Verification technologies for the zero-yield standard

Julien de Troullioud de Lanversin[1], Christopher Fichtlscherer[2], Jiehui Li[1], Moritz Kütt[3]

[1]The Hong Kong University of Science and Technology
[2]RWTH Aachen
[3]The University of Hamburg

香港科技大學
THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

INTRODUCTION AND MAIN RESULTS

The zero-yield standard bans supercritical fission experiments but allows subcritical ones, which nuclear states conduct for arsenal stewardship. Recently, tensions have grown from suspicions of violations at very low yields, undetectable by the IMS. This work presents gamma spectroscopy methods combined with machine learning, tested via simulations (neutronics, isotopic evolution, photon transport), for on-site verification of very low-yield tests.

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Background

The CTBT's zero yield standard bans nuclear supercritical tests while permitting subcritical experiments. Such very low-yield tests are typically performed in underground chambers compressing and irradiating plutonium targets in containment vessels (**Fig. 1**). However, no established technical methods or on-site inspection protocols currently exist to verify compliance with the zero-yield standard for very low-yield tests.

In this work, we show that gamma spectroscopy analysis of residual radioactive debris in the vessel can reveal key details about the test's yield and criticality, even weeks to months after the test. This approach could inform the creation of robust verification protocols for the zero yield standard at very low yields.

Method principles and results

Machine learning methods (ML) have been trained on millions of synthetic spectra measurements generated by simulating high-fidelity very low-yield test models and gamma detector responses. These simulations span across a wide range of test and measurement settings impacting the measured spectra to ensure the robustness of the ML method. These include the test yield, the time between the test and the measurements, the shielding effects, the plutonium mass, and the pre-test configuration of the plutonium target. **Fig. 2** shows the performance of a trained ML algorithm based on XGBoost to estimate the yield of tests at 1 g and 1 kg TNT equivalent, 6 months after occurrence.

The yield estimated by the ML method can then be used to narrow down the possible criticality levels of the test by using the following relations between the two factors:

$$Y = E_f N_0 \int_0^T e^{\alpha(t)t}\,dt$$

Where Y is the yield, E_f is the fission energy, N_0 the number of initiating fissions, T the duration of the test and $\alpha(t)$ the prompt neutron decay, indicating the criticality of the test. Information on N_0 can be inferred by on-site inspections of neutron source equipment used to initiate fissions in the target.

As shown on **Fig. 3**, narrowing down values for Y and N_0 yields insights into possible ranges of $\alpha(t)$ and compliance of the zero yield standard. While a 1 kg TNT test would necessarily be supercritical, more information on N_0 would be needed to draw a conclusion for the 1 g TNT test.

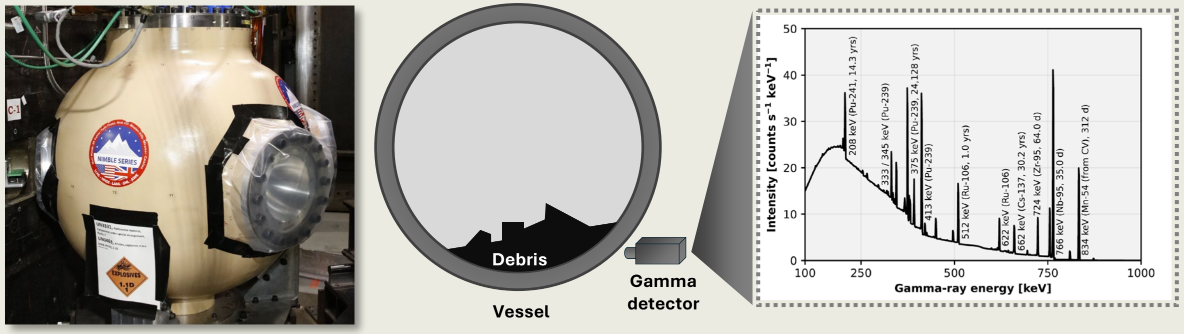

Figure 1: Photograph of a containment vessel used for a subcritical test part of the U.S. Nevada National Security Site (NNSS) and notional configuration of gamma measurement after a test is conducted.

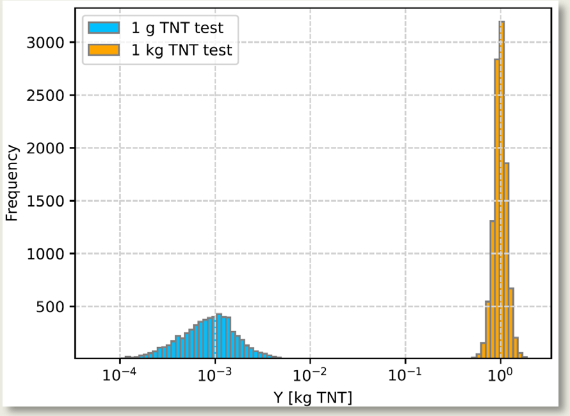

Figure 2: Yield estimations of the ML method on various gamma spectra for very low-yield tests at 1 g TNT and 1 kg TNT. Each set of data consisted of 6,000 synthetic gamma spectra.

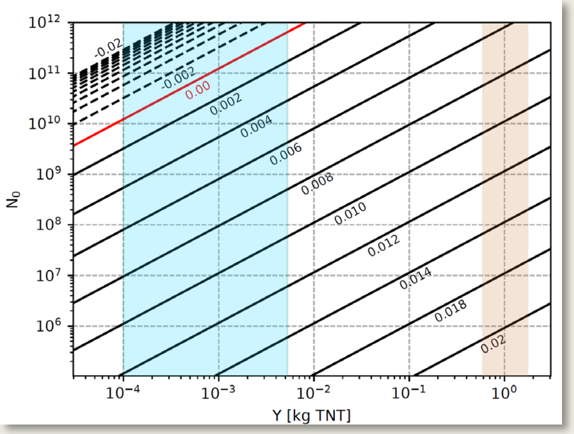

Figure 3: Contour lines of α_m, the maximum value of $\alpha(t)$, against N_0 and Y. The red lines indicate tests of perfect criticality ($\alpha_m = 0.0$). Plain lines indicate supercritical tests while dashed lines indicate subcritical tests. The label next to lines indicate the value of α_m in shakes^{-1}. The shaded regions correspond to notional uncertainties on the estimated yield from the ML method.

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