NUCLEAR SCIENCE AND TECHNOLOGY

Volume 11, Number 2, June 2021

Editorial Board

Editor-in-chief
Tran Huu Phat (VINATOM)

Executive Editors
Vuong Huu Tan (VARANS)
Tran Chi Thanh (VINATOM)
Cao Dinh Thanh (VINATOM)
Hoang Anh Tuan (VAEA)

Editors
Nguyen Kien Cuong (VINATOM) Le Hong Khiem (IOP)
Nguyen Nhi Dien (VINATOM) Dao Tien Khoa (VINATOM)
Nguyen Thi Kim Dung (VINATOM) Tran Hoai Nam (Duy Tan University)
Ho Manh Dung (VINATOM) Dang Duc Nhan (VINATOM)
Nguyen Nam Giang (VINATOM) Nguyen Hao Quang (VINATOM)
Trinh Van Giap (VINATOM) Nguyen Mong Sinh (VINATOM)
Le Ngoc Ha (108 Military Central Hospital) Tran Duc Thiep (IOP)
Phan Son Hai (VINATOM) Dang Quang Thieu (VINATOM)
Le Huy Ham (VAAS) Le Ba Thuan (VINATOM)
Nguyen Quoc Hien (VINATOM) Nguyen Trung Tinh (VARANS)
Le Van Hong (VINATOM) Tran Ngoc Toan (VINATOM)
Nguyen Tuan Khai (VARANS) Duong Thanh Tung (VINATOM)
Pham Dinh Khang (HUST) Nguyen Nu Hoai Vi (VARANS)

Science Secretary
Hoang Sy Than (VINATOM)

Published by
Tel: 84-24-39420463 Fax: 84-24-39424133 Email: nuscitech@vinatom.gov.vn
Vietnam Atomic Energy Institute, 59 Ly Thuong Kiet, Hanoi, Vietnam
Tel: 84-24-39420463 Fax: 84-24-39422625 Email: infor.vinatom@hn.vnn.vn
Cao Chi is 90

On 25 April, Prof. Dr. Cao Chi turned 90.

VAES and VINATOM’s Presidents, friends and colleagues congratulated Prof. Dr. Cao Chi on his birthday and wished him good health, well-being of the family and new creative achievements.
Contents

Applying machine learning method in neutrons and gamma-rays identification according to their pulse shapes

*Le Xuan Chung, Vi Ho Phong, Le Tuan Anh, Nguyen Duc Ton, Nguyen Hoang Phuc, Bui Duy Linh*................................................................................................................................. 01

A convolutional neural network for Y90 SPECT/CT scatter estimation

*Ho Thi Thao, Le Tuan Anh, Phan Viet Cuong, Nguyen Hong Ha, Nguyen Duc Ton, Nguyen Dinh Khai*....................................................................................................................................... 09

Application of Artificial Neural Network for Prediction of Local Void Fraction in Vertical Subcooled Boiling Flow

*Nguyen Ngoc Dat, Nguyen Van Thai*................................................................................................................................. 14

Neutronic design of a PWR fuel assembly with accident tolerant-composite for the long-life core

*Hoang Van Khanh, Tran Viet Phu, Nguyen Thi Dung*................................................................................................................. 23

Determination of warning level at Lang Son environmental radiation monitoring station

*Nguyen Van Khanh, Duong Van Thang, Nguyen Thi Oanh, Nguyen Thi Thu Ha, Doan Thuy Hau, Le Thi Hoa, Cao Duc Viet, Duong Duc Thang*................................................................................................. 37

Establish the training program of alternating current field measurement - level ii according to SNT-TC-1A

*Le Duc Thinh, Ngo Thi Kieu Oanh*................................................................................................................................. 44
Applying machine learning method in neutrons and gamma-rays identification according to their pulse shapes

Le Xuan Chung\textsuperscript{1}, Vi Ho Phong\textsuperscript{2}, Le Tuan Anh\textsuperscript{1}, Nguyen Duc Ton\textsuperscript{1}, Nguyen Hoang Phuc\textsuperscript{1} and Bui Duy Linh\textsuperscript{1}

\textsuperscript{1}Institute for Nuclear Science and Technology, VINATOM, P.O.Box 5T-160, Nghia Do, Hanoi, Vietnam
\textsuperscript{2}Hanoi University of Science, 334 Nguyen Trai, Thanh Xuan, Hanoi, Vietnam

(Received 26 July 2021, accepted 30 September 2021)

Abstract: Neutrons and gamma-rays from a \textsuperscript{152}Cf source have been measured and separated based on the time of flight (TOF) technique. Their pulse shape characteristics measured by EJ-299-33 scintillator were used to train an artificial neural network (ANN) in a machine learning method. Afterwards, the ANN was used to predict another set of pulse shape data to identify neutron and gamma-ray events. Comparing to the charge-comparison method, the ANN gave better identification. This result proves a potential application of machine learning method in the nuclear data analysis.

Keywords: ANN, machine learning, neutrons, gamma-rays, time of flight.

I. INTRODUCTION

Artificial intelligence (AI) is widely applied in many aspects of society. Its aim is to enable computers to simulate human intelligence based on logic, rules, decision trees, and machine learning. In which, machine learning (ML) is an AI subfield including deep learning (DL) which contains a stack of hidden layers. The operation of ML can be based on an artificial neural network which mimics human brain [1]. In this manner, the ANN is trained by a sufficiently enormous data (given inputs with given outputs). Afterwards, it can find out the logic and be able to predict the outputs of new inputs. Therefore, the ANN has an advantage that it does not require an unambiguously mathematical input/output relationship.

In nuclear physics study, machine learning has been applied in for decades [2-3] and recently became intensive thanks to the computer’s fast calculating speed and large storage. The ANN models were applied to derive successfully nuclear charge radii [4], nuclear mass in neutron star [5], mass and binding energy [6], ground-state energy and the ground-state point-proton root-mean-square radius along with their extrapolation uncertainties [7], or automatic feature extraction in heavy ion collisions [8].

Concerning neutron and gamma-ray, many nuclear structural information, such as spin and parity [9], half-lives [10, 11], et cetera, can be obtained by detecting them. In such studies, the detection of neutrons is normally accompanied by gamma-rays. This fact demands the identification of them. The well-known method is charge comparison (CC) which relies on the neutron and gamma-ray pulse shape difference (almost in the tail components) as seen in Fig. 1. In this method the charge ratio of the pulse-to-total waveform were calculated [12-13]. According to these difference, neutrons and gamma-rays can be identified.

As an alternative approach, similar to the work reported in [3, 14], this paper presents the application of ML method in neutron and gamma-ray identification via their waveform
difference. Firstly, an experiment to measure and identify neutrons and gamma-rays using time of TOF technique was performed. Thanks to the experimental availability, the neutron and gamma-ray waveform data were digitized suitable for applying the ML method. 15729 data samples were used to train the ANN and 43460 left for testing. The results were compared to those obtained from charge comparison method.

![Graph](image)

**Fig. 1.** Neutron and gamma pulse shapes normalized to the same amplitude. The difference appears in the tail components at about 70 ns. This figure is taken from [13]

**II. TOF MEASUREMENT AND DATA PREPARATION**

The main experimental setup is presented in Fig. 2. A $^{252}$Cf neutron source which also emits gamma of up to several MeV energies was placed in front of an EJ-299-33 scintillator [15]. Another scintillator of the same type was placed around 1.2 m away from it. They were coupled to high-optic-efficiency H11265 Hamamatsu photomultiplier (PMT) operated at 1000 V. These two detectors provided start and stop signals, respectively. Their PMT signals were fed to 2 channels of a CAEN V1730 flash ADC. The trigger was active only when both detectors detected signals and the signal in the second one was above a given threshold.

![Diagram](image)

**Fig. 2.** Experimental setup for neutron and gamma-ray TOF measurement, see text for details
The TOF was extracted by constant fraction discrimination (CFD) algorithm [16]. The time resolution in our experiment was 185 ps full width half magnitude (FWHM).

The uncalibrated TOFs of neutrons and gamma-rays from the $^{252}$Cf source is presented in Fig. 2. Two peaks are observed at around 0 and 7 (a.u.). The first one corresponds to gamma-rays because they have the speed of light and the left to neutrons with slower speed. These two components can be delimited by a vertical line at 2.5 (a.u.) as shown in this figure.

The flash ADC digitized the entire signal waveforms from the detectors. The digital data were analyzed by two methods to identify ones induced by neutron and gamma-ray: CC and ANN pulse shape discriminations (PSD). For the ANN PSD, firstly the waveform was digitized into 400 samples (equivalent to an 800-ns-time window) whose amplitudes were denoted as $X_i$ (i=0-399). According to TOF (see Fig. 2) they were certainly identified as neutron or gamma-ray tagged as 1 and 0, respectively, forming an “Activity” matrix. The first 5 events’ digital data structures are illustrated in Tab. 1.

<table>
<thead>
<tr>
<th>$X_0$</th>
<th>$X_1$</th>
<th>$X_2$</th>
<th>$X_3$</th>
<th>$X_4$</th>
<th>$X_5$</th>
<th>$X_6$</th>
<th>$X_7$</th>
<th>$X_8$</th>
<th>$X_9$</th>
<th>...</th>
<th>$X_{397}$</th>
<th>$X_{398}$</th>
<th>$X_{399}$</th>
<th>Activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.037903</td>
<td>0.037659</td>
<td>0.038086</td>
<td>0.038025</td>
<td>0.037903</td>
<td>0.038025</td>
<td>0.037903</td>
<td>0.037964</td>
<td>0.037720</td>
<td>...</td>
<td>0.039062</td>
<td>0.038635</td>
<td>0.038208</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>0.037720</td>
<td>0.037664</td>
<td>0.037903</td>
<td>0.037476</td>
<td>0.037781</td>
<td>0.037720</td>
<td>0.038025</td>
<td>0.037964</td>
<td>0.037659</td>
<td>0.037598</td>
<td>...</td>
<td>0.037781</td>
<td>0.037598</td>
<td>0.037720</td>
<td>1</td>
</tr>
<tr>
<td>0.037964</td>
<td>0.037659</td>
<td>0.037781</td>
<td>0.038025</td>
<td>0.038086</td>
<td>0.037964</td>
<td>0.037781</td>
<td>0.037903</td>
<td>0.038208</td>
<td>0.037903</td>
<td>...</td>
<td>0.038391</td>
<td>0.037964</td>
<td>0.037964</td>
<td>1</td>
</tr>
<tr>
<td>0.037537</td>
<td>0.037781</td>
<td>0.037537</td>
<td>0.037903</td>
<td>0.037842</td>
<td>0.037781</td>
<td>0.037842</td>
<td>0.038025</td>
<td>0.037964</td>
<td>...</td>
<td>0.038147</td>
<td>0.037903</td>
<td>0.037903</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>0.037781</td>
<td>0.037781</td>
<td>0.037903</td>
<td>0.037964</td>
<td>0.037964</td>
<td>0.037781</td>
<td>0.037903</td>
<td>0.037720</td>
<td>0.037537</td>
<td>0.037903</td>
<td>...</td>
<td>0.037903</td>
<td>0.037537</td>
<td>0.037903</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 1. The first 5 digital data structures. Each data sample is a vector of 400 elements ($X_{0-399}$). The last “Activity” column implies neutron and gamma-ray events tagged as 1 and 0, respectively.

III. PSD METHOD AND RESULT

3.1. Charge comparison

As mentioned above, in the CC PSD, the charge ratio of the pulse-to-total waveform were calculated. The pulse charge ($Q_p$) and the total charge ($Q_t$) were integrated within the short and long gates, respectively. This method is
illustrated in Fig. 3 where the width of such gates were optimized using the commonly used figure-of-merit (FOM) that quantify the discrimination capability of the CC PSD results.

![Diagram](image)

**Fig. 3.** Illustration of charge comparison method. The long gate covers the whole component. While the short one covers almost the pulse

In the next step, the charge ratio of the pulse-to-total waveform (PSD$_{CC}$) was calculated as PSD$_{CC} = (Q_t - Q_p)/Q_t$. The result is presented in Fig. 4. Due to the fact that PSD$_{CC}$ is characterized by neutron and gamma-ray, according to the figure, these events are delimited by the vertical line at 0.34.

![Histogram](image)

**Fig. 4.** Charge ratio of the pulse-to-total waveform (PSD$_{CC}$). Neutron and gamma-ray components are delimited by the vertical line at 0.34

### 3.2. Artificial neural network

An ANN model has been built using “Sequential” model, the simplest Keras neural network type. Keras is high-level Deep Learning Application Programming Interface [17] which is bundled in Tensorflow [18], an open source Machine Learning Platform. The model construction is illustrated by part of the Python code as follows:
The first is “Flatten” layer acting as input layer. Its role is to convert each input into 1D array. In this layer, the input shape should be specified, for example “input_shape = 400” for data structure in Tab. 1.

There are 2 hidden “Dense” layers consisting of 80 and 20 neurons, respectively. They use the “relu” activation function [19]. Each layer manages its own weight matrix connecting the neurons to their inputs. When all neurons in a layer are connected to everyone in the previous layer, it is call “Dense layer”. If input data is passed, it computes the perceptron h as [1]:

$$h_{W,b}(X) = \phi(XW+b) \quad (1)$$

where, $X$ represents the input matrix (see Tab. 1 for an example), $W$ contains all the connection weights, the bias vector $b$ contains all connection weights between bias neuron and the artificial neurons, $\phi$ is the activation function [19].

The last one is output layer consisting of a single neuron. Because as mentioned in section II, the output (PSD\textsubscript{ANN}) is a number between 0 and 1 the current problem belongs to a binary classification. Therefore, the “Sigmoid” activation function [19] was chosen.

The above “Sequential” model was trained by 15729 data samples from the experiment. The training process was carried out through 600 epochs to assure the accuracy conversion as shown in Fig. 5. One can see that the training accuracy steadily increases, while the training loss decreases. The model accuracy on the training set was 91.45%.

![Fig. 5. Training accuracy versus epochs](image-url)
After training, the ANN model was applied to predict neutrons and gamma-rays according to their pulse shapes digitized as $X_i$ (i=0-399). 43460 experimental data samples were used. The ANN outputs (denoted as “PSD$_{\text{ANN}}$”) are shown in Fig. 6. The neutron and gamma-ray components are delimited by vertical line at PSD$_{\text{ANN}}$=0.5.

Fig. 6. ANN pulse shape discrimination (PSD$_{\text{ANN}}$) for $n$ and $\gamma$ delimited by a line at 0.5

3.2. Method evaluation
To evaluate CC and ANN methods, the TOFs of gamma-ray and neutron events selected by their condition on PSD$_{\text{CC}}$ and PSD$_{\text{ANN}}$ are plotted in Figs. 7 and 8, respectively. For gamma-rays, the identification accuracy is nearly the same in both methods, ~95 % in Fig. 7. While for $n$ identification, the ANN’s (89.26 %) is much better than the CC’s (79.60 %). The accuracy is defined as the ratio of true-to-total event number. The true events in Fig. 7 are with TOF smaller than 2.5 (a.u.) and vice versa for the true neutron events on Fig. 8.

Fig. 7. TOF of gamma-ray events selected by ANN and CC methods. The inset is the same figure but in logarithmic scale for $y$ axis. See text for more details
For gamma-ray identification, the dashed line is higher in the TOF range from 2.5-7 (a.u.) but lower than the solid line with TOF > 7 (a.u.), see the inset in Fig. 7. This means that the CC method is worse for fast neutron discriminating than the ANN one. This fact is also observed in Fig. 8. The contrast behaviors of the dashed and solid lines show that the ANN method discriminates fast neutrons better than the CC one does. Note that identifying fast neutrons is more challenging because they are close to the gamma components in the TOF method.

![Graph](image)

**Fig. 8.** TOF of neutron events selected by ANN and CC methods. See text for more details

IV. CONCLUSION

The neutrons and gamma-rays were measured and their TOFs in about 1.2 m were determined to identify them, accordingly. These events were also discriminated by CC and ANN methods via their waveforms induced on the EJ-299-33 scintillator. In the latter, the artificial neural network with 2 hidden layers of 80 and 20 neurons, respectively, was successfully built and trained. The results showed that gamma identification accuracy in both methods is similar. While for neutron identification, the ANN accuracy is better than the CC’s. In both cases, the ANN identifies fast neutrons better than the CC does. As the result, the ANN method is potentially applicable in nuclear data analysis.

ACKNOWLEDGMENT

This work is supported by the Vietnam Atomic Energy Institute under the Grant No. CS/21/04-02.

REFERENCES


[12]. https://indico.cern.ch/event/737461/contributions/3730613/contribution.pdf


[16]. https://www.caen.it/download/?filter=CoMPASS

[17]. https://keras.io

[18]. https://www.tensorflow.org/

[19]. https://keras.io/api/layers/activations/
A convolutional neural network for Y90 SPECT/CT scatter estimation

Ho Thi Thao¹, Le Tuan Anh², Phan Viet Cuong³, Nguyen Hong Ha¹, Nguyen Duc Ton², Nguyen Dinh Khai⁵

¹School of Mechanical Engineering, Kyungpook National University, South Korea
²Institute for Nuclear Science and Technology, Vietnam Atomic Energy Institute
³Research and Development Center for Radiation Technology, Vietnam Atomic Energy Institute
⁴MI General Physics, Paris-Saclay University, 91405 Orsay Cedex, France
⁵Military Institute of Medical Radiology and Oncology, Vietnam

(Received 25 April 2021, accepted 14 June 2021)

Abstract: Monte Carlo-based scatter modeling in SPECT has demonstrated the ability on improving image quality and quantitative accuracy but high computational cost. In this study, we describe a deep learning method-based on a convolutional neural network (CNN) to increase the image quality, decrease the computation time for SPECT/CT reconstruction. Monte Carlo (MC) simulation and true scatter data are used for training and validation phase and the CNN network is trained to match the MC scatter estimation. In the testing step with a liver subject, visual image quality by CNN was better than MC scatter estimation method. Besides, the CNN scatter estimate was generated over a much shorter period of time than MC model (about 15 seconds for CNN vs ~2 hours for MC). The short processing time with CNN while maintaining quality has high clinical significance for quantitative SPECT imaging.

1. INTRODUCTION

In SPECT technique, scatter correction involves estimating the contribution of scattered gamma quanta to the photo-peak region. The scattered photons, which come from outside the detector, cause the blurring and haziness of the image, reduce the quantitative accuracy¹.

Many methods have been introduced for the correction of the scatter. Most of those methods include estimation and subtraction of the scattered contribution by using dual and triple energy window¹. An accurate method for scatter estimation is based on Monte Carlo simulation²,³. However, this method is very computationally expensive. Recently, the advance of machine learning method brings the opportunity to improve the computation cost and the accuracy of MC and energy-window-based methods⁴.

The work of Haowei⁵ presented a method to correct the scatter using a deep convolution network. Based on this study, we have developed a new deep learning model for scatter estimation with different dataset and improving approaches. The testing results for new clinical subjects have also been presented to describe the change in contrast of SPECT images.

2. METHODS

The SPECT’s projections and the projected CT-based attenuation image becomes the inputs for our CNN model, as shown in Fig 1. The estimation of scattering for each projection would be obtained. The CNN is trained to minimize the mean square error (MSE) between the output and “ground truth” data in
the training process. In our work, the ground truth data is the true scatter simulated by MC\textsuperscript{6,7}. Ordered Subset Expectation Maximization (OSEM) is used for SPECT/CT reconstruction\textsuperscript{2}.

2.1. Dataset

The ground truth data for the supervised CNN model was obtained from Dewaraja et al study\textsuperscript{2,8} by MC method. The training data included: two (2 x 128 projections) SPECT phantoms, four (4 x 128 projections) Y-90 SPECT/CT subjects\textsuperscript{2,8} and 2 (2 x 128 projections) SPECT/CT subjects for validation data with the size of 128 x 80 for each projection.

2.2. CNN architecture and training method

Figure 1 illustrates our 2D CNN architecture with 19 deep layers. We use a concatenation of SPECT’s projections and CT attenuation maps as input images. According to our experiment, each branch includes 4 convolution layers with the size of 3 x 3 and the number of filters is defined as 32, 64, 128, 256 for encoder part and decrease in order of 256, 128, 64, 32 for decoder part. Following each convolution layer is batch normalization layer to normalize the output of previous layer. Our model is trained with Adam optimization, the learning rate is 0.0001, and the mean square error (MSE) is used as loss function. The CNN is trained with 500 epochs with the batch size of 50 samples with Keras. The hyperparameters are tuned and selected to avoid overfitting, work well on existing dataset and to match the power of the computer in use.

![Fig. 1. The proposed CNN architecture](image)

3. RESULTS

3.1. Training process

Figure 2 shows the dependence of MSE value on epochs for training and validation datasets. The training and validation loss decreased continuously from Figure 2. This proves that the model is not overfitting during training process. It takes 16 minutes to train on Intel (R) Core (TM) i9-10900 CPU @
2.8GHz (20 CPUs) and GPU NVIDIA GeForce RTX 1080 Ti machine.

3.2. Testing results

Reconstructed images in Figure 3 for liver subject show similar image quality with CNN and MC scatter estimates. Figure 3 shows that results from the proposed method were sharper and clearer than the MC-based results. The contrast between the liver region and the surrounding background is clearly improved in comparison with the MC method. Figure 3 also shows the sample profiles in projection domain for MC scatter estimation and CNN scatter estimation. These two curves are almost the same.

![Mean square error](image)

**Fig. 2.** MSE vs. epochs for training and validation datasets

4. DISCUSSION

In this study, image quality with the CNN scatter estimation method showed the same result as of Monte Carlo-based approach. In addition, the CNN scatter estimate is generated over a much shorter period of time than MC model. This is of particular clinical significance when time is of the essence. Our study used limited data, so we will collect more data from some hospitals in Vietnam and perform quantitative assessments in the future studies.

ACKNOWLEDGEMENTS

The authors would like to thank the support of Vietnam Ministry of Science and Technology under Grant No. DTCB.12/19/TTNCTK.
Fig. 3. Reconstructed slices with MC, CNN and total by MC scatter estimates and sample profiles in projection domain for 2 above slices.
REFERENCES


[7]. Lim, H., Dewaraja, Y. Y-90 patients PET/CT & SPECT/CT and corresponding contours dataset. (University of Michigan - Deep Blue, 2019.

Application of Artificial Neural Network for Prediction of Local Void Fraction in Vertical Subcooled Boiling Flow

Nguyen Ngoc Dat¹, Nguyen Van Thai¹

¹Department of Nuclear Engineering and Environmental Physics, School of Engineering Physics
Hanoi University of Science and Technology
E-mail: thai.nguyenvan@hust.edu.vn

(Received 04 May 2021, accepted 22 September 2021)

Abstract: This paper presents the feasibility study of potential application of multi-layer feed-forward Artificial Neural Networks (ANN) to predict local void fraction of subcooled boiling flows in vertical upward annular channel. A total of 638 experimental data points performed at KAERI and reported in literature was selected for training and testing ANN model. The seven basic parameters are chosen to be input variables and then the optimal structure of ANN which consist of two hidden layers with 131 neurons was determined based on traditional Trial-and-Error method after balancing the trade-off between the performance and training time. Results showed that the ANN model is capable to accurately predict the local void fraction with $R^2$ value of 0.99931 for training data, $R^2$ value of 0.99483 for testing data and $R^2$ value of 0.99828 for all data. Also, it proved that the ANN training will be more effective with an extensive experimental database.

Keywords: Artificial Neural Network, Subcooled Boiling, Void fraction.

I. INTRODUCTION

Subcooled boiling flow at low pressure condition have become challenging issues in safety analysis of water-cooled nuclear power reactors since the physical mechanisms of void growth and related thermal-hydraulic behaviors of system are still not fully understood. The two-fluid model currently implemented in system codes and multiphase computational fluid dynamics (MCFD) solvers has been widely recognized as a promising tool for dealing with the boiling scenario and simulating transients and accidents in nuclear power plant. However, a lot of constitutive models and correlations are required to make the conservation equations solvable. The process of sequential calibration and validation to obtain model parameters and coefficients of correlation is prone to generating conflicting parameters tuned on different datasets from Separate-Effect and Integral-Effect Tests [1]. This classical approach could lead to unsatisfactory prediction for all quantities of interests over a variety of input conditions due to the uncertainties of model parameters and model forms [2].

The artificial neural network (ANN) is a powerful machine learning tool for modeling and solving some complicated physical problems that cannot be described with simple mathematical models, and thus can be able to cope with the uncertainty issues. Many investigators proposed ANN methods to predict the void fraction, flow pattern, pressure drop and heat transfer coefficient, demonstrating the predictive capability of the model [3-9]. It is worth to noting that there is no study on using ANN model to predict the local parameters of subcooled boiling flow in vertical channel. Therefore, the ability of ANN model for local void fraction prediction is investigated in this study.
II. METHODS

1. Data and Input Parameters Selection

Due to the complexity of the phenomena, the experimental study has been the main research approach to develop empirical correlations and models which provide the engineers and designers suitable choices in engineering practice [4]. With ANN approach, experimental databases are used in the training process in which the network and weights are modified to attain better approximation of the desired output. The subcooled boiling flow phenomena are primarily governed by the flow boundary conditions as well as the geometry of the flow domain, therefore these key parameters must be selected as inputs for ANN structure design and optimization. In this work, databases performed at KAERI [10-11] in the vertical annulus channel (radius of $r_{out}$) with an indirect heater rod (radius of $r_{in}$) at a channel center was selected for designing and training the ANN network. Five key parameters of flow boundary conditions including mass flux ($G$), heat flux ($q''$), inlet subcooling ($\Delta T_{sub}$), inlet and outlet pressures ($P_{in}, P_{out}$) are chosen as input variables of ANN structure. Additionally, two more variables indicating the location of measured and predicted points are the axial length ($L/d_{H}$: the ratio between the flow length from the inlet of heated section $L$ and the hydraulic diameter $d_{H}$) and the radial length $r^*$ which is defined as:

$$r^* = (r - r_{in})/(r_{out} - r_{in})$$  \hspace{1cm} (1)

Table I presented 12 cases of SUBO experiments including total 638 data points used in this study.

<table>
<thead>
<tr>
<th>Case</th>
<th>Heat flux (kW/m$^2$)</th>
<th>Mass flux (kg/m$^2$s)</th>
<th>Inlet subcooling (K)</th>
<th>Inlet pressure (kPa)</th>
<th>Outlet pressure (kPa)</th>
<th>Heating length (m)</th>
<th>Hydraulic diameter (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>470.6</td>
<td>1132.6</td>
<td>19.1</td>
<td>192.9</td>
<td>157.3</td>
<td>3.087</td>
<td>25.52</td>
</tr>
<tr>
<td>C2</td>
<td>363.7</td>
<td>1119.6</td>
<td>19.0</td>
<td>192.7</td>
<td>156.7</td>
<td>3.087</td>
<td>25.52</td>
</tr>
<tr>
<td>C3</td>
<td>563.0</td>
<td>1126.9</td>
<td>18.3</td>
<td>188.9</td>
<td>155.7</td>
<td>3.087</td>
<td>25.52</td>
</tr>
<tr>
<td>C4</td>
<td>465.7</td>
<td>2126.5</td>
<td>19.6</td>
<td>196.9</td>
<td>156.9</td>
<td>3.087</td>
<td>25.52</td>
</tr>
<tr>
<td>C5</td>
<td>567.9</td>
<td>2128.8</td>
<td>19.5</td>
<td>197.6</td>
<td>158.0</td>
<td>3.087</td>
<td>25.52</td>
</tr>
<tr>
<td>C6</td>
<td>465.5</td>
<td>1103.9</td>
<td>29.6</td>
<td>190.7</td>
<td>155.0</td>
<td>3.087</td>
<td>25.52</td>
</tr>
<tr>
<td>C7</td>
<td>473.7</td>
<td>1124.7</td>
<td>17.7</td>
<td>193.9</td>
<td>161.6</td>
<td>3.087</td>
<td>25.52</td>
</tr>
<tr>
<td>C8</td>
<td>373.6</td>
<td>1122.9</td>
<td>17.2</td>
<td>188.3</td>
<td>155.1</td>
<td>3.087</td>
<td>25.52</td>
</tr>
<tr>
<td>C9</td>
<td>565.7</td>
<td>1115.3</td>
<td>17.5</td>
<td>192.8</td>
<td>161.5</td>
<td>3.087</td>
<td>25.52</td>
</tr>
<tr>
<td>C10</td>
<td>471.4</td>
<td>2093.2</td>
<td>17.6</td>
<td>192.2</td>
<td>158.5</td>
<td>3.087</td>
<td>25.52</td>
</tr>
<tr>
<td>C11</td>
<td>563.7</td>
<td>2086.6</td>
<td>18.1</td>
<td>195.7</td>
<td>162.1</td>
<td>3.087</td>
<td>25.52</td>
</tr>
<tr>
<td>C12</td>
<td>470.8</td>
<td>1113.8</td>
<td>29.6</td>
<td>191.8</td>
<td>158.1</td>
<td>3.087</td>
<td>25.52</td>
</tr>
<tr>
<td>Overall</td>
<td>363.7-567.9</td>
<td>1103.9-2128.8</td>
<td>17.2-29.6</td>
<td>188.3-197.6</td>
<td>155.0-162.1</td>
<td>3.087</td>
<td>25.52</td>
</tr>
</tbody>
</table>

2. Structure of Neural Network

The type of ANN used in this work is the multilayer feedforward net. Most commonly used transfer function in input and output layer is linear transfer function (purelin), while the functions of hyperbolic tangent sigmoid (tansig) is commonly
employed transfer functions in the hidden layer. It is worth noting that a three-layer network (two hidden layers) can approximate any non-linear function [12].

To determine the number of neurons in each hidden layer, a traditional Trial-and-Error method was utilized by changing the number of neurons in the hidden layer and checking the values of the mean square error (MSE) and the coefficient of determination $R^2$ as defined below:

$$MSE = \frac{\sum_{k=1}^{n}(y_{target} - y_{pred})^2}{n}$$ (2)

$$R^2 = 1 - \frac{\sum_{k=1}^{n}(y_{target} - y_{pred})^2}{\sum_{k=1}^{n}(y_{target} - y_{mean})^2} \in [0,1]$$ (3)

**3. ANN Training and Testing**

The SUBO data is collected and randomly divided into two parts based on practical experience: 75% is used for training and 25% is used for testing. Each of these models has its weights and biases initialized using Nguyen-Widrow method and its subsequently trained with the Levenberg-Marquardt algorithm. The test data is considered to have the same role as the validation data. The error of the test data is continuously monitored during the training process. After a certain number of iterations (or epochs), if the test error keeps increasing, the training process is stopped. This method is called “early stopping” criterion applied to avoid overfitting, which occurs when the model produces high accurate results on the training set but does not work well on the testing set; in other words, the model is not generalizable.

**III. RESULTS AND DISCUSSION**

After testing different configurations of two hidden layers, some findings are listed as bellows:

- Training performance will be better as the number of neurons in the hidden layer increases; however, training time will also increase. There is a need to balance performance and time accordingly.
- If the number of neurons in the last hidden layer is greater than 1 (2, 4, 9 and 16), the predicted values are negative as shown in Figure 1. Consequently, the number of neurons in the second hidden layer is set to 1.
Therefore, the ANN configuration used in this study have a general structure as [7 - (hidden layers) - 1 – 1]. The next step is to find the optimal number of neurons in the hidden layers. Each ANN configuration is trained 15 times with random initiated weights and bias, and then the averaged values of training performance (or training accuracy) and coefficient of determination in test data were obtained.

Table II shown the gradual improvement of the performance (MSE) and the $R^2$ coefficient for testing data as the number of neurons in the hidden layer increase. However, the corresponding training time also increases, requiring a balance between training accuracy and time. After testing with many different configurations, it is possible to get notes and recommendations in choosing an appropriate ANN based on the values of MSE and $R^2$. It can be seen that the most suitable of ANN configuration is (7-80-50-1-1).

**Table II.** Comparison of different configurations

<table>
<thead>
<tr>
<th>No. of neurons</th>
<th>Configuration</th>
<th>Criteria</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>31</td>
<td>$7 - 30 - 1 - 1$</td>
<td>2.06E-05</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>$7 - 15 - 15 - 1 - 1$</td>
<td>3.99E-07</td>
<td>31</td>
</tr>
<tr>
<td>61</td>
<td>$7 - 30 - 30 - 1 - 1$</td>
<td>3.91E-09</td>
<td>242</td>
</tr>
<tr>
<td>81</td>
<td>$7 - 50 - 30 - 1 - 1$</td>
<td>1.38E-09</td>
<td>268</td>
</tr>
<tr>
<td></td>
<td>$7 - 30 - 50 - 1 - 1$</td>
<td>1.17E-09</td>
<td>300</td>
</tr>
</tbody>
</table>
APPLICATION OF ARTIFICIAL NEURAL NETWORK FOR PREDICTION OF ...

<table>
<thead>
<tr>
<th></th>
<th>Configuration</th>
<th>MSE (10^-4)</th>
<th>R^2</th>
</tr>
</thead>
<tbody>
<tr>
<td>101</td>
<td>7 - 40 - 40 - 1 - 1</td>
<td>8.94E-10</td>
<td>0.93125</td>
</tr>
<tr>
<td>111</td>
<td>7 - 50 - 50 - 1 - 1</td>
<td>9.41E-10</td>
<td>0.94893</td>
</tr>
<tr>
<td>121</td>
<td>7 - 60 - 50 - 1 - 1</td>
<td>7.16E-10</td>
<td>0.95949</td>
</tr>
<tr>
<td>131</td>
<td>7 - 70 - 50 - 1 - 1</td>
<td>6.06E-10</td>
<td>0.96277</td>
</tr>
<tr>
<td>141</td>
<td>7 - 80 - 50 - 1 - 1</td>
<td>5.30E-10</td>
<td>0.96622</td>
</tr>
<tr>
<td>151</td>
<td>7 - 80 - 60 - 1 - 1</td>
<td>4.73E-10</td>
<td>0.96590</td>
</tr>
<tr>
<td>161</td>
<td>7 - 80 - 80 - 1 - 1</td>
<td>4.30E-10</td>
<td>0.96041</td>
</tr>
</tbody>
</table>

Figure 2 show the comparison results between the training and the test errors (MSE values) during the training process of some ANN configurations which reflect the quality of the training model. The test error and the training error are similar and tend to decrease in the few starting epochs. However, after the "Best" point corresponding to the epoch where the test error reaches its minimum value, the value of the test error increases while the value of the training error decreases. This proves that overfitting occurs at the epochs behind the “Best” position. Therefore, the ANN model at the “Best” position is saved as the best model in the corresponding training session. From this point of view, overfitting can be avoided by using the early stopping method.

Figure 3 shown a comparison of the predicted results with experimental results using 75% data for training, with the coefficients $R_{\text{Test}} = 0.99483$ and $R_{\text{All}} = 0.99828$. Most of the data points are located near the 1:1 linear regression line and within 15% error, showing good capability to accurately predict the local void fraction. The results predicted by the ANN model are also presented in Figure 4 in terms of the radial distribution of the Local Void Fraction for some cases at different heights $L/d_H$. It can be seen that the predictive power of the ANN is relatively consistent with the experimental data in which the ANN has been trained. There are some predicted results with high deviation because they are not in the training data (Figure 4a, 4f). Figure 5 shows a comparison results of local void fraction distribution at height $L/d_H = 18.4$ of case C9 when training data has no information of experimental data points in this case (Figure 5a) and when the training data with information points in experimental data (Figure 5b). This is an example that shows the ability of ANN model to predict and interpolate in a data range.
Fig. 2. Comparison results between the training and test errors during the training process
Fig. 3. Compare predictive and experimental results for testing data (a) and all-data (b) uses 75% of the data for training

Fig. 4. Comparisons of radial distribution between the predicted results and experimental results
IV. CONCLUSIONS

In this study, 638 experimental data points of SUBO test facility were used to train and test a 5-layers feedforward neural network with 7 input parameters and total 131 neurons for prediction of local void fraction in vertical annular subcooled boiling channel. The results clearly showed the possibility that the ANN could be used in predicting local parameters of two-phase flow. Due to the limitation in the training data, the ANN-based model in this study is recommended to be limited to the data region of the SUBO data. In order to improve the accuracy and extend the predictability of the model, it is necessary to add more databases. Besides, the next important research is to develop the method of optimization of ANN structural. This study is the first step to build the ANN model to replace mathematical models implemented in CFD code.

ACKNOWLEDGEMENT

This research is funded by the Hanoi University of Science and Technology (HUST) under project number T2020-PC-059.

REFERENCES


Neutronic design of a PWR fuel assembly with accident tolerant-composite for the long-life core

Van Khanh Hoang1, Viet Phu Tran1, Thi Dung Nguyen1

1Institute for Nuclear Science and Technology (INST), Vietnam Atomic Energy Institute (VINATOM), 179 Hoang Quoc Viet str., Cau Giay District, Hanoi 100000, Vietnam
*E-mail: hvkhanh21@gmail.com; hoangvankhanh@vinatom.gov.vn
(Received 12 July 2021, accepted 30 August 2021)

Highlights

Neutronic investigation of the composite fuels including UN- 30 wt. % U3Si2 and 33 vol. % UO2-UN for a long-life core in a PWR has been conducted in comparison with that of the conventional UO2 fuel.

For implementation of the accident tolerant fuel concept, the conventional Zircaloy-4 cladding is replaced with SiC cladding material.

It is possible to achieve sufficient criticality up to 100 GWd/tHM burnup without compromising the safety parameters.

Abstract: For the future of nuclear power, the design and development of an economical, accident tolerant fuel (ATF) for use in the current pressurized water reactors (PWRs) are highly desirable and essential. It is reported that the composite fuels are advantageous over the conventional UO2 fuel due to their higher thermal conductivities and higher uranium densities. Due to higher uranium densities of the composite fuels, the use of composite fuels would lead to the significant increase of discharged burnup, thereby enhancing fuel cycle economy compared to that of the UO2 fuel. The higher thermal conductivities of composite fuels will increase the fuel safety margins. For implementation of the accident tolerant fuel concept, this study also investigates on the replacement of the conventional Zircaloy-4 cladding with SiC to minimize the hydrogen production due to interaction of water with cladding at high temperature. In the present work, neutronic investigation of the composite fuels for a PWR has been conducted in comparison with that of the conventional UO2 fuel. Numerical calculations have been performed based on a lattice model using the SRAC2006 system code and JENDL-4.0 data library. Various parameters have been surveyed for designing a fuel with the UO2 and composite fuels such as U-235 enrichment, fuel pin pin pitch. In order to reduce the excess reactivity, Erbium was selected as a burnable poison due to its good depletion performance. The temperature coefficients including fuel, coolant temperature reactivity coefficients, and both the small and large void reactivity coefficients are also investigated. It was found that it is possible to achieve sufficient criticality up to 100 GWd/t burnup without compromising the safety parameters including that four reactivity coefficients are considered those associated with the fuel temperature, coolant temperature, small (5%) void and large (90%) void. Further analysis of the performance of the UO2 and composite fuels in a full core model of a PWR is being conducted.

Keywords: UO2 fuel, composite fuels, PWR assembly, neutronic analysis.

1. INTRODUCTION

1.1. Motivation for consideration of alternate fuel and cladding concepts

Nearly all nuclear fuel made with uranium dioxide (UO2) pellets and zirconium-based cladding has been successfully used for all power reactors, [1], [2], [3], [4]. The
conventional fuel, UO$_2$, is stable, and has a high melting point 2850 °C, [5]. However, the UO$_2$ has a rather low thermal conductivity, 7 W/m·K at 573 K [5], which decreases with increased temperature and burnup, leading to significant temperature gradients within the ceramic pellets, and would result in thermal stress and potential cracking, [6]. The zirconium alloys, having very low neutron capture cross-section, are used in reactor design to support and contain the fuel pellets, as well as containing fission products. On the other hand, zirconium is vulnerable to oxidation in steam at elevated temperatures. Once an energetic exothermic, hydrogen producing reaction is occurred, it would lead to early cladding failure.

The accidents at Fukushima Daiichi in March 2011 and the Three Mile Island accident in 1979 showed that the current fuel was not adequate and sufficient for the beyond design basis accidents. These beyond design basis accidents would occur at somewhat higher frequencies than previously predicted, and that the financial liabilities of such accidents can cripple a utility [7]. Following the Fukushima Daiichi nuclear accident in 2011, the world nuclear fuel R&D activities have shifted to pursue new fuel materials that provide significant increases in the time for the reactor operator to respond to unforeseen events before significant releases of the fuel materials and fission products occur [8], [9]. The accident tolerant fuel (ATF) systems have attracted significant attention to mitigate the consequences of a future severe accident, by better retaining fission products and/or providing operators more time to implement emergency measures of commercial light water reactors. The desired ATF needs to against a loss of cooling for a considerably long period, and improve fuel performance while enhancing fuel safety at normal operation. Any developed ATF products would increase operating cost, and enhance safety for commercial application. It is described in the previous studies, [10], [11], the development of ATF/cladding systems are focused on:

1) Improve or replace the ceramic oxide fuel: aims are to increase uranium loading; to increase thermal conductivity; and to extend fuel cycles due to higher energy content of fuel without higher enrichment cost.

2) Modify or replace the zircaloy cladding: goals are to achieve improved oxidation resistance, including application of coating layer; to increase fuel rod failure temperature, resistance to thermal cycling and irradiation induced degradation; to decrease thermal neutron cross section for cladding; to increase resistance to expansion and warping; to increase thermal conductivity; and to reduce rate of oxidation.

According to the previous investigations, [11], [12], the silicon carbide fiber-reinforced SiC matrix ceramic composites (SiC/SiC) is a potential cladding material due to their low thermal neutron absorption cross section, retention of strength up to very high temperatures, good radiation resistance, and good oxidation resistance in air and steam up to temperatures of at least 1600 °C. The study in [13] shows that because of a low neutron absorption, the SiC cladding material could meet lifetime requirements even with a 0.1% reduction in enrichment. Regarding the nuclear fuel, high density fuels including uranium-molybdenum fuels, uranium nitride fuels, uranium carbide fuels, and uranium silicide fuels are being considered for ATF solutions. Uranium mononitride (UN) fuel forms have a long historical application for power reactors [13]. Due to have high uranium loading and high thermal conductivity, the uranium mononitride
is desirably used as a nuclear fuel [14], [15]. However, the reactivity of UN with water has been a concern in nuclear reactor applications [14], [15]. For this reason, uranium sesquisilicide (U$_3$Si$_2$) and UO$_2$ have been combined with the UN as composite fuels to provide a protective barrier. It is reported in previous study, [5], that a fuel composed of UN and U$_3$Si$_2$ will significantly improve the fuel’s thermal conductivity over UO$_2$ and increase uranium density and therefore enhancing fuel loading. The studies, [14], [16], also show that the UO$_2$-UN composite fuels are advantageous over the conventional UO$_2$ fuel due to its higher thermal conductivity and higher uranium density. In particular, the UO$_2$-UN composite fuel with 33 vol. % of UO$_2$ has a higher uranium density about 13% and a higher thermal conductivity about 100% at 800°C compared to the UO$_2$ fuel.

The classic approach to generate nuclear energy is to use fuel made with the uranium dioxide (UO$_2$) pellets and zirconium-based cladding. This method is successfully implemented on industrial scale level for power reactors. Usually, the fuel concept enrichment requires uranium with U-235 fraction less than 20 % (low enriched uranium, LEU). This low enriched uranium fuel is not treated as a nuclear material for direct use in weapon manufacturing, therefor it gives a upper limitation for challenging the uranium fuels for the long-life core. The approach adopted for this study is to use conventional fuel, UO$_2$, and composite fuels, (including UN- 30 wt. % U$_3$Si$_2$ [5] and 33 vol. % UO$_2$-UN [16]), combining with SiC cladding material to estimate the attainable burnup for a wide range of combinations of lattice pitch, P, of interest and for a number of different uranium enrichments. 

1.2. Study objective

The primary objective of the present study is to estimate the attainable burnup, 100 GWd/tHM burnup without compromising the safety parameters, for a wide range of combinations of lattice pitch, P, of interest and for a number of different uranium enrichments. The fuel cell is made with UO$_2$, composite fuels, (including UN- 30 wt. % U$_3$Si$_2$ referred to as UNSi and 33 vol. % UO$_2$-UN referred to as UNO), and SiC cladding. The attainable burnup is the maximum burnup of the fuel discharged from a once-through burning fuel subjected to negative reactivity coefficients during the fuel life. Four reactivity coefficients are considered those associated with the fuel temperature, coolant temperature, small (5%) void and large (90%) void. An infinite multiplication factor (k-$\infty$) value at the end of cycle (EOC) is conservatively assumed to be 1.05 for the lattice investigations.

1.3. Study scope

Two types of composite fuels are considered - UNSi and UNO. As far as it is known, these composite fuels have been fabricated, even though laboratory experience exists. The material properties of these composite fuels have been extensively studied and are summarized in some companion papers, [5], [14], [16]. It is shown that these composite fuels tested and found suitable for reactor operation.

The first part of the current study is devoted to a scoping study of PWR unit cell that investigated a wide range of combinations of lattice pitch (P - hereby referred to as “geometries”), and different uranium enrichments of different fuel types including UO$_2$, UNSi, and UNO. The aim of this investigation is to determine the neutronically attainable burnup for each of the geometries and
the different fuel compositions, subjected to negative reactivity coefficient constraints. The reactivity coefficient constraints are all negative for coolant temperature coefficient of reactivity (CTC), prompt fuel temperature coefficient of reactivity (FTC), and the reactivity effect of both small voiding 5 % (SVRC) and large voiding 90 % (LVRC) of the coolant. For the examinations with high U-235 enrichment fuel, it would lead to an initial high reactivity excess. It opens a necessary application of burnable poisons (BP) to reduce initial high reactivity excess as in previous studies [17], [18], [19], [20], [21]. Among these mentioned researches, it is found that selected Erbium as a most promising candidate for the long-life core with once-through burning fuel. Thus, in this study, the excess reactivity is compensated by adding burnable poisons of Erbium.

The second part of the study is devoted to a scoping study of UO₂, UNSi, and UNO fueled PWR assembly. A detailed neutronic analysis of the maximum burnup fuel offering a minimum uranium enrichments and no expanding beyond the present day fuel cycle technology that the fuel is burnt up to 100 GWd/t [22] is presented.

2. METHODOLOGY

2.1. Analysis tools and calculational model

The calculations for this study were performed with the SRAC code system [23] applied to the lattices configuration using the PIJ module derived 16 energy group libraries generated using the JENDL-4.0 [24]. In this paper, neutronic study investigation is limited to infinite pin cell and assembly level calculation with material, temperature, and fuel cell characteristics listed in Table I and Fig. 1.

The reference geometry and specific power assumed for fuel cells are given in Table I. The data for the reference unit cell correspond to the Westinghouse PWR fuel design that loaded fuel of the 4.45 % wt. U-235 enrichment, [25]. The typical Westinghouse PWR fuel assembly (FA) of 17x17 array, comprises of 289 total lattice locations, of which 24 are for control rod and 1 in the center is instrument thimble, [25]. In simplified fuel assembly calculational models, no water reflector is modeled and spacer grid effects are neglected as well. As described in the previous section, in order to enhance strength and ductility accident tolerant fuel cladding mitigate against severe, SiC is selected as the cladding material [26]. For the high burnup, i.e., long-life core, especially with a burnable poison of Erbium, it is reasonably expected a hardener neutron spectrum and higher pressure of gaseous fission products compared to the reference case. Thus, for the high burnup, up to 100 GWd/t, the fuel would experience in a condition of high porosity. In this study, the porosity of the fuel is conservatively chosen of 15 %.

2.2. Calculated characteristics parameters

In this study, the investigations are U-235 enrichment with ranging from 5 to 20 % and lattice pitch-to-diameter ratio (P/D) ranging from 1.05 to 2.65. Calculations for each of the cases studied are the achievable once-through burnup and the reactivity coefficients along the fuel life without soluble boron in the water. The achievable burnup is assumed basing on combining of negative reactivity coefficients and infinite multiplication factor (k-inf) value at the end of cycle (EOC) is 1.05. For the fuel assembly model, there is no water reflector is modeled and spacer grid effects are neglected as well. The reflective boundary conditions of FA is chosen.

The analysis of each fuel model is included the calculation of the achievable
burnup and of reactivity coefficients of a once-through burning fuel. The reactivity coefficients examined are including the fuel temperature coefficient of reactivity (FTC), the coolant temperature coefficient of reactivity (CTC), and the small and large void coefficients of reactivity (SVRC and LVRC). The FTC is evaluated by increasing the fuel temperature by 100 K from 950 to 1050 K. For the CTC the water temperature is increased from the nominal value of 576.50 K by 10 K to 586.50 K. In case of void coefficients, both small and large, the temperature of the water is left unchanged while the density of the moderator is reduced by, respectively, 5 % or 90 %.

3. PARAMETRIC STUDY RESULTS

3.1. Single fuel cell analysis

The parametric study is undertaken to estimate the effect of P/D on the attainable discharge burnup. The attainable discharge burnup is assumed to be subjected to negative reactivity coefficient constraints and k-inf value at the EOC is 1.05. The pin pitch is considered as a design variable. The soluble boron in the coolant, water, is not accounted for in this study. The burnable poison, Erbium, is doped into the fuel helps to reduce the high excess reactivity.

Table II summarizes the selected characteristics calculation for fuel pin cells with various different initial fuel compositions having different P/D values. Increasing the U-235 enrichment results in increasing of both maximum achievable burnup and k-inf value at the BOC as given in Table II and Fig. 2. Higher U-235 enrichment in fuel gives larger P/D ranging to achieve the high burnup. This is because of the increase of fissile isotope, U-235, in the heavy metal inventory. It is found that the fuel of ≥15 % wt. U-235 enrichment is potential for a long-life core design. In order to enhance economy of fuel usage and minimize the high excess initial activities, the fuel of 15 % wt. U-235 enrichment is selected for the UO2, UNO fuel types, and 17.5 % wt. U-235 enrichment is chosen for the UNSi fuel composition. The required P/D ranging is from 1.25 to 1.85, 1.25 to 1.95, and 1.15 to 2.05 for fuel cell with, respectively, 15 % wt. U-235 of UO2, 15 % wt. U-235 of UNO, and 17.5 % wt. U-235 of UNSi. The potential maximum achievable burnup would reach up to 120 GWd/t as shown in Table II.

As mentioned in the previous section, the main idea behind the present paper is to use low enrichment uranium as a once-through burning and no expanding beyond the present day fuel cycle technology that the fuel is burnt up to 100 GWd/t. Therefore, the P/D = 1.27, belonged to the required P/D ranges, is preferably chosen option in following investigations. As mention above, the high initial reactivity excess is expected to be suppressed by adding burnable poison of Erbium. In this study, the BP is assumed to be homogeneously mixed to the fuel.

For the identified fuel pin cells (that of 15 % wt. U-235 of UO2, 15 % wt. U-235 of UNO, and 17.5 % wt. U-235 of UNSi, and P/D = 1.27), Fig. 3, Fig. 4, and Fig. 5 depict the design space of the fuel pin cells loaded different fuel types with BP addition. The possible designs are colored in blue that fulfill all criteria including reactivity safety parameters, moderator temperature coefficient, void coefficients, and Doppler coefficient along fuel cycle. It is found that, with the fuel of ≤1.5 % BP addition, even though the fuel cells are fulfilled all safety criteria, the k-inf values at some beginning burnup stages are higher than that of the reference fuel cell, k-inf being equal to 1.3950 as seen in Table II. For the fuel of ≥
3.5 % BP addition, it is not preferable for designing because of positive feedback reactivity coefficients for both the UO₂ and UNO fuel type. Meanwhile, the fuel of ≥ 2.5 % BP addition to the fuel of UNSi is unreasonable for the designing.

Figure 6, Fig. 7 show k-inf evolution as a function of burning time and the BOC neutron spectrum, respectively, for some outstanding cases examined. In this study, the neutron lethargy is defined as \( \ln(E_0/E) \), where \( E_0 \) is emitted neutron energy, and \( E \) is slowing down neutron energy. It is clear to see that the neutron spectra of the preferable design fuel cells are all harder than that of the reference fuel cell. The higher percentage of BP addition in fuel pellet is, the harder neutron spectrum of the fuel cell is, as shown in Fig. 7. It is found that the neutron spectra of the preferable design fuel cells are all harder than that of the reference fuel cell at both the begin of cycle (MOC), and the end of cycle (EOC) as well.

### 3.2. Fuel assembly analysis

Depletion analysis of the fuel assemblies made with composite fuels and SiC clad is carried out against standard operating conditions and other parameters of the typical Westinghouse PWR fuel assembly. The burnup analysis fuel assembly is carried out up to 120 GWD/t. The identified fuel pin cells (that of 15 % wt. U-235 of UO₂, 15 % wt. U-235 of UNO, and 17.5 % wt. U-235 of UNSi, and P/D = 1.27), achieved as results in the previous section are used for fuel assembly investigation. The initial k-inf value of the reference fuel assembly, 1.4205, is chosen as the upper value of initial criticality to be controlled for other fuel designs.

The analysis results are summarized in Table 3. The gray colored numbers indicate the companion designs that those k-inf values are higher than controlled value of 1.4205 or feedback reactivity coefficients are positive. It is clear to see that it is possible to use the UO₂ and composite fuels in long-life core with once-through burning fuel, up to 100 GWD/t burnup without compromising the safety parameters. The required BP addition to fuel is 1.5 to 2.5 % for both UO₂ and UNSi fuel type. Regarding the UNO fuel type, the required BP addition to fuel is 1.5 % for the once-through burning fuel with the target burnup of 100 GWD/t.

The pin-power peaking factor (PPF) of all the proper fuel assembly designs are less than 1.10 at the begin of cycle (BOC), and are all higher than that of the reference assembly (1.068). Figure 8, Fig. 9 show k-inf evolution as a function of burning time and the BOC neutron spectrum, respectively, of the proper fuel assembly designs. The maximum k-inf over cycle of the new designs are comparable to that of the reference assembly at ceiling enrichment of 4.45 wt. % U-235 of UO₂ fuel. This ensures that it is possible control core reactivity once loading the new fuel assembly design into the conventional core. The neutron spectrums of the new fuel assembly designs are all harder than that of the reference fuel assembly but no effects on safety.

### 4. CONCLUSIONS

This paper presents the neutronic analysis of fuel design for a long-life core in a pressurized water reactor made of composite fuels, (including UN- 30 wt. % U₃Si₂ and 33 vol. % UO₂-UN), and SiC cladding in comparison to the uranium oxide fuel UO₂. It is found that use of the fuel of 15 % wt. U-235 of UO₂, 15 % wt. U-235 of UNO, and 17.5 % wt. U-235 of UNSi,
with P/D = 1.27 and 1.0 to 2.5 % of Erbium as burnable poison addition makes it possible to design a PWR fuel that achieves high burnup. The fuel temperature coefficient of reactivity and both small and large void reactivity coefficients of the fuel designs are negative along fuel cycle with the concerned burnup target, 100 GWd/t burnup without compromising the safety parameters.

In the future study, this preliminary study would be refined and extended including full-core coupled neutronic-thermal-hydraulic analysis, stability analysis, transients and accidents analysis, as well as economic analysis. Furthermore, how to make use of the once-through burning fuel for energy production with employing fuel reprocessing would be considered in further study.

Data Availability

Data will be available upon request.

Conflict of interest

All authors declare no conflict of interest.

ACKNOWLEDGMENT

This research is funded by Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number 103.04-2019.37.

Author would like to express gratitude to Dr. Pham Nhu Viet Ha of the Institute for Nuclear Science and Technology, VINATOM, Vietnam for giving comment and suggestion.

Help provided by Dr. Tran Hoai Nam of the Institute of Fundamental and Applied Sciences, Duy Tan University, Ho Chi Minh city, Vietnam is highly appreciated.

Author would like to express gratitude to Prof. Toru Obara of the Laboratory for Advanced Nuclear Energy, Institute of Innovative Research, Tokyo Institute of Technology, Japan for constantly providing discussion about analysis results.

The calculations in this work have been done on the VINATOM - HPC system.

REFERENCES

[7]. Lahoda E.J., Hallstadius L., Boylan F., et al., 2014. What should be the objective of accident
NEUTRONIC DESIGN OF A PWR FUEL ASSEMBLY WITH ACCIDENT TOLERANT-COMPOSITE ...


Table I. Parameters of the fuel cells and assembly

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Reference</th>
<th>New design</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel diameter</td>
<td>0.8192</td>
<td>0.8192</td>
</tr>
<tr>
<td>Clad inside diameter, [cm]</td>
<td>0.8357</td>
<td>0.8357</td>
</tr>
<tr>
<td>Clad outside diameter, [cm]</td>
<td>0.9500</td>
<td>1.0357</td>
</tr>
<tr>
<td>Lattice pitch, P, [cm]</td>
<td>1.2598</td>
<td>Variables</td>
</tr>
<tr>
<td>P/D, [-]</td>
<td>1.3262</td>
<td>Variables</td>
</tr>
<tr>
<td>Equivalent pin pitch, [cm]</td>
<td>--</td>
<td>1.3118</td>
</tr>
<tr>
<td>Equivalent P/D, [cm]</td>
<td>--</td>
<td>1.2666</td>
</tr>
<tr>
<td>Rod array, [-]</td>
<td></td>
<td>17x17</td>
</tr>
<tr>
<td>Assembly pitch, [cm]</td>
<td>21.5</td>
<td>Variables</td>
</tr>
<tr>
<td>Linear heat rate, [W/cm]</td>
<td></td>
<td>176.5</td>
</tr>
<tr>
<td>Average coolant temperature in core, [K]</td>
<td>576.5</td>
<td></td>
</tr>
<tr>
<td>System pressure, nominal, [Mpa]</td>
<td></td>
<td>15.5</td>
</tr>
<tr>
<td>Average temperature for fuel, [K]</td>
<td></td>
<td>950.0</td>
</tr>
<tr>
<td>Average temperature for clad, [K]</td>
<td></td>
<td>607.0</td>
</tr>
</tbody>
</table>

Table II. Fuel cell selected characteristics versus P/D and U-235 enrichment.

<table>
<thead>
<tr>
<th>Enrichment [wt. %]</th>
<th>Max. burnup, [GWD/t]</th>
<th>P/D for burnup ≥ 100 GWD/t</th>
<th>k-inf at BOC, [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>UNO</td>
<td>UNSi</td>
<td>UO₂</td>
<td>UNO</td>
</tr>
<tr>
<td>4.45</td>
<td>--</td>
<td>30.0</td>
<td>--</td>
</tr>
<tr>
<td>5.00</td>
<td>40.0</td>
<td>40.0</td>
<td>40.0</td>
</tr>
<tr>
<td>10.00</td>
<td>80.0</td>
<td>82.5</td>
<td>80.0</td>
</tr>
<tr>
<td>15.00</td>
<td>&gt; 120</td>
<td>&gt; 120</td>
<td>&gt; 120</td>
</tr>
<tr>
<td>17.50</td>
<td>&gt; 120</td>
<td>&gt; 120</td>
<td>&gt; 120</td>
</tr>
<tr>
<td>20.00</td>
<td>&gt; 120</td>
<td>&gt; 120</td>
<td>&gt; 120</td>
</tr>
</tbody>
</table>
### Table III. Fuel cell and fuel assembly selected characteristics for various fuel compositions.

<table>
<thead>
<tr>
<th>% Er₂O₃</th>
<th>15 wt. % - UO₂</th>
<th>15 wt. % - UNO</th>
<th>17.5 wt. % - UNSi</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fuel cell FA</td>
<td>Max. burnup PPF</td>
<td>Fuel cell FA</td>
</tr>
<tr>
<td>0.0</td>
<td>1.5568 1.5805</td>
<td>-- --</td>
<td>1.5394 1.5639</td>
</tr>
<tr>
<td>0.5</td>
<td>1.4770 1.5015</td>
<td>-- --</td>
<td>1.4693 1.4939</td>
</tr>
<tr>
<td>1.0</td>
<td>1.4145 1.4389</td>
<td>-- --</td>
<td>1.4138 1.4380</td>
</tr>
<tr>
<td>1.5</td>
<td>1.3631 1.3870</td>
<td>100.0 1.090</td>
<td>1.3678 1.3912</td>
</tr>
<tr>
<td>2.0</td>
<td>1.3194 1.3426</td>
<td>100.0 1.090</td>
<td>1.3285 1.3511</td>
</tr>
<tr>
<td>2.5</td>
<td>1.2814 1.3038</td>
<td>100.0 1.091</td>
<td>1.2941 1.3159</td>
</tr>
<tr>
<td>3.0</td>
<td>1.2478 1.2694</td>
<td>97.5 1.091</td>
<td>1.2636 1.2845</td>
</tr>
<tr>
<td>3.5</td>
<td>1.2175 1.2382</td>
<td>97.5 1.092</td>
<td>1.2360 1.2560</td>
</tr>
<tr>
<td>4.0</td>
<td>1.1899 1.2098</td>
<td>95.0 1.092</td>
<td>1.2108 1.2300</td>
</tr>
<tr>
<td>4.5</td>
<td>1.1645 -- --</td>
<td>-- --</td>
<td>1.1875 -- --</td>
</tr>
<tr>
<td>5.0</td>
<td>1.1410 -- --</td>
<td>-- --</td>
<td>1.1659 -- --</td>
</tr>
<tr>
<td>5.5</td>
<td>1.1191 -- --</td>
<td>-- --</td>
<td>1.1456 -- --</td>
</tr>
<tr>
<td>6.0</td>
<td>1.0984 -- --</td>
<td>-- --</td>
<td>1.1266 -- --</td>
</tr>
<tr>
<td>6.5</td>
<td>1.0790 -- --</td>
<td>-- --</td>
<td>1.1085 -- --</td>
</tr>
<tr>
<td>7.0</td>
<td>1.0605 -- --</td>
<td>-- --</td>
<td>1.0914 -- --</td>
</tr>
<tr>
<td>7.5</td>
<td>1.0430 -- --</td>
<td>-- --</td>
<td>1.0751 -- --</td>
</tr>
<tr>
<td>8.0</td>
<td>1.0263 -- --</td>
<td>-- --</td>
<td>1.0594 -- --</td>
</tr>
</tbody>
</table>

![Fig. 1. Layout of fuel assembly (GT: guide thimbles; IT: instrumentation thimble; others: Fuel rods.](image-url)
Fig. 2. $k_{\text{inf}}$ at BOC as a function of P/D
**Fig. 3.** Design space of UO$_2$ fuel cell loaded 15 % U-235 enrichment fuel with BP

**Fig. 4.** Design space of UNO fuel cell loaded 15 % U-235 enrichment fuel with BP
**Fig. 5.** Design space of UNSi fuel cell loaded 17.5 % U-235 enrichment fuel with burnup, [GWd/tHM].

**Fig. 6.** K-infinity variation with burnup.

**Fig. 7.** Neutron flux per lethargy at BOC.
Fig. 8. $k$-infinity of FAs versus burnup

Fig. 9. Neutron flux per lethargy of FAs at BOC
Determination of warning level at Lang Son environmental radiation monitoring station

Nguyen Van Khanh*, Duong Van Thang, Nguyen Thi Oanh, Nguyen Thi Thu Ha, Doan Thuy Hau, Le Thi Hoa, Cao Duc Viet, Duong Duc Thang

Institute for Nuclear Science and Technology (INST), 179 Hoang Quoc Viet – Cau Giay – Ha Noi

*Corresponding email: nguyenvankhanh.hus88@gmail.com

(Received 26 January 2021, accepted 20 June 2021)

Abstract: In this study, a method to estimate the baseline of ambient dose equivalent rate (ADER) of the Lang Son radioactive monitoring station was presented. The warning level is calculated from the arithmetic mean and standard deviation of the terrestrial background value. The terrestrial background value estimated from the Radon peak removal algorithm is 39.85 nSv/h with a standard deviation of 7.58 nSv/h. For comparison, the soil samples around the monitoring equipment were collected and analyzed the activity concentration of nuclides $^{226}$Ra, $^{232}$Th, $^{40}$K. The terrestrial background value estimated from these values of activity concentration is of $41.10 \pm 2.96$ nSv/h. There is a good agreement between the results evaluating ADER from Radon peak removal algorithm and from the activity concentration of nuclides $^{226}$Ra, $^{232}$Th, $^{40}$K.

Keywords: Warning level, ADER, Radon peak.

I. INTRODUCTION

At present, there are many nuclear power plants that are being built and operating in the southeast of China, close to our northern border. The construction of environmental radiation warning and monitoring stations in the provinces along the border is a necessity in order to: timely detect any unusual radiation levels; actively support for response to nuclear and radiological accidents; provide a national database of environmental radiation for serving the State management in the field of atomic energy and nuclear safety. Several online monitoring stations have been set up in some provinces.

Meteorological conditions greatly affect the ambient dose equivalent rate. Rain leads to the accumulation of Radon's progeny on the soil surface by depositing aerosols containing Radon progeny in the atmosphere. Radon progeny deposited on the soil surface has the ability to emit Gamma radiation (mainly $^{214}$Pb and $^{214}$Bi), leading to an increase in the ambient dose equivalent rate. These respective peaks are often referred to as radon peaks or rain peaks [1, 3] as shown in Figure 1. The elimination of this component's influence on the ADER is essential in order to better identify abnormal radioactive releases, that is, to be able to identify radiation events due to nuclear incidents at a far distance without confusing it with the random release of Radon and its progeny in the environment. From there, get more accurate radiation warning levels for proactively responding to radiation incidents, nuclear incidents.
Fig.1. Time series of ambient dose equivalent rate and precipitation recorded during 2 months at the Lang Son station.

II. MATERIALS AND METHODS

A. Site and measurements

The study area is located in Lang Son, which is a mountainous province in northeastern Vietnam. The device monitoring the ambient dose equivalent rate of ENVINET firm (Germany) is located in the premises of Lang Son meteorological station (Figure 2). The vegetation coverage rate is high and no high radiation background area exists in the area.

The monitoring data of dose rate are logged every 10 minutes.

Fig.2. Location map and SARA device located in Lang Son
B. Radon peak removal algorithm - Average method

In the following, we present a method to estimate the baseline of ambient dose equivalent rate. All based on the analysing long-time data series of the 3-years ambient dose equivalent rate (from 2017 to 2019). The measuring device must not move during the period of data selected for processing. It can lead to errors in the determination of terrestrial background values because the natural radioactivity varies from place to place. The next step is to remove the Radon peak. Radon peak removal algorithm is written in Python software with the following content [2]:

Within a window of a given length, (20 days chosen) of 10 minutes averaged data of ADER, starting at the beginning of the series, arithmetic mean (AM) and standard deviation (SD) of the values are computed.

Values more than or less than AM ± \( \alpha(\text{remove}) \times \text{SD} \) are excluded (\( \alpha(\text{remove}) = 1.65 \) chosen). The procedure is repeated until no more values are being excluded from the window. Then the window proceeds one-time step ahead (1 day chosen), until the end of the series. Usually, three or fewer iterations are required.

The algorithm assigns a baseline value for each time step (1 day), resulting in an estimate of the baseline's time series. The AM of these values is calculated; This is defined as the mean of baseline or terrestrial background value. [3]

![Fig. 3. Algorithm for terrestrial background calculation (AM is the arithmetic mean value, SD its standard deviation).](image)

C. Gamma spectrometry measurements

Besides, we collected soil samples around the measuring equipment and estimated the value of the terrestrial background that contributed to the ambient dose equivalent rate to compare with the terrestrial background values obtained from the Rn peak removal algorithm. The total
number of samples taken is 03 samples. The procedure for sampling and sample pre-treatment for gamma radioactivity measurement was as follows: surface soils of a depth of 30 cm were taken using a corer of 7 cm inner diameter. In each location, 1–2 kg of soil was collected. In the laboratory, the samples were first allowed to dry in the air, and then it was dried at 105°C overnight. The samples then were ground and sieved through a sieve of 1-mm mesh to remove gravels as well as plant roots and leaves. Afterward, Marinelli beakers were filled with ~ 600 g soil samples and then sealed off to attain the radioactive equilibrium. The sealed samples were left for a month to ensure the equilibrium of $^{226}$Ra nuclide with its decay products in the uranium series. The activity concentration of $^{226}$Ra, $^{232}$Th, and $^{40}$K was measured on a low background gamma spectrometer with CANBERRA’s HPGe GC5019 detector, which has the energy resolution and relative efficiency at the peak of 1332.5 keV of $^{60}$Co being of 1.8 keV and 50%, respectively. The spectrometer is calibrated using the IAEA RGU-1, IAEA RGTh-1, and IAEA-soil 6 reference samples of comparable geometry. The procedure for measuring soil samples is in accordance with ISO - 17025.

III. RESULTS AND DISCUSSION

A. The results of the baseline of ambient dose equivalent rate and dynamical warning levels at Lang Son station

The dynamical warning level is intended to distinguish the increase in ADER due to nuclear incidents from the increase in ADER due to the influence of meteorological parameters. Natural radioactivity varies from place to place, the alarm level values are adjusted according to the respective local conditions.

The baseline of ambient dose equivalent rate and dynamical warning level results are shown in Figure 4. The mean value of the baseline or terrestrial background value at Lang Son station for 3 years (2017 - 2019) was 39.85 nSv/h with a standard deviation of 7.58 nSv/h (see Figure 5).

![Fig. 4. Diagram showing the estimated baseline of ADER and dynamical warning level](image-url)
The dynamical warning level is determined by the formula [4]:

[Dynamical warning level] = ([Mean dose rate] + [standard deviation * 6])

(1)

Where: Mean dose rate is the mean value of the terrestrial background value over a period of 20 days. Standard deviation is the standard deviation of the terrestrial background value.

B. Results determining the ADER value from the activity concentration of nuclides $^{226}$Ra, $^{232}$Th, $^{40}$K in Lang Son soil samples

The results of determining the activity concentration of radioactive nuclides $^{226}$Ra, $^{232}$Th, $^{40}$K in soil samples collected at Lang Son station are presented in Table 1.

According to Ngo Quang Huy et al [5], the dose rate of gamma radiation in the air at an altitude of 1m above the ground will be calculated from the activity concentration of radioactive isotopes $^{40}$K, $^{226}$Ra, and $^{232}$Th through the equation:

$$D = (0.5993 \cdot C_{Th} + 0.4368 \cdot C_{Ra} + 0.0417 \cdot C_{K})$$

nGy/h

(2)

Where $C_{Th}$, $C_{Ra}$, and $C_{K}$ are the activity concentrations in the soils of $^{232}$Th, $^{226}$Ra, and $^{40}$K, respectively (in Bq/kg), and D is the absorbed dose rate in the air (in nGy/h).

According to the error propagation formula, the standard deviation for the absorbed dose rates are:

$$\Delta D = \sqrt{\left(\frac{\partial D}{\partial C_{Th}}\right)^2 \Delta C_{Th}^2 + \left(\frac{\partial D}{\partial C_{Ra}}\right)^2 \Delta C_{Ra}^2 + \left(\frac{\partial D}{\partial C_{K}}\right)^2 \Delta C_{K}^2}$$

(3)
Table I. The activity concentration of radioactive nuclides $^{226}\text{Ra}$, $^{232}\text{Th}$, $^{40}\text{K}$ (Bq/kg) in Lang Son soil

<table>
<thead>
<tr>
<th>Samples</th>
<th>$^{226}\text{Ra}$</th>
<th>$^{232}\text{Th}$</th>
<th>$^{40}\text{K}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>DLS 20.1</td>
<td>23.59 ± 0.51</td>
<td>29.59 ± 0.61</td>
<td>128.09 ± 2.57</td>
</tr>
<tr>
<td>DLS 20.2</td>
<td>22.83 ± 0.50</td>
<td>29.19 ± 0.59</td>
<td>124.36 ± 2.51</td>
</tr>
<tr>
<td>DLS 20.3</td>
<td>23.29 ± 0.51</td>
<td>29.53 ± 0.60</td>
<td>126.37 ± 2.54</td>
</tr>
</tbody>
</table>

Table II. The dose rate values are contributed by radioactive nuclides in soil

<table>
<thead>
<tr>
<th>Samples</th>
<th>$D$ (nGy/h)</th>
<th>$H^*$(10) (nSv/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DLS 20.1</td>
<td>33.38 ± 2.40</td>
<td>41.82 ± 3.01</td>
</tr>
<tr>
<td>DLS 20.2</td>
<td>32.65 ± 2.35</td>
<td>40.44 ± 2.91</td>
</tr>
<tr>
<td>DLS 20.3</td>
<td>33.14 ± 2.39</td>
<td>41.03 ± 2.95</td>
</tr>
<tr>
<td>Mean</td>
<td>33.06 ± 2.38</td>
<td>41.10 ± 2.96</td>
</tr>
</tbody>
</table>

We calculate the absorbed dose rate by formula (2), and the standard deviation is calculated using formula (3). The calculated absorbed dose rate ($D$) values are given in Table 2. The relationship between air kerma rates and ambient dose equivalent rates for the measured terrestrial radiation fields was found to be $H^*$(10) = 1.21 $K_a$ + 1.26 where $H^*$(10) is the ambient dose equivalent rate in nSv/h and $K_a$ is air kerma rate in nGy/h. [6]

From the value of $H^*$(10) in Table II, we can see that the terrestrial background value contributed from natural radioactive nuclides in the soil is approximately the terrestrial background determined by the Radon peak removal algorithm. Thus, it can be seen that the Radon peak removal algorithm gives a reliable terrestrial background value.

IV. CONCLUSIONS

The research team has built up an algorithm to determine the baseline of the ambient dose equivalent rate and the dynamical warning level for Lang Son environmental monitoring station with high reliability. This dynamical warning level will be applied at the operating room of the national environmental radioactive monitoring network - Institute of Nuclear Science and Technology in the coming time.

From the developed algorithm, we have determined the terrestrial background value of ADER to be 39.85 nSv/h with a standard deviation of 7.58 nSv/h. Soil samples around the measuring equipment were collected and estimated the value of the terrestrial background that contributed to the ambient dose equivalent rate is 41.10 ± 2.96 nSv/h. There is a good agreement between the results
evaluating ADER from Radon peak removal algorithm and from the activity concentration of nuclides $^{226}$Ra, $^{232}$Th, $^{40}$K.

ACKNOWLEDGMENTS

This work was funded by Vietnam Atomic Energy Institute (Vinatom) under grant CS/20/04-03.

REFERENCES


Establish the training program of alternating current field measurement - level ii according to SNT-TC-1A

Le Duc Thinh, Ngo Thi Kieu Oanh

Center for Non-Destructive Evaluation, 140 Nguyen Tuan street – Thanh Xuan district – Ha Noi city.
Email: thinhlt@gmail.com

(Received 26 November 2021, accepted 01 June 2021)

Abstract: Alternating Current Field Measurement (ACFM) is a technique of the Electromagnetic method used to detect surface defects of metal materials. Currently, this technique is widely applied in the field of maintenance of Oil and Gas projects as an alternative to the Magnetic Particle Testing method. The establishment of ACFM training program according to Recommended Practice No. SNT-TC-1A of The American Society for Nondestructive Testing (ASNT) will increase the autonomy of the domestic testing human resources, especially advanced techniques. Based on documents and standards combined with the actual survey, training programs, training materials, question banks, examinations developed meet the requirements of international standards and in accordance with the conditions applied in Vietnam.

Keywords: Nondestructive Testing, Alternating Current Field Measurement, Magnetic Particle Testing, ASNT, NDT, ACFM, MT, SNT-TC-1A.

I. INTRODUCTION

Non-Destructive Testing (NDT) has a long history of development, starting with conventional methods using simple testing equipment and tools that has brought benefits by creating products with high quality and reliability. Nowadays, dramatic advances in science & technology development have led to constantly invention of new test principles with the equipment systems integrating many features and supporting software continuously developing toward modernity. Based on that characteristic, the world has formed a classification with two categories that are conventional methods and advanced techniques with new principles and complex equipment system for specific applications. Alternating Current Field Measurement (ACFM) is one of the standout techniques.

The ACFM technique is commonly used for detecting surface defects of metallic materials (both ferromagnetic and non-ferromagnetic). This technique has more upsides than the Magnetic Particle (MT) and Eddy Current (ECT) test, especially providing both length and depth information of cracks in carbon steel welds at the same time through the test results. These results are stored for a long time as a signal that enables authorized personnel to retrieve the reassessment at any time and use them to track and calculate the rate of development of defects, which leads to decision on the right time to repair or replace. It can result in the project operating safely and increasing economic efficiency.

The ACFM technique is used in the annual maintenance inspection program, providing input information for calculating the remaining life in fields such as: Oil and gas, thermal or nuclear power, transportation, lifting equipment, etc.

The increasing demand for applying ACFM techniques in Vietnam leads to the need of developing human resources trained,
assessed and certified in accordance with international standards.

II. CONTENT

II.1. Objects and Methods

II.1.1 Introduction to ACFM technique \cite{1}, \cite{2}, \cite{3}

ACFM is a technique based on the principle of electromagnetic induction as described in Figure 1. A primary magnetic field is generated by passing an alternating current through a coil. When the coil is placed near the surface of the conductive material test object, the magnetic field will induce an inductive current flowing in that object (eddy currents). When the coil goes through a cracked area, eddy currents will be disturbed to flow around and below the crack which changes the magnetic field above the surface of the test object. The ACFM probe uses two coil sensors, one used to measure the vertical magnetic field (Bz) and the other used to measure the horizontal magnetic field (Bx) relative to the surface.

![ACFM principle](image1)

**Fig. 1.** ACFM principle

The disturbed magnetic field around the crack is obtained by sensors from the tips of the crack (Bz) and the depth of the crack (Bx). When these signals are combined simultaneously on a graph with the Bx and Bz axes perpendicular to each other, they create a circle and is called a “Butterfly plot” as shown in figure 2. During the test the operator will rely on these signals to detect the presence of a crack as well as determine the length and depth of the crack. All of these data are saved by the equipment system to serve for review, evaluation and reporting.

![ACFM signals](image2)

**Fig. 2.** ACFM signals
Based on its characteristic test principle, the ACFM technique has advantages and disadvantages compared with other surface inspection techniques such as Eddy Current Testing (ECT) and Magnetic Particle Testing (MT).

Table I. Characteristics of ACFM compared to other techniques

<table>
<thead>
<tr>
<th>Đặc điểm</th>
<th>ACFM</th>
<th>ECT</th>
<th>MT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Through-coating detection</td>
<td>√</td>
<td>√</td>
<td>x</td>
</tr>
<tr>
<td>No need for chemicals</td>
<td>√</td>
<td>√</td>
<td>x</td>
</tr>
<tr>
<td>Duplex and non-ferromagnetic metal detection</td>
<td>√</td>
<td>√</td>
<td>x</td>
</tr>
<tr>
<td>Remote deployment</td>
<td>√</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Long-term storage results as accurate and re-evaluated signals</td>
<td>√</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Sizing crack length and depth</td>
<td>√</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>High probability of detection (PoD) and low false call rate</td>
<td>√</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

Note: √: Yes x: No

Besides the above features, ACFM technique also has certain downsides such as:

- Should be used only to detect surface defects such as fatigue cracks;
- Defect sizing models available for certain types of materials;
- Defect sizing models based on planar cracks and not work on complex branched cracks;
- Expensive model technology equipment;
- The technicians have been required more trained and experience than the MT method.

II.1.2 Research method

The actual survey of ACFM technical application needs is focus on the industrial sector, especially in the oil and gas which often has high requirements on the quality of the project as well as has enough economic potential for application of advanced testing technique. Survey results show that all organizations need to train ACFM staff according to the organization in charge certification system (under SNT-TC-1A) and/or the Central certification system (CSWIP) to apply for weld testing during the operation and maintenance of objects such as drilling rigs, pressure tanks, lifting equipment.

From the survey results and practical conditions in Vietnam, the NDE Center has established a training program under the organization in charge certification system by following the training program requirements of the SNT-TC-1A document and training contents included in ANSI/ ASNT CP-105 document, researching the technical requirements contained in the standards ASTM and ASME. According to the requirements of the training program to content standards, main topic content, references and equipment manuals, the team elaborates on developing the training program, training materials, question bank, assessment test to meet practical needs applied to the industrial sectors in Vietnam.
II. 2. Results

Through the survey results on actual application needs and research on popular standard documents in the world, the project team has achieved the following results:

II.2.1 Training program \([4],[5]\)

<table>
<thead>
<tr>
<th>No.</th>
<th>Contents</th>
<th>Training Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Introduction to common welding methods and related discontinuities</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>Introduction to Nondestructive Testing (NDT)</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>Principle of Electromagnetic Testing (ET)</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>Principle of Eddy Current Testing (ECT)</td>
<td>4</td>
</tr>
<tr>
<td>5</td>
<td>Principle of Alternating Current Field Measurement (ACFM)</td>
<td>4</td>
</tr>
<tr>
<td>6</td>
<td>Alternating Current Field Measurement equipment systems</td>
<td>8</td>
</tr>
<tr>
<td>7</td>
<td>Procedure</td>
<td>8</td>
</tr>
<tr>
<td>8</td>
<td>Practice of Testing</td>
<td>32</td>
</tr>
<tr>
<td>9</td>
<td>Introduction to application standards</td>
<td>8</td>
</tr>
<tr>
<td>10</td>
<td>Review and discussion</td>
<td>4</td>
</tr>
</tbody>
</table>

| Total duration time | 80 |

*Note: 60 minutes per hour training*

II.2.2 Training materials \([1],[2],[7],[8]\)

The training materials including Training book, Presentation Lectures cover the contents of the training program.

II.2.3 Review question bank \([6]\)

The review question bank has 130 edited multiple-choice questions based on the ASNT Electromagnetic Question and Answer published by ASNT and the creativity of the team. The questions include 04 answers and cover the following contents: Welding process and related discontinuities; Principle basis; Methods and techniques; Equipment system used; Standard validation and Test applications.

II.2.4 Examinations \([4]\)

The examinations for ACFM level II meet the requirements of the recommended practice No. SNT-TC-1A, 2016 edition, including:

a) Vision examinations: the content to test the ability to near vision acuity and color contrast differentiation.

b) General examination: includes 40 multiple-choice questions with 04 answer options, similar questions but not the same review questions bank provided to students. The content focuses on the basis of test principles, equipment operating principles, pros and cons of testing techniques, welding processes and related discontinuities. The duration is 60 minutes. Candidates are not allowed to use other documents except relevant documents such as graphs, tables, diagrams, etc. provided with the examination.

c) Specific examination: includes 20 multiple-choice questions with 04 answer options. The question address the equipment (used), testing procedures, applicable standards. The duration is 60 minutes. Candidates are allowed to use the references (procedures, applicable standards).

d) Practical examination: requires the candidate to demonstrate the ability to operate the equipment system proficiently, standard/confirm the standard before and after
the test, perform on 02 different samples, detect and define the position parameters of the discontinuity size, evaluate the discontinuity based on given criteria. The test must have at least 10 different checkpoints to evaluate the candidate's ability. The duration is 120 minutes.

II.2.5 Drawing and manufacturing of reference standards [7], [8]

Generally, NDT methods’ nature are indirect. Therefore, the equipment needs to be standardized / validated before conducting, especially Ultrasonic or Electromagnetic Test, which helps the test results to be consistent and reliable.

With the ACFM technique, both the standards ASTM E2261 / E2261M and the ASME BPV section V code, article 15 specify that the equipment must be validated through the reference standards before and after each test. Based on the requirements of each standard, the team designed and fabricated the ones as shown in Figures 4 and 5.
After the fabrication process, the reference standards are accepted to ensure dimensional parameters given in the drawings. Finally, the ones are verified by a calibrated ACFM equipment, a cut of 50 x 5 mm on each sample produces a Butterfly signal with a length x width of about 175 x 50% of the screen display of the device (Figure 5).

**Fig. 5.** Reference standards according to ASTM E2261/2261M and ASME V, article 15

### II.3. Discussion

- The ACFM training program has been established over 80 hour duration, ensuring to satisfy the requirements of the recommended practice No. SNT-TC-1A given for technician to study directly to Level II.

- Developing the contents for theoretical and practical examinations as the basis for the individual qualification process under the in-house certification system.

- The successful fabrication of reference standards with high precision requirements has helped to master technology from design to manufacturing in Vietnam, minimizing dependence on foreign countries. In addition, the on-site fabrication should reduce shipping costs and import duties, which leads to lower testing costs.

- The ACFM training program has initially applied for NDE Center and Petroleum College (PVMTC) - a unit with high demand in using ACFM technique to test welds in the oil and gas industry in Vietnam. This achieved good results and received positive reviews from representatives of PVMTC and trainees.

- The initial training program is specifically designed for weld inspection in the oil and gas field, Which is the first step for continuing to develop training programs for other applications such as energy - thermal power, bridges, roads, railways, ... 

- The completion of the ACFM level II training program could create the foundation of the training program development for Electromagnetic Testing level III with knowledge cover three techniques: Eddy Current Testing (ECT), Alternating Current Field Measurement (ACFM) and Remote Field Testing (RFT).

### III. CONCLUSION

The ACFM training program has met the requirements of SNT-TC-1A standards with the introduction of a system supporting documents for the training program including training materials, lectures, question bank, examination in Vietnamese which could be suitable to the needs of practical application in Vietnam.
REFERENCE


[7]. ASNT E2261/2261M-12: Standard Practice for Examination of Welds Using the Alternating Current Field Measurement Technique.

INSTRUCTIONS FOR AUTHORS

GENERAL INFORMATION
Nuclear Science and Technology (NST), an international journal of the Vietnam Atomic Energy Society (VAES) and Vietnam Atomic Energy Institute (VINATOM), quarterly publishes articles related to theory and application of nuclear science and technology. All papers and technical notes will be refereed. It is understood that the paper has been neither published nor currently submitted for publication elsewhere. The copyright of all published papers and notes will be transferred in VAES.

DETAILED FIELDS

MANUSCRIPT SUBMISSION
Manuscript for publication should be submitted to the Editorial Office in triplicate by postal mail. For electronic submission use nuscitech@vinatom.gov.vn.

Submission Address
Department of Planning, R&D Management
Vietnam Atomic Energy Institute, 59 Ly Thuong Kiet Street, Hanoi, Vietnam
E-mail: nuscitech@vinatom.gov.vn.

MANUSCRIPT PREPARATION
Manuscripts must be written in English with adequate margins and indented paragraph. All manuscript must use SI (metric) units in text, figures, and tables. Manuscripts should in general be organized in the following order: title, names of authors and their complete affiliation including zip code, abstract (not exceeding 200 words), keywords (up to 7), introduction, main body of a paper, acknowledgments, references, appendices, table & figure captions, tables and figures. Unnecessary sections may be omitted.

Headings: Use I, II,… for major headings and A, B, … for secondary headings.

Mathematical formulas: All mathematical formulas should be clearly written, with special consideration to distinctive legibility of sub-and superscripts. Equation (at least the principal ones) should be numbered consecutively using Arabic numerals in parentheses in the right hand margin.

Tables and Figures: Tables should be numbered with Roman numerals. Figures should be numbered consecutively with Arabic numerals in order of their first appearance and have a complete descriptive title. They should be typed on separate sheets. Tables should no repeat data which are available elsewhere in the paper. Figures should be original ink drawing or computer drawn figures in the original and of high quality, ready for direct reproduction. Figures should be referred to in the text as, for example, Fig. 1., or Fig. 2.

Reference: References should be listed at the end of the text and presented as follows:
KHOA HỌC VÀ CÔNG NGHỆ HẠT NHÂN

Chỉ trích nhiệm xuất bản
TRẦN HỮU PHÁT

Chỉ trích nhiệm nội dung
TRẦN HỮU PHÁT
TRẦN CHÍ THÀNH

Trình bày
LÊ THÚY MAI

In 200 cuốn, khổ 19x26,5cm tại Công ty TNHH Trần Công
Địa chỉ: số 12 ngách 155/176 Đường Trường Chinh, Hà Nội
Giấy đăng ký kế hoạch xuất bản số: 770/GP-BTTTT cấp ngày 20 tháng 5 năm 2011
In xong và nộp lưu chiếu Quỹ IV năm 2021

25 000đ