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MODENA project: decay heat prediction using non-destructive assay

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Abstract. The long-term safety of nuclear waste disposal is a major challenge for countries with nuclear energy programs. Across Europe, (deep) geological repositories have been identified as the best solution for the permanent isolation of spent nuclear fuel (SNF) and high-level radioactive waste. These repositories use multi-barrier systems, including both engineered and geological barriers, to ensure that radioactive materials are isolated from the biosphere for thousands of years. A critical factor for the safety of geological repositories is managing the decay heat, which is the thermal energy produced by radioactive decay in SNFs. Although heat generation decreases over time, significant amounts are emitted for many years after the SNF is removed from a reactor. Improper management of decay heat can compromise the integrity of the repository barriers. Calorimetric measurements can directly measure the decay heat, but they are time-consuming and resource-intensive. To address this, the MODENA project is focused on developing a fast method to estimate decay heat that relies on measurements that will be performed on every SNF before its encapsulation to verify calculated fuel properties to fulfil international safeguards regulations. These measurements are non-destructive gamma and neutron measurements. The model uses only key radionuclides such as Cs-137 and Eu-154, along with neutron emissions, which allows the prediction of decay heat without the need for additional measurements. The strength of the methodology developed in the MODENA project is its flexibility. The model is based on measurement data from radionuclides that are expected to be measurable at encapsulation and can be adapted to well-known measurement instruments, which makes it easy to apply this model in different countries. Improving decay heat prediction could lead to a more efficient use of available resources, ultimately ensuring optimized sustainability of the repository.

1 Context of the project

The disposal of spent nuclear fuel (SNF) and high-level radioactive waste represents one of the most significant challenges in the nuclear energy sector, particularly when it comes to ensuring long-term safety and environmental protection. Across Europe, countries are developing (deep) geological repositories as the preferred solution for the disposal of high-level waste. These repositories are designed to isolate radioactive materials from the biosphere for several thousands of years. The implementation of geological repositories is based on the principle of multi-barrier systems, which rely on a combination of engineered and geological barriers to ensure containment and compliance with the legal framework and regulatory guidelines. European countries such as Finland, France, Sweden and Switzerland are at the forefront of developing such repositories, with various concepts tailored to their specific nuclear fuel cycle and geological conditions.

EURAD (European Joint Program on Radioactive Waste Management), an initiative of the European Union, is fostering cooperation between European nations to improve the management of nuclear waste worldwide. This collaboration allows member states to share knowledge, technology, and best practices, ensuring that all countries can address the complexities of nuclear waste management. Two countries, Finland and Sweden, have already begun the construction of their geological repository at Onkalo and Forsmark, respectively. Other countries have advanced plans, like France with the Cigeo project. The strategy of each country is shaped by its unique geological conditions, the nature of the nuclear waste produced, and long-term safety goals.

Even though all countries with advanced final disposal programs have their specificity, they are all based on the multi-barrier system, which combines engineered barriers and geological features to ensure the containment of

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radioactive materials for an extended period of time. The spent nuclear fuel assemblies (SNFs) are placed in sealed canisters made of e.g. copper or steel. After emplacement of the canisters in the geological repository, the tunnels are backfilled with materials such as bentonite. The canisters, backfill material and host rock are all part of the multi-barrier system. All proposed geological repositories are planned to be located several hundred meters below the surface.

One of the key challenges addressed by waste management organizations is the management of decay heat. Decay heat is the passive thermal energy produced by the radioactive decay of radionuclides in the spent nuclear fuel. Although the rate of heat production decreases over time, significant amounts of heat continue to be produced by the fuel for many years after the SNFs have been removed from the reactor. Managing this heat is essential to maintain the integrity of the canisters and the surrounding materials as part of the repository's multi-barrier system.

Decay heat must be considered in every stage of the waste management process. Before the SNF is encapsulated in canisters, precise predictions of decay heat are required to ensure that safety limits are adhered to. The decay heat is estimated using benchmarked and verified depletion codes. However, measurements could help to make more precise determinations of decay heat or alternatively be used to verify the calculated values. Calorimetric measurements, which directly measure the heat generated by SNF, are unfortunately time-consuming and resource-intensive, especially given the large number of SNF that will eventually need to be disposed of. Currently, the only calorimeter in the world in use for determining decay heat from SNFs is located in the Clab facility, the central interim storage facility for SNFs in Sweden. Other countries such as Switzerland have also planned for a calorimeter, but it is not a commonly used measurement device.

In order to fulfill international safeguards regulations, non-destructive measurements will be performed on every SNF in Sweden and Finland before their encapsulation, as this is the last point in time in which SNFs are easily accessible for measurement. The choice of the measurement station is different in Finland and Sweden, but both are proposed to be composed of a combination of gamma and neutron instruments. The MODENA (MOdel for Decay hEat prediction using Non-destructive Assay) project is investigating an alternative method for decay heat predictions using non-destructive gamma and neutron measurements intended for safeguards assessments. The idea behind the MODENA project is to make maximum use of collected data and investigate whether these can also be used to meet needs of the operators, e.g. to predict decay heat. The data in this project come from previously performed measurements on Swedish SNFs, but the project's approach tries not to rely on a precise measurement device so that, ultimately, as many countries as possible can use the method. Therefore, the MODENA project contributes to improving the safety of geological repositories in Sweden and across Europe. The main results of the MODENA project are published in Solans et al. "Prediction of decay heat using non-destructive assay" [1] and in the thesis [2]. They are summarised in this review paper.

The decay heat is predicted by training a machine learning model on simulated data. The simulated data used are described in Section 2. In order to improve the simulated data to better reflect realistic measurement conditions, the model has been calibrated using part of the experimental data, described in Section 2. The remaining experimental data are used to test the model. A description of the methodology and model is presented in Section 3. The main results are described in Section 4. Section 5 details the advantages and impact of the project. The conclusions of this work are given in Section 6.

2 Description of data used in the project

The research conducted is based on the use of simulated and measurement data. While this project uses measurement data, such data is rare and thus the measured data set is limited; hence, the use of simulated data is required. The simulated data were primarily used to develop and test the performance of machine-learning algorithms, while the measurement data available were primarily used to calibrate and validate the results obtained from the simulations.

2.1 Simulations

The simulated data used in this project were obtained from reference [3]. They were created using a Serpent2 2D pincell model of a PWR fuel rod, infinitely reflected in water. A large number of depletion calculations were run to span a wide range of initial enrichments in the range of 1.5%–6%, burnups up to 70 MWd/kgHM and cooling times up to 70 years. This range of parameters is expected to include the vast majority of existing SNF that is to be encapsulated. All simulations assumed an annual fuel irradiation of 10 MWd/kgHM followed by a 30-day downtime, which was repeated until the desired discharge burnup was reached.

In total, the fuel library comprised 789 406 fuel samples, or unique combinations of initial enrichment, burnup and cooling time. For each of these samples, the fuel library contains information on the concentration of 279 radionuclides, spontaneous fission rate and decay heat.

2.2 Measurements

The measurement data used in this work were obtained from a number of different measurement campaigns, where different instruments were used. This section will explain the fuel assemblies that were measured and the data that were collected during the measurement campaigns.

2.2.1 Measured fuel assemblies

The most important set of fuel assemblies that were measured is referred to as the SKB-50 fuel set. This fuel set consists of 25 BWR fuels and 25 PWR fuels. The initial enrichments of the fuels range from 2.1 to 4.1%, the burnup values are in the 23–53 MWd/kgHM interval, and the cooling times at the time of the measurements range between 7 and 33 years. For more information, see reference [4].

In addition to the measurements of the SKB-50 fuels, some additional fuel assemblies were also measured: the so-called BT-5 fuel assemblies [5] and the SKB-2006 fuel assemblies [6]. The former set comprised five SNFs with initial enrichment between 3.6 and 3.95%, burnup of 50–55 MWd/kgHM and a cooling time of 4.5–21 years, while the latter have an initial enrichment of 2.1–3.4%, a burnup of 20–51 MWd/kgHM, and a cooling time of 15–33 years.

2.2.2 Measurement campaigns

The SKB-50 fuels were measured multiple times at the Clab facility in Sweden:

- *Static and axial gamma spectroscopy scans* using an HPGe detector in 2014 [7,8].
- *Axial gamma spectroscopy scans* using an HPGe detector were performed in 2016 on 18 of the SKB-50 BWR fuels [9].
- *Axial gamma spectroscopy scans* using an HPGe detector were performed in 2019 on 23 of the SKB-50 PWR fuels [9].
- *Neutron coincidence measurements* using the DDSI prototype instrument in 2018 [10].
- *Calorimetric measurements* in several different measurement campaigns between 2018 and 2021 [5,11].

The BT-5 and SKB-2006 fuel assemblies were only measured with a calorimeter.

For the 2014, 2016 and 2019 gamma spectroscopy measurements, time-stamped list mode data were collected for all measurements. For the 2018 DDSI measurements, the number of coincident neutrons was detected, and the total neutron count rate was used for the analysis in this project. For the calorimetric measurements of the SKB-50, the BT-5 and SKB-2006 fuels, the speed of the temperature increase and the dose rate (to estimate the gamma escape power) were recorded.

Measurements on entire spent nuclear fuel assemblies are very rare, and even rarer are different types of measurements (gamma, neutron and calorimetric) on the same SNFs. To obtain these measurement data, several measurement campaigns with different measurement equipments were arranged, thus requiring adjustments to the recorded data (such as adjustments related to the cooling times of the SNF). Details about the adjustments are given in [1]. These experimental data also highlight the uniqueness of this work, as further detailed in Section 5.

3 Decay heat prediction methodology

3.1 Selection of non-destructive assays signatures

The aim of this work is to use measured non-destructive assay observables and a machine-learning (ML) model to predict the decay heat of a measured SNF. Ideally, the observables should not depend on selected measurement instruments so that they can generalize to the needs of different organizations doing SNF management and their specific experience with various measurement instruments (see Sect. 5.2). Typically, the measurement techniques need to be able to quantify selected radionuclides or groups of radionuclides. Some key features of the selected radionuclides include:

- the radionuclides should have a sufficiently long half-life that they are measurable at the time of encapsulation.
- The radionuclides should be sufficiently abundant and active to be readily measurable.
- The radiation emission should be of sufficient energy that the radiation can readily reach a detector.
- The abundance of the radionuclides should correlate to fuel parameters of interest and to the decay heat.

Based on these criteria, three observables were selected ([12]). Also shown and presented in Section 4 is that these observables are sufficient for decay heat predictions. Two of the selected observables are gamma emissions, from Cs-137 and Eu-154. The experimental data have shown that the gamma emissions are measurable, also for SNFs with long cooling times; and they can be relied upon in an ML model. Measurements of the gamma emissions require a detector with some spectroscopic capability. For the experimental data used here, an HPGe detector was used. Potentially, a detector of lower resolution can be sufficient to quantify the radiation emission and, hence, the abundance of the selected gamma-emitting radionuclides.

The third observable is the total neutron emission rate. This observable is mainly sensitive to the spontaneous fission rate in the SNF for the various radionuclides undergoing spontaneous fission. More complicated neutron detectors, such as coincidence detectors, can, in principle, provide more data, but as shown in papers [12,13], they can be sensitive to noise and might require extensive modeling and analysis to obtain reliable data.

The different input features provide distinct types of information about the SNF, all of which are crucial for determining decay heat. For example, Cs-137 contributes approximately 30% of the total decay heat at 30 years of cooling time [14] and has a linear relationship with burnup. Eu-154, with its relatively short half-life and unique production pathway, offers valuable insights into both cooling time and burnup when analyzed alongside Cs-137 data. Additionally, the neutron count rate serves as an indicator of Cm-244 content, providing insight into the neutron fluence in the reactor.

For this work, calorimetry data on the decay heat were used to validate the decay heat predictions. For an organization aiming to determine the decay heat in the future using the methodology presented here, it could be sufficient to calorimetrically measure a few selected assemblies to validate and calibrate the ML model, but otherwise use the ML model to predict the decay heat of the bulk of the SNF.

3.2 Calibration of the simulated data

As ML models typically require significant amounts of data for training, and as the amount of experimental data is limited, it is necessary to use the extensive, simulated data presented in Section 2.1 for training. However, as there are differences between the simulated and measured data, a calibration must be performed to convert the simulated data into a form equivalent to the measured data. The advantage of calibrating the simulated data is that the trained ML model can then use the measured data to directly predict the fuel parameters.

The calibration procedure is more thoroughly detailed in paper [1], but begins by converting the 2D-simulated SNF to an equivalent 3D representation to obtain the intensity of measurable radiation emissions:

- converting radionuclide concentrations from atomic densities in $[10^{24}/\text{cm}^3]$ to an activity (in Bq), for all radionuclides of interest. This takes into account the fuel volume and radionuclide decay constants. Based on the activity, it is possible to calculate the emission intensity of the gamma lines from the selected radionuclides.
- Converting the simulated decay heat, given as power per cm of rod, to the decay heat of the full 3D fuel assembly. This requires taking into account the fuel length and the number of rods.
- Converting the simulated spontaneous fission rate per cm of rod to a neutron emission rate. For the experimental measurements used in this project, the SNFs are sufficiently similar so that the same spontaneous fission neutron multiplicity can be assumed, but more care is required if MOX or non-LWR fuel is to be characterized using this methodology.

Once the simulated results have been converted to a 3D equivalent, they need to be calibrated against the measurements to take into account effects such as geometric attenuation and detector efficiency. Thus, this calibration needs to be done once per detector setup, should different setups be used, or should a setup be updated. The main steps include:

- dividing the available experimental data into a calibration dataset, composed of 80% of the measurements, and a test set of 20% of the measurements, to test the performance of the calibration (5-fold cross-validation).
- As the simulated fuel database will not have SNF with the exact parameters of the measured SNF used for the calibration, an equivalent simulated SNF must be obtained by interpolating from the closest SNF in the simulated database. As the simulated database has regularly spaced fuel parameters and a fine grid, linear interpolation is sufficient. The end result provides values that correspond to each measured SNF for the simulated gamma and neutron emissions and decay heat.
- For each of the SNF observables, i.e. the individual measurable gamma lines, total neutron rate and decay heat, a linear fit is made to relate the measured values to the simulated ones. This calibrates the simulated and measured observables to directly correspond to each other.
- For each observable, the corresponding fit is applied to the simulated database, converting it into values equivalent to those that can be measured.

After performing these steps, the simulated database will contain observables calibrated to the measurements. Hence, any measurements can be compared directly to the calibrated database, and an ML model trained on the calibrated database will be able to accept measured values without any further conversion due to the detector setup or the simulation details.

3.3 Developing a Gaussian process regression model

To determine which machine-learning model performed best to predict decay heat, multiple models were trained and evaluated. In the end, a model based on Gaussian processes (GPs) was selected, as it performed well and was suitable for the task at hand. GPs are powerful due to their non-parametric nature, where relationships that are complex and non-linear can be modeled without specifying a predetermined functional form [15]. In a GP, kernel functions are used, which specify the covariance between points and capture properties such as the smoothness of the function to be fitted. A few kernel functions are commonly used due to their performance capability. In addition, GPs allow for a straightforward handling of uncertainties, which can be implemented in future work.

As with many ML models, GPs require substantial amounts of training data, although they tend to need fewer data than numerous other common ML methods. For this work, the GPs were trained on 50 000 data points from the simulated and calibrated fuel library, which provided a good balance between the time required to train and use the model, and the performance of the model.

4 Results

4.1 Prediction accuracy of the method

The results of the presented method have previously been reported in [1]. Here, only the main results are summarized. The method was tested against both simulated and experimental data using five-fold cross-validation. Hence, all results presented here are on unseen data. The performance metric used for the method is the magnitude of the relative deviation, $|(C-E)|/E$, where C is the predicted decay heat using the model and E is the reference value from the measurement or the simulated database. A summary table of the main results on simulated and measured PWR SNF is presented in Table 1.

When testing on the simulated data, an assumed measurement uncertainty was incorporated into the model by perturbing the input signatures with 4% [9], resulting in a mean magnitude of the relative deviation of 4.6% (labelled as "Simulated data with perturbations" in Tab. 1). In the somewhat unrealistic scenario where no measurement

Table 1. Summary of the main results. Values extracted from table 9 in [1].

	$\lvert(C-E)\rvert/E$ [%]
Simulated data without perturbations	1.3
Simulated data with perturbations	4.6
Experimental data SKB-50 17 × 17	4.0
Experimental data SKB-50 15 × 15	1.8

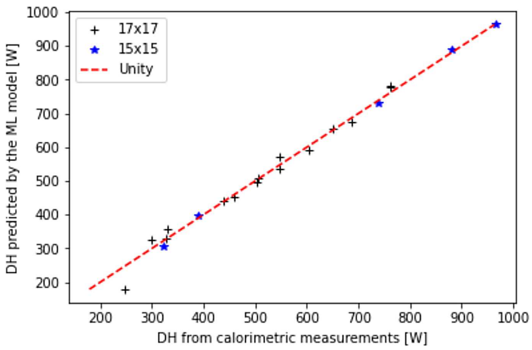

Fig. 1. Comparison between decay heat from the calorimetric measurements and the predicted decay heat by the ML model. Figure initially published in [1].

uncertainty is assumed, a mean magnitude of the relative deviation of 1.3% is obtained. This represents the lower bound of the method's performance, given the experimental signatures used in the presented test case (labelled as "Simulated data without perturbations" in Tab. 1).

The method is also evaluated using the SKB-50 experimental data. The model was evaluated on both 17 × 17 and 15 × 15 SNFs, yielding relative deviation magnitudes of 4.0% and 1.8%, respectively. Figure 1 shows the decay heat prediction from the model compared to calorimetric measurements for the SKB-50 SNFs. These deviations can be explained by the model's accuracy, differences between the real power histories and the assumed ones in the simulated dataset, uncertainties in the input gamma and neutron data and, to a lesser extent, uncertainties in the calorimetric data. With that in mind, the observed deviations are in line with the results from the perturbed simulated data. The higher deviation for the 17 × 17 SNFs can, to some extent, be explained by the fact that this dataset contains an SNF with a very unusual irradiation history (the SNF with the lowest decay heat in Fig. 1). This also underscores a weakness of the model, i.e. its difficulty in accurately predicting SNFs with irradiation histories that deviate significantly from those assumed in the simulated dataset used to train the model.

4.2 Impact of input signatures

One advantage of the model is its ability to assess the impact of the different input features described in Section 3.1. This has been explored through both a perturbation study and the removal of specific input features from the model.

In a perturbation study conducted on the simulated data, the magnitude of the perturbation was varied individually for each of the three signatures. The results show that uncertainties in the Cs-137 activity have by far the greatest impact on deviation. Uncertainties in Eu-154 and, to an even greater extent, neutron count rate had a minimal impact on the overall error. More details can be found in reference [1], figure 9.

The model was also tested on simulated data without Eu-154 and neutron count data, resulting in a clear deterioration in performance. An increased deviation was also observed when testing the model on measurement data with these features removed. As discussed in Section 3.1, Eu-154 activity is a key input feature for providing information on the cooling time. To evaluate whether the Eu-154 activity could be replaced, the model was tested using the declared cooling time instead of Eu-154 activity. The results showed that the model performed equally well with the cooling time as an input feature as it did with an unperturbed Eu-154 feature. Similar work was done with the total neutron count rate, and it was shown that it is closely related to Cm-244, which provides information on the neutron fluence in the reactor core during irradiation.

5 Advantages and impact of the project

5.1 Novel experimental investigation

Internationally, many initiatives are focused on reducing the decay heat uncertainty from depletion calculations. While these initiatives are greatly needed, the MODENA project offers a novel approach to estimating decay heat. The MODENA project offers a first-of-its-kind solution by integrating non-destructive gamma and neutron measurements with a Gaussian process regression model to predict decay heat in SNF. The prediction of decay heat is therefore based on experimental measurements. While calorimetric methods could be used to accurately measure decay heat, measurement devices able to measure entire SNFs are extremely rare (currently, the only one in the world is at Clab), and are also labor-intensive and limited in scalability. The MODENA project presents an innovative alternative by using data from radionuclides such as Cs-137 and Eu-154, alongside neutron count rates, to deliver accurate and efficient decay heat predictions. This model also makes it possible to predict decay heat in a fraction of a second. As a result, it can be efficiently used online during operation of the encapsulation plant. This combination of advanced nuclear measurements and machine learning is innovative within the field of nuclear waste management, representing a new approach to solving the challenges of SNF heat prediction.

5.2 Versatile framework for other countries

The methodology has been purposely developed in this project to be highly applicable across various countries and facilities, making it particularly relevant to the global nuclear industry. The choice of input signatures are common signatures that can be expected in various gamma and neutron measurement devices. Moreover, these signatures rely on measurements that are already required for international IAEA safeguards regulations. The use of simulated data in combination with real-world calibration ensures that the model can be adapted to other SNF inventories, enabling replication in various countries with different fuel types and fuel parameters.

Moreover, the scalability of the project makes it adaptable to various repository designs and fuel types, offering a versatile solution. As more countries move toward long-term nuclear waste management, the MODENA project is strongly supporting the international effort regarding a deep geological repository. Moreover, in agreement with the recommendation of the European Commission, open access to all published papers has been provided. Therefore, all studies in the MODENA project are openly available and can be reused and modified without limitations.

5.3 Leveraging machine learning to the needs of the nuclear industry

The decay heat prediction model is based on the use of a Gaussian process, a highly flexible and well-established probabilistic machine-learning approach widely used for regression due to its ability to model uncertainties. The MODENA project used the Gaussian process to demonstrate that decay heat can be predicted using only a limited set of experimental signatures – specifically, the activities of Cs-137 and Eu-154 along with the total neutron count rate. Once this link has been demonstrated, countries that do not wish to use machine-learning techniques can directly compare the experimental observables with what is obtained from depletion calculations. The MODENA project demonstrated that if the three observables align, this provides a strong indication that the decay heat is also accurate. The project has also focused on showing the limitations of the model, for instance, what the consequences are if one of the observables is not measured or if their uncertainty is higher than recommended.

5.4 Economic benefits and impact on nuclear industry

The MODENA project offers significant economic benefits by addressing one of the most critical limiting factors in canister loading: decay heat. For most countries planning or implementing geological repositories, decay heat is a key constraint in determining the size and, therefore, also cost of the geological repository because the loading of the SNFs in the canisters is restricted by decay heat and criticality. By increasing the confidence in decay heat predictions through non-destructive gamma and neutron measurements, the project may directly impact the number of canisters required. According to an SKB estimate in a EURAD paper [16], a 1% reduction in decay heat uncertainty directly correlates to a 1% decrease in the total number of canisters needed. This optimization leads to substantial cost savings, as fewer canisters mean lower costs for the material, excavation and backfilling as well as saving resources and support sustainability. Furthermore, fewer canisters also lead to reduced costs for long-term monitoring and maintenance of the repository.

Moreover, this methodology for predicting decay heat comes without additional costs for the nuclear waste management organizations and their facilities, as it uses infrastructure such as measurement stations that will already be in place to comply with safeguards regulations and measurement time requirements. The MODENA project merely offers an additional use of the data collected to increase the degree of confidence in the heat uncertainty.

6 Conclusion

This project has successfully developed a method to predict decay heat from SNF using non-destructive gamma and neutron measurements. The approach to using data from radionuclides such as Cs-137 and Eu-154 along with total neutron count rates provides a highly accurate, efficient and scalable solution for estimating decay heat, thereby achieving a relative deviation of just 2–4%. This is an alternative method for predicting decay heat based on experimental measurements without using calorimetric measurements, which are greatly needed but time-consuming and impractical for large-scale applications. The methodology incorporates both simulated and measurement data, thereby ensuring that predictions closely reflect real-world conditions, while calibration steps account for potential discrepancies between models and actual measurements. One of the primary benefits of this project is its increased efficiency. The use of non-destructive measurement methods significantly reduces the time and resources required to predict decay heat compared to calorimetric approaches. This makes the process scalable for large inventories of SNF, which is crucial for the long-term management of nuclear waste in geological repositories. Additionally, the gamma and neutron measurements used in this project are essential not only for decay heat predictions but also and mainly for fulfilling international safeguards requirements of the International Atomic Energy Agency (IAEA). This ensures both the safety of the nuclear waste management process and compliance with global nuclear non-proliferation standards. Accurate decay heat prediction also enhances safety margins by maintaining the structural integrity of containment systems such as canisters and bentonite clay buffers in geological repositories. Precise heat estimates reduce the risk of material degradation and radionuclide leakage, thereby contributing to the long-term safety of these disposal facilities. Although the project focuses on Swedish data, the methods developed are adaptable to nuclear waste management programs of other countries. The process can be applied to different repository designs and regulatory frameworks, making it a valuable tool for international efforts to improve nuclear waste safety. Furthermore, the incorporation of uncertainty analysis into the methodology ensures that the model can account for measurement inaccuracies and prioritize improvements in measurement techniques to further refine predictions. In summary, this project represents a significant advancement in the field of nuclear waste management, offering a more practical and reliable means of predicting decay heat, improving safety margins, and supporting international efforts to reduce uncertainty in decay heat. Its contributions serve as a valuable resource for all countries as they develop and implement their own nuclear waste disposal strategies.

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Conflicts of interest

The authors declare that they have no competing interests to report.

Data availability statement

This article has no associated data generated.

Author contribution statement

Virginie Solans: Writing – original draft, review & editing, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. Erik Branger: Writing – original draft, review & editing, Supervision. Sophie Grape: Writing – original draft, review & editing, Supervision. Henrik Sjöstrand: Writing – original draft, review & editing, Supervision.

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