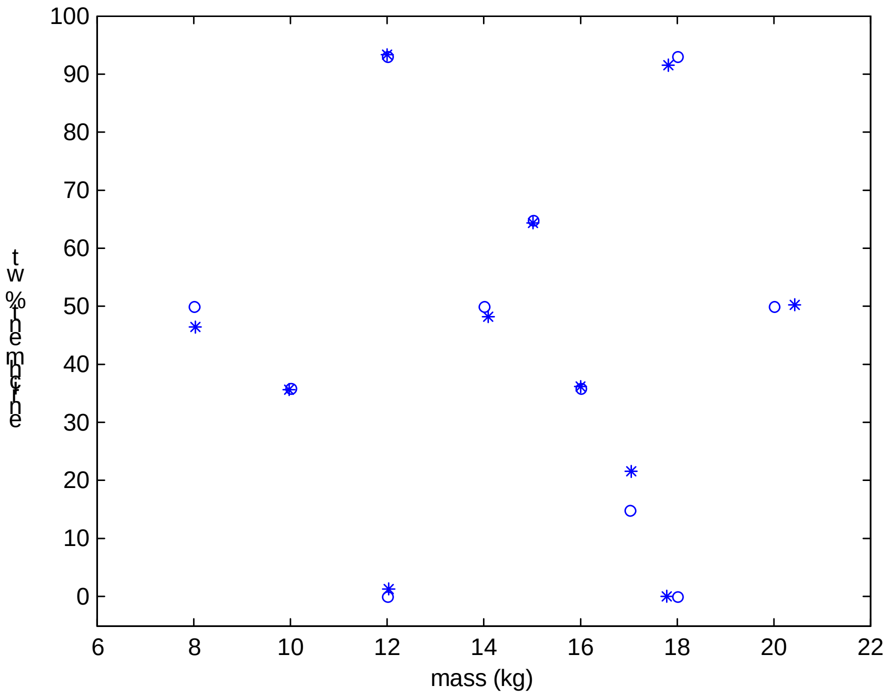


Uranium metal spheres

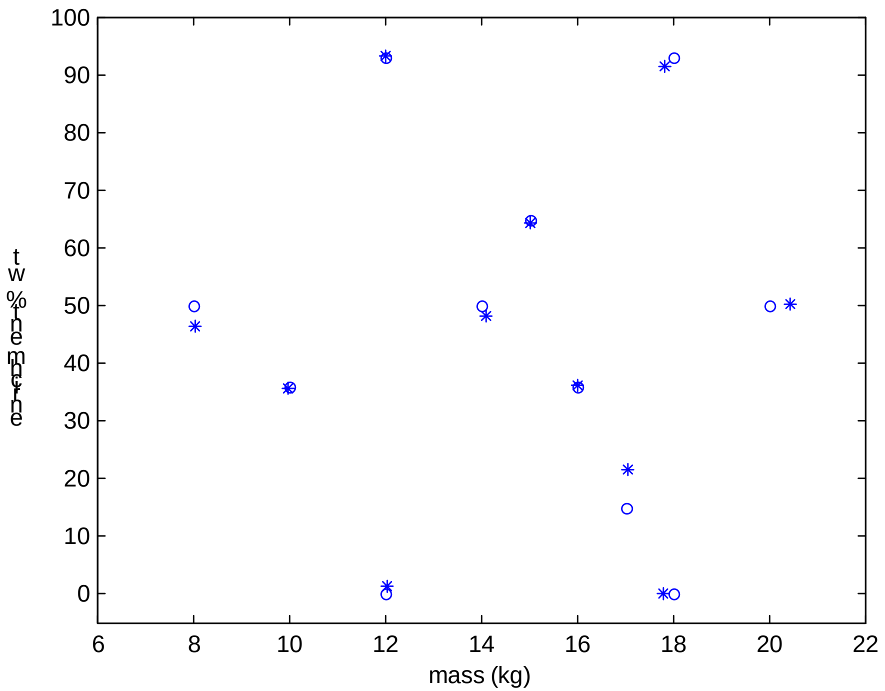


Results: test set of cylindrical and spherical samples

Uranium metal cylinders

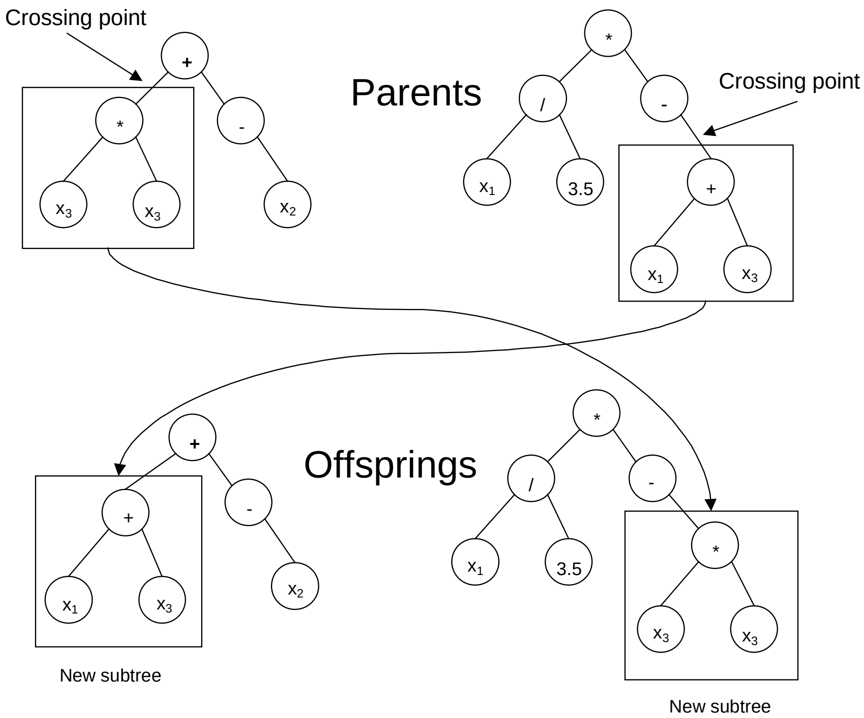


Uranium metal spheres



Genetic Programming

Cross-over operation:



Solution for the cylindrical samples:

Mass = (((((F1 - -0,514) * ((F1 - ((((F1 * F1) - F1) + -0,876) / (-0,502 + -0,584))) * -0,58)) * -0,582) * -0,574) - (((-0,876 - F1) + ((F1 * ((((F1 * F1) - F1) + -0,882) / (-0,49 + -0,544))) * (F1 * F1))) / (-0,498 + -0,59)))

Enrichment = (((F4 - (-0,014 * (F4 - (-0,014 / F4)))) - (((F2 * 0,748) * ((F3 * 0,366) + (F4 - (-0,014 / ((F1 + ((F4 - (-0,014 / (F2 - (F4 * F3)))) - (-0,014 * F4))) - (F4 * (F3 / 0,748))))))) * F3)) + F2)

Comparison of results:
Genetic Programming, Neural Network, and Linear Regression relative errors.

Cylinder	**PREDICTED BY GP**		**PREDICTED BY NN**		**PREDICTED BY Regression**	
	MASS	**ENRICH**	**MASS**	**ENRICH**	**MASS**	**ENRICH**
Training	**0.71%**	**1.67%**	**0.22%**	**2.07%**	**3.05%**	**14.81%**
Test	**1.34%**	**2.16%**	**0.81%**	**2.14%**	**2.69%**	**12.68%**
Extra	**0.45%**	**8.18%**	**0.13%**	**9.05%**	**1.87%**	**10.52%**

Sphere	**PREDICTED BY GP**		**PREDICTED BY NN**		**PREDICTED BY Regression**	
	MASS	**ENRICH**	**MASS**	**ENRICH**	**MASS**	**ENRICH**
Training	**0.17%**	**2.95%**	**0.27%**	**2.20%**	**1.95%**	**21.37%**
Test	**0.15%**	**2.38%**	**0.27%**	**4.59%**	**2.18%**	**14.71%**
Extra	**0.38%**	**14.00%**	**0.72%**	**13.33%**	**1.08%**	**43.40%**

$$Error = \frac{\sum_i \left| real_i - predicted_i \right|}{\sum_i real_i}$$

Conclusions

- Good performance of both Artificial Neural Networks and Genetic Programming in predicting sample’s total mass and enrichment

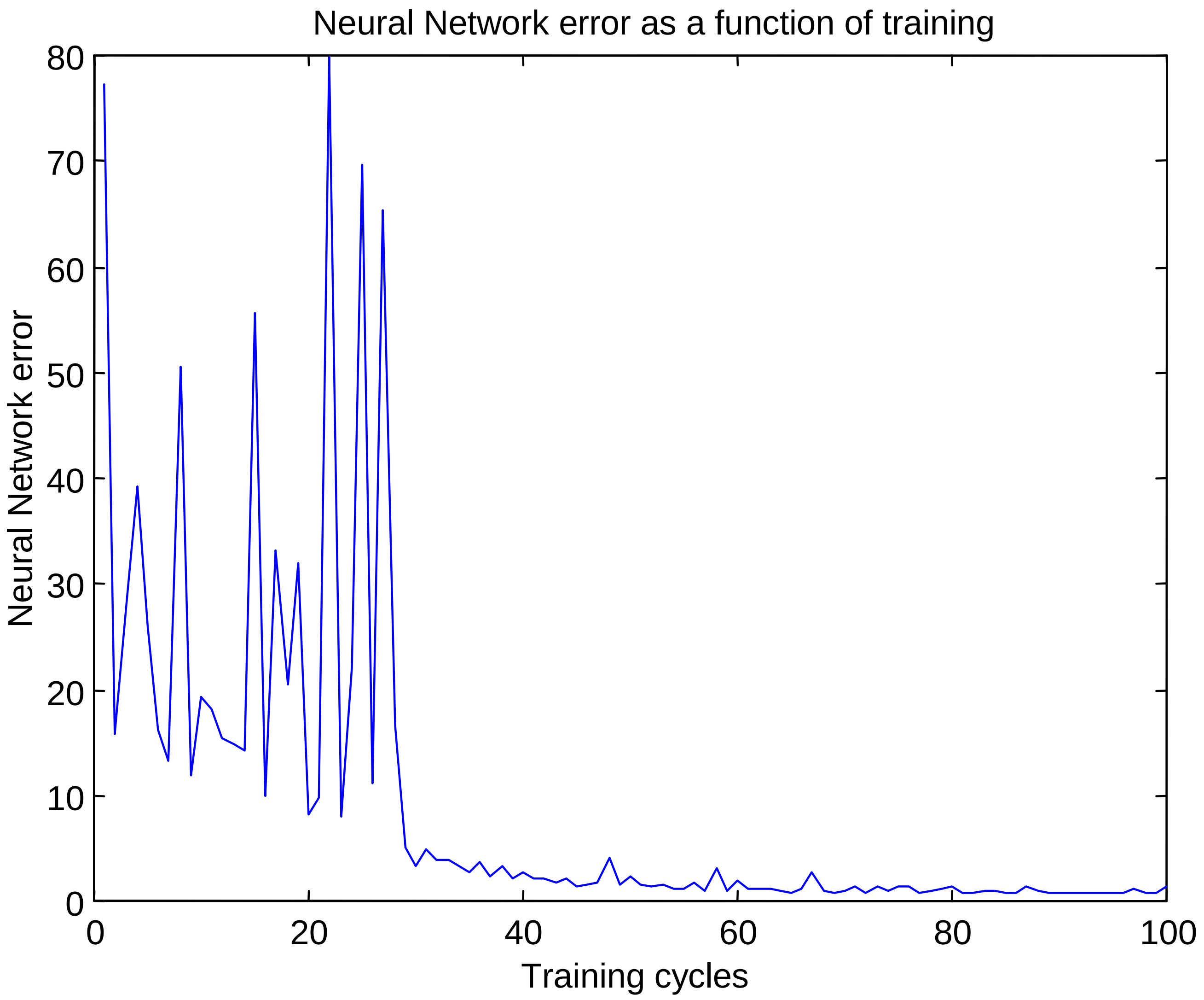
- Application of this method to safeguards operations allows for real-time sample identification

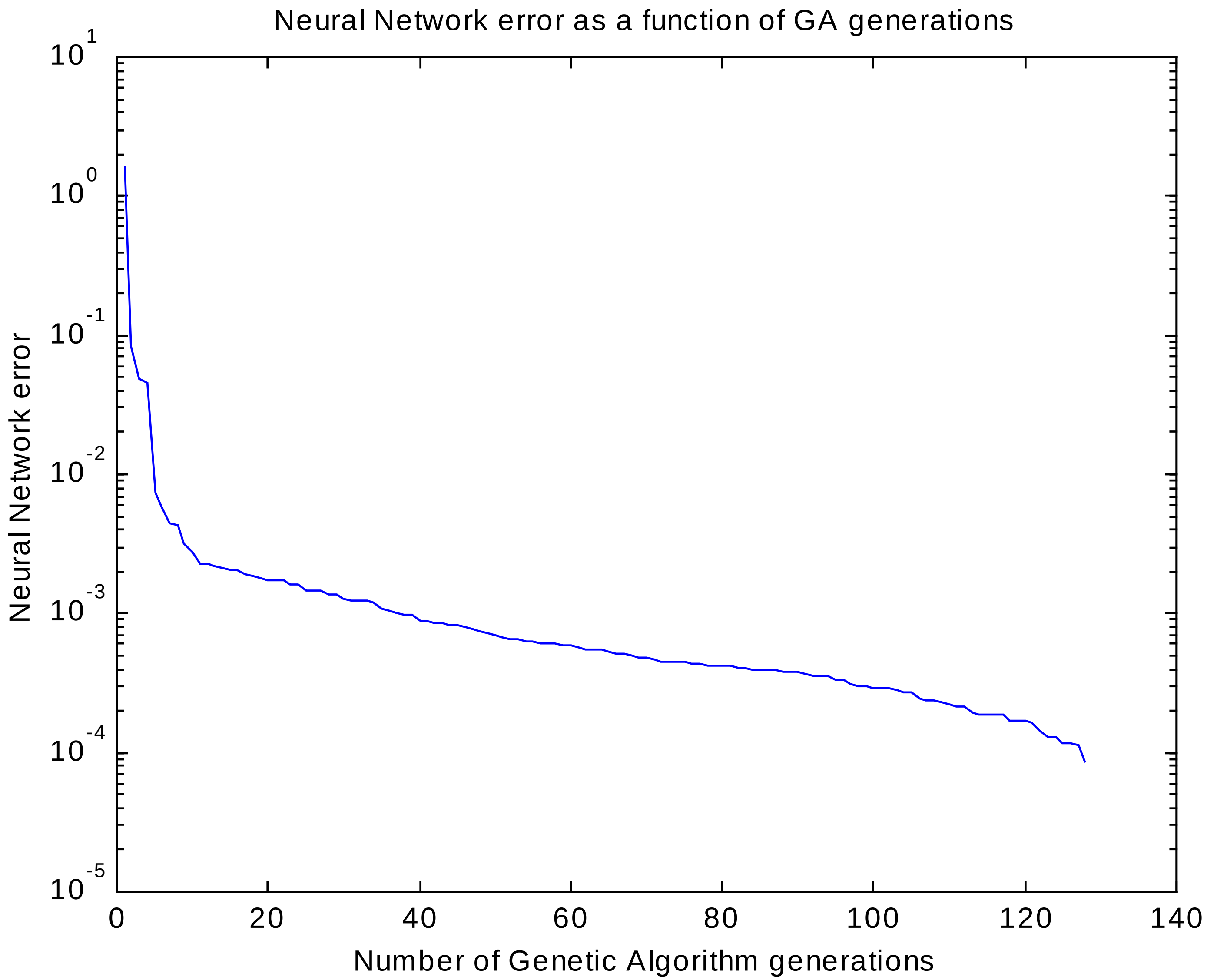
Future work

- Extension of this methodology to experimental data

Table of correlation coefficients for cylinders

	F1	F2	F3	F4	enrichment	mass
F1	1.00					
F2	0.86	1.00				
F3	-0.39	0.03	1.00			
F4	-0.39	0.02	0.84	1.00		
enrichment	-0.01	0.45	0.76	0.84	1.00	
mass	-0.88	-0.83	0.48	0.41	0.00	1.00


Neural Network error as a function of training
Neural Network error
Training cycles
0
10
20
30
40
50
60
70
80
0
20
40
60
80
100


Neural Network error as a function of GA generations
Neural Network error
Number of Genetic Algorithm generations
10^1
10^0
10^-1
10^-2
10^-3
10^-4
10^-5
0
20
40
60
80
100
120
140