INL/CON-22-66157-Revision-0

Understanding Fission Gas Bubble Distribution and Zirconium Redistribution in Neutron-irradiated U-Zr Metallic Fuel Using Machine Learning

August 2022

Changing the World's Energy Future

Tiankai Yao, Daniele Salvato, Daniel J Murray, Luca Capriotti, Joshua J Kane, Cynthia A Adkins, Jeffrey J Giglio, Fidelma Giulia Di Lemma, Michael T Benson, Min Xian, Fei Xu, Lu Cai

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Annular Metallic Nuclear Fuel Informatics at 50 nm Resolution

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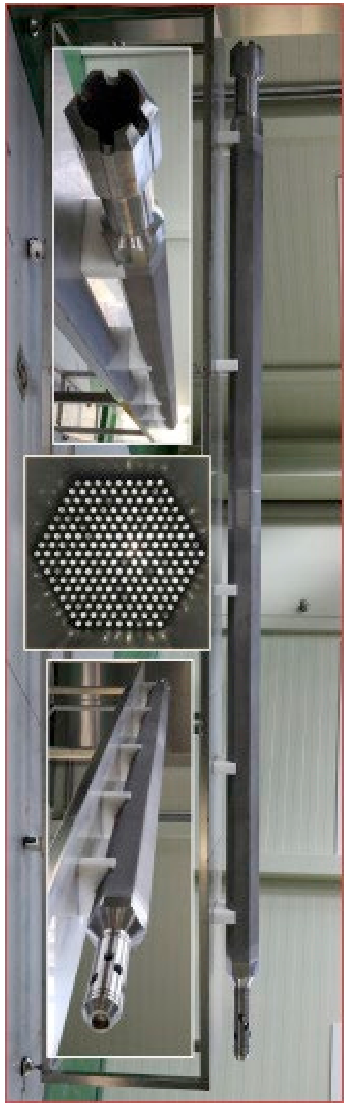
Fei Xu; Lu Cai; Daniele Salvato; Fidelma Dilemma; Jeffrey J. Giglio;. Michael Benson; Daniel J. Murray; Cynthia A. Adkins; Joshua J. Kane, Min Xian; Luca Capriotti; Tiankai Yao

Outline

- Metal fuel development challenges – Background and Motivation
- Our approach – workflow
  - Decision Tree
- An example
  - Porosity and bubble classification
  - Phase Identification
- Conclusion

Nuclear Test Reactors

Background – Cladding Integrity



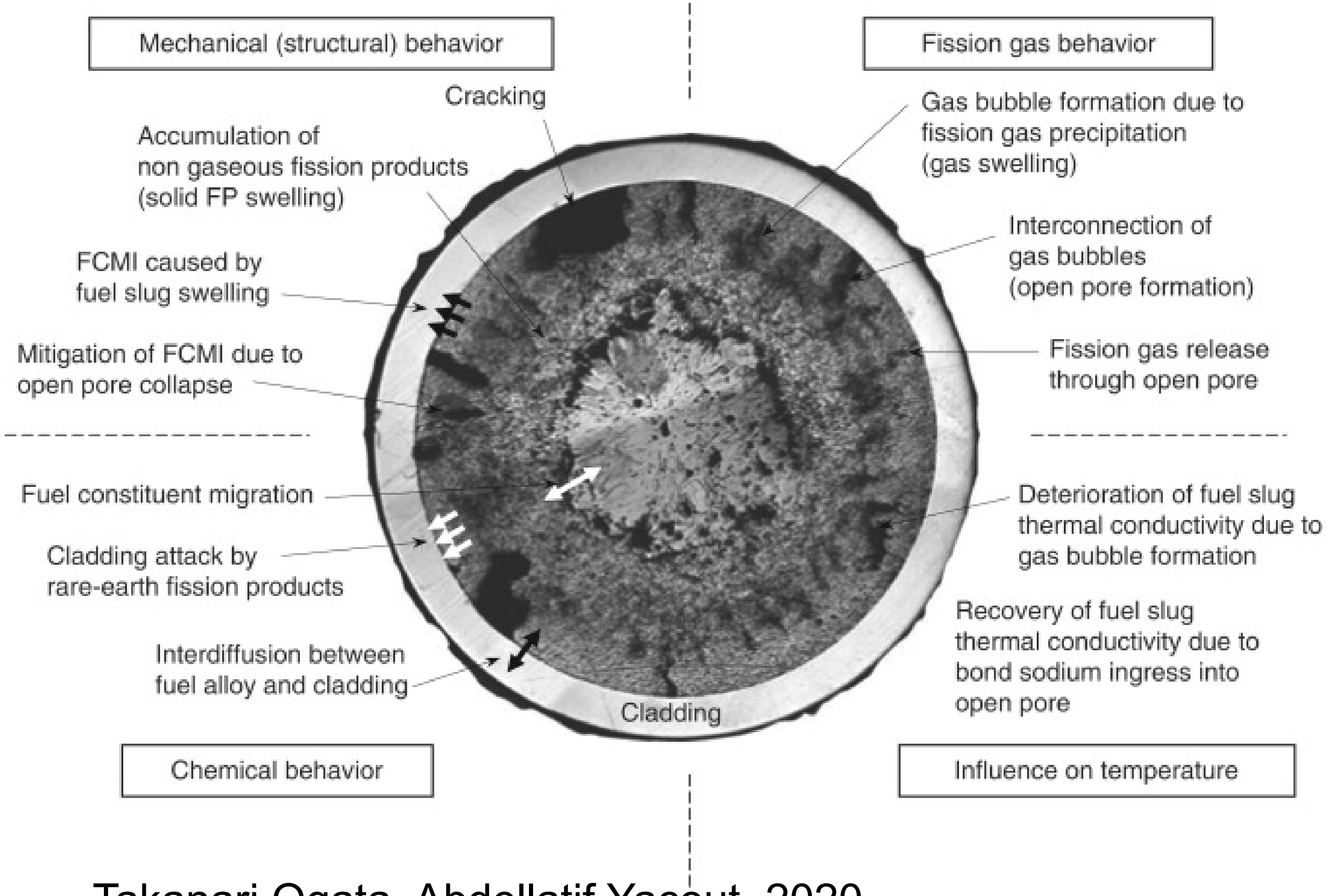
→ Fuel bundle

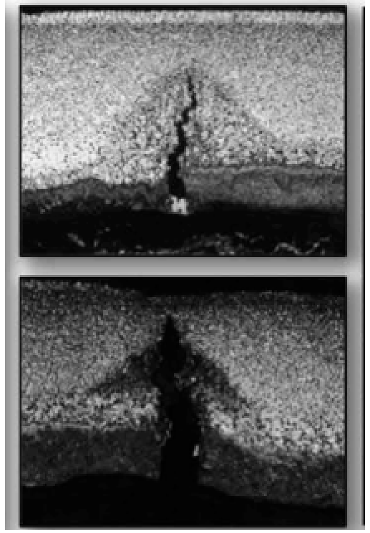
Fuel rod

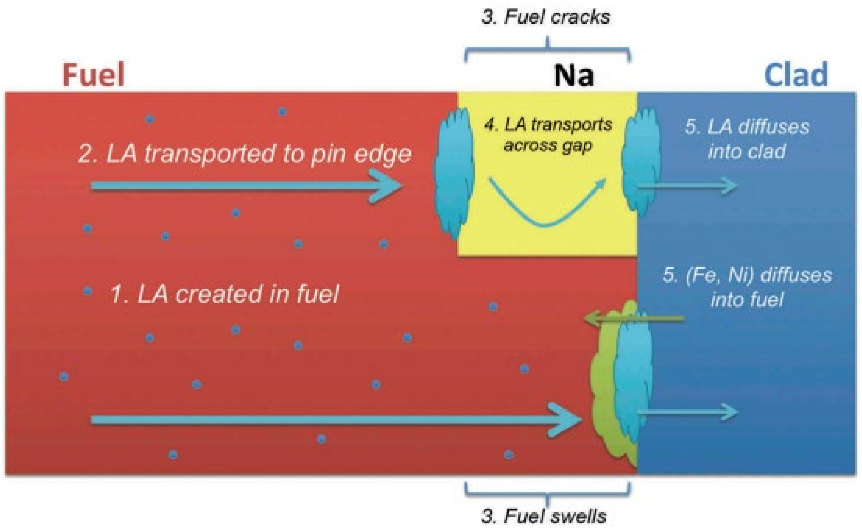
Cladding is the thin-walled metal tube that forms the outer jacket of a nuclear fuel rod. It prevents corrosion of the fuel by the coolant and the release of fission products into the coolant. It is a **first barrier** for retention of fission products.

Source: Tanju et al, Nuclear Sci. Tech. 2015; W.J. Williams et al. / Annals of Nuclear Energy 136 (2020) 107016; Olander, 1976; Takanari Ogata, Abdellatif Yacout, 2020

Background - Metal fuel irradiated microstructure







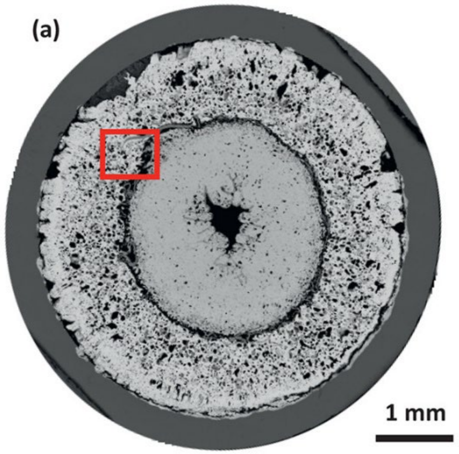
Takanari Ogata, Abdellatif Yacout, 2020
Mattews C. et al, Nuc. Tech. 2017

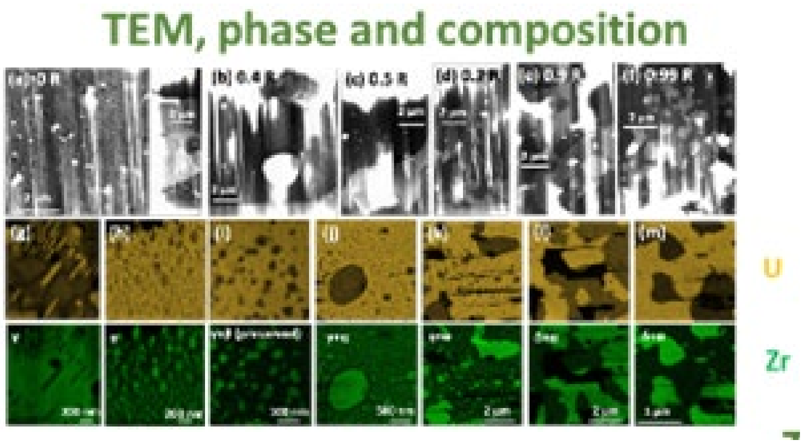
Motivation – A big picture

Huge microstructure data

Metallography

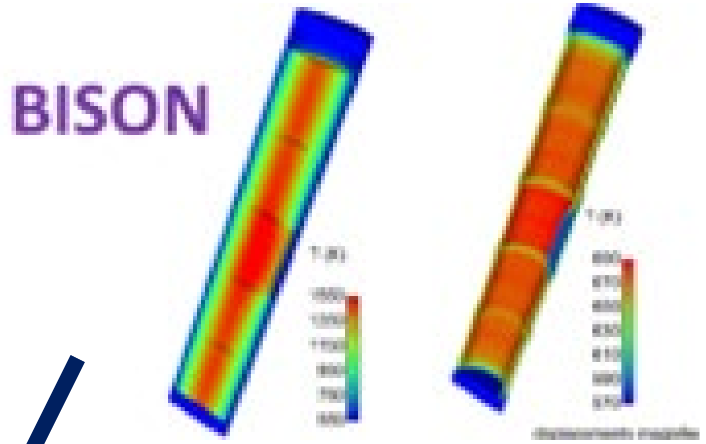
SEM/FIB





Machine learning to aid mechanistic understanding

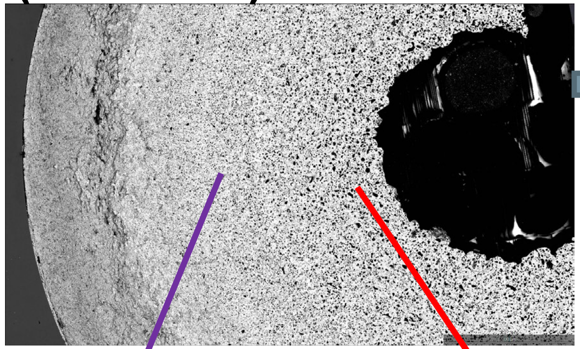
Fuel modeling code to better predict fuel performance



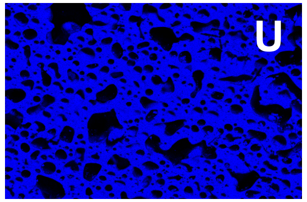
Fuel qualification and licensing

Approach - Workflow

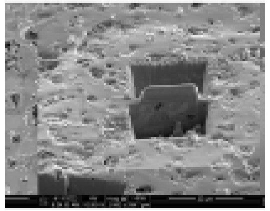
Irradiated fuel microstructure (SEM/FIB)



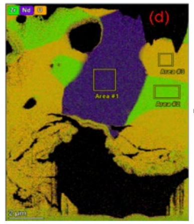
Phase determination through advanced characterization



EDS

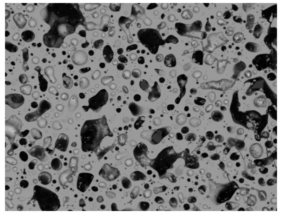


FIB

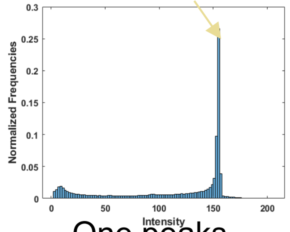


TEM/EDS

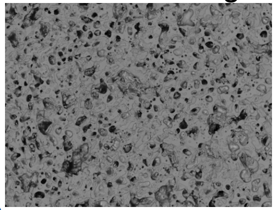
phase determination through image processing



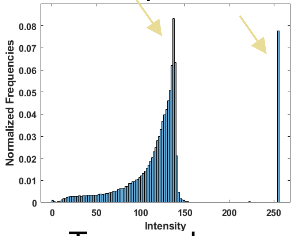
Central region



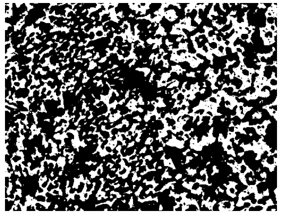
One peaks



Edge region

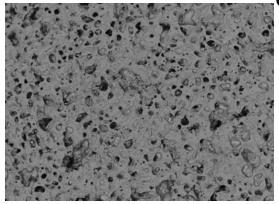


Two peaks

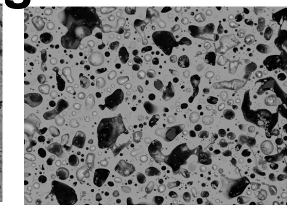


UZr_2 phase

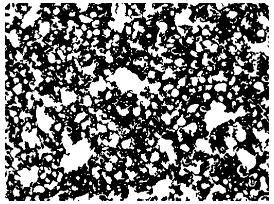
Bubble segmentation



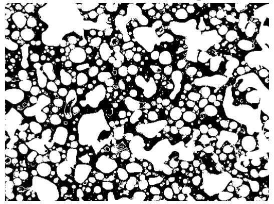
Edge region



Central region

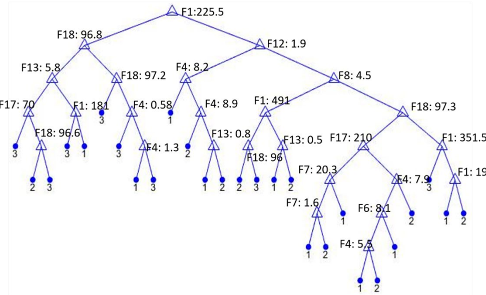


Bubble detection



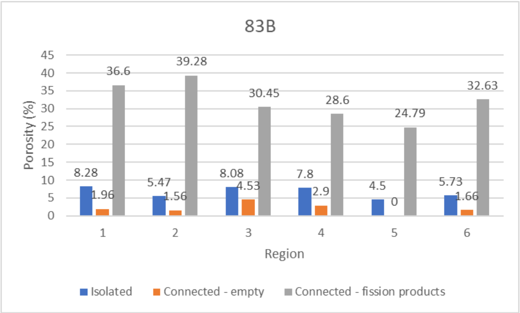
Bubbles detection

Bubble Classification

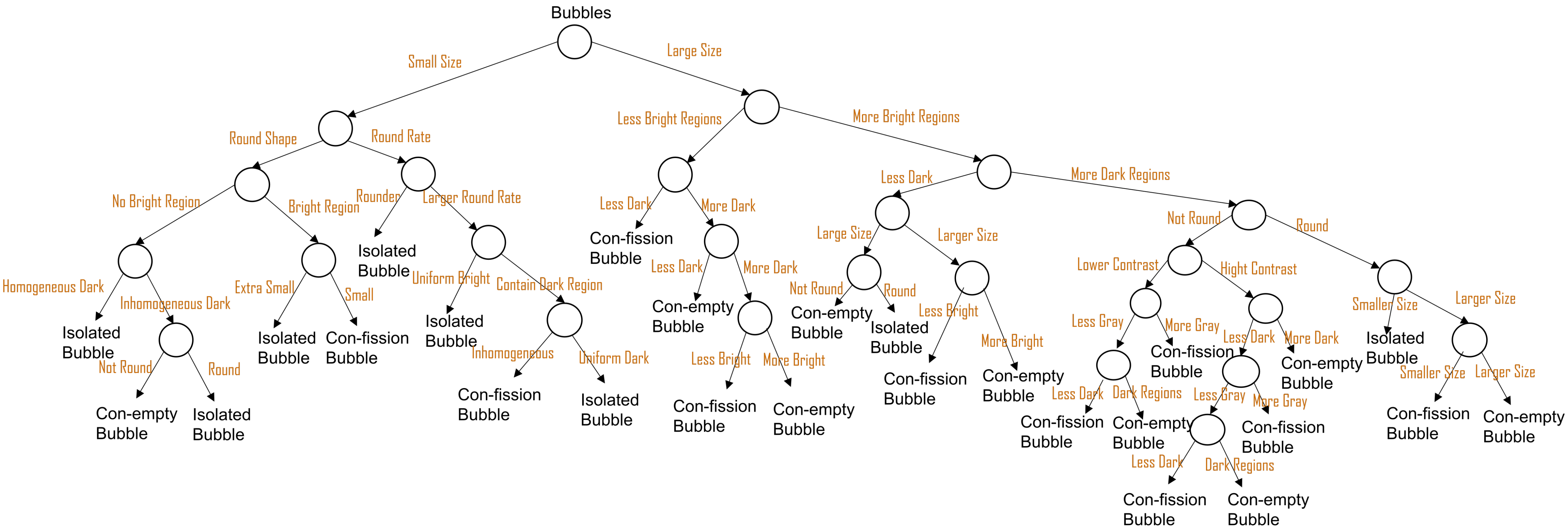


Applying the trained decision tree model

Quantitative results



Machine Learning – Decision Tree



Three bubble categories: isolated, connected w/o Ln, connected with Ln

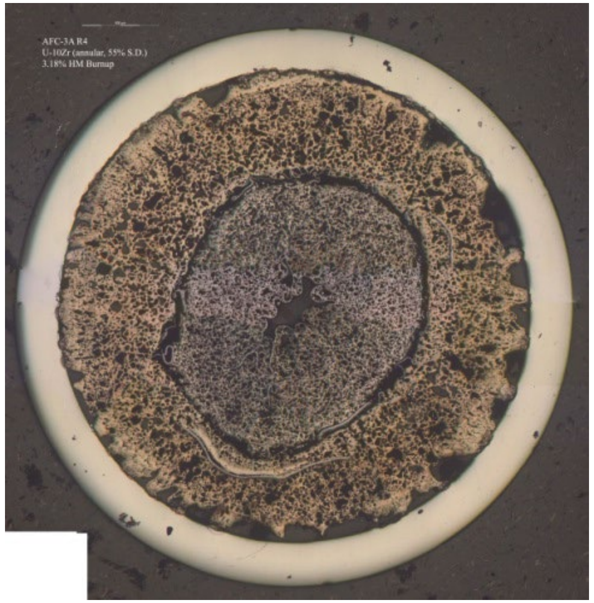
Manually bubble classification: 800 bubbles (80% training, 20% testing)

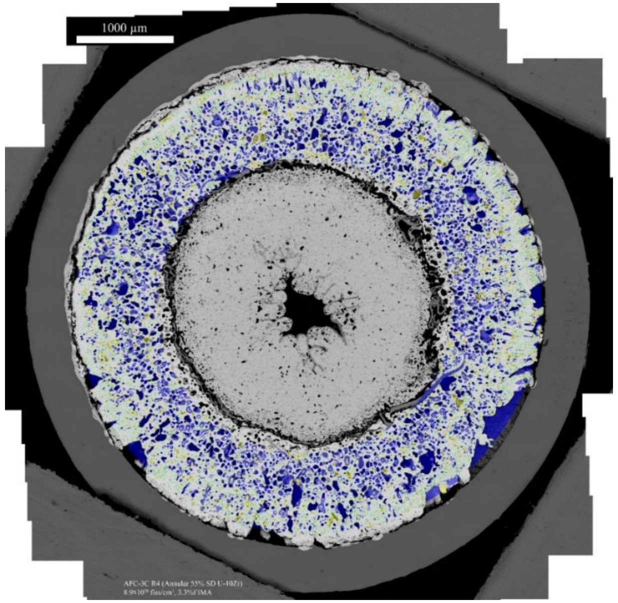
18 features including bubble's mean intensity, size, standard deviation of intensity, intensity histogram, intensity range and the shape convexity

Xu et al, Mater. Characterization 2022

A showcase - Two metallic fuel cross-sections

21 X





83 B

Cast into annular molds

U-10Zr, 55% SD, annular, He,

3.3%FIMA, 540-600+ C

Machined holes after cast

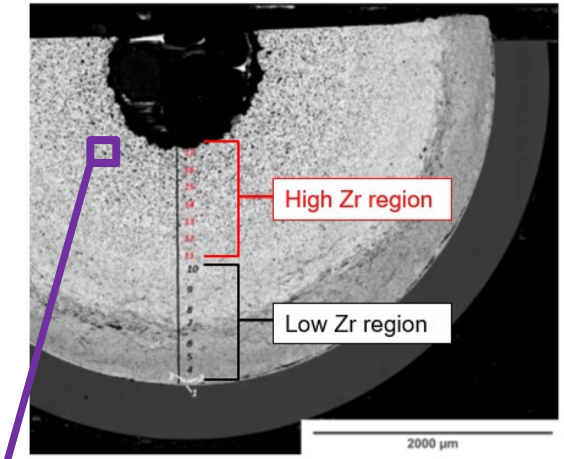
U-10Zr, 55% SD, annular, He,

4.3% FIMA, 600^{o}C

83 B better fuel performance, low FCCI

Machining, gap 50 um (21X) vs. 17 um (83B) ➔ 177^{o}C vs. 60^{o}C

Manual Verification – Bubble Segmentation

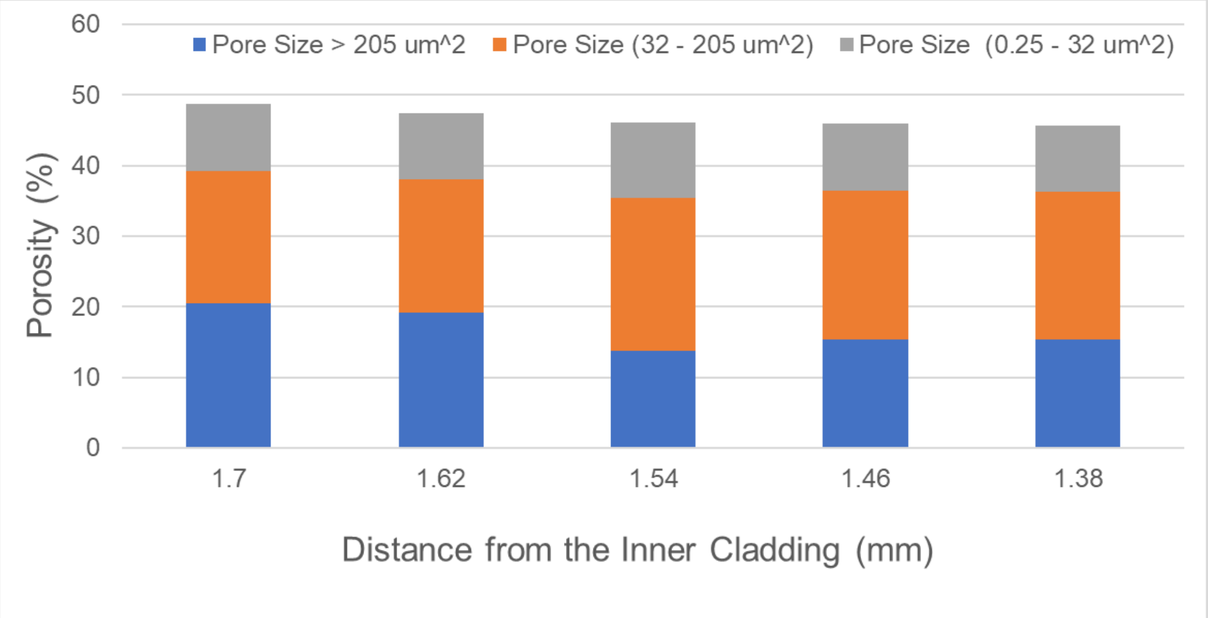


AFC-3D R1 (U-10Zr, 55% SD, annular, He, 4.3%FIMA, 600 C)

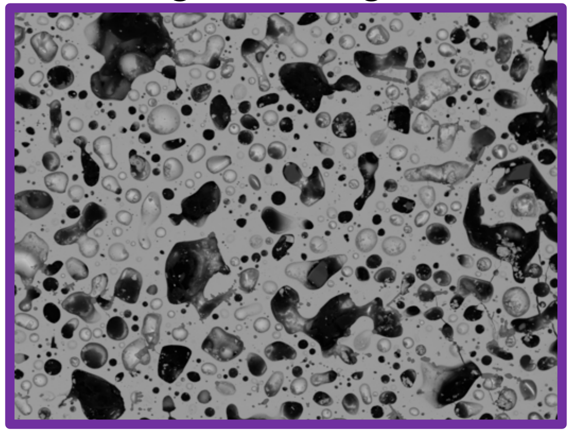
Automatic bubble segmentation

Machine learning

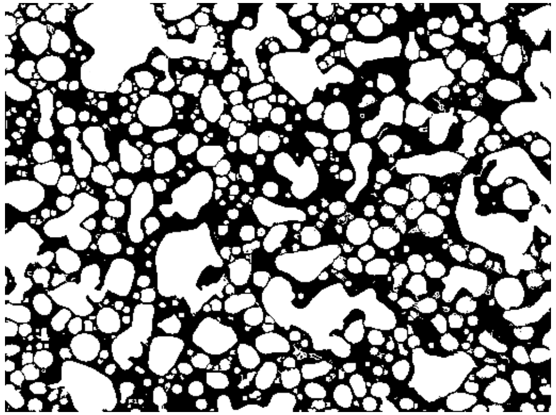
High Zr region



Original image

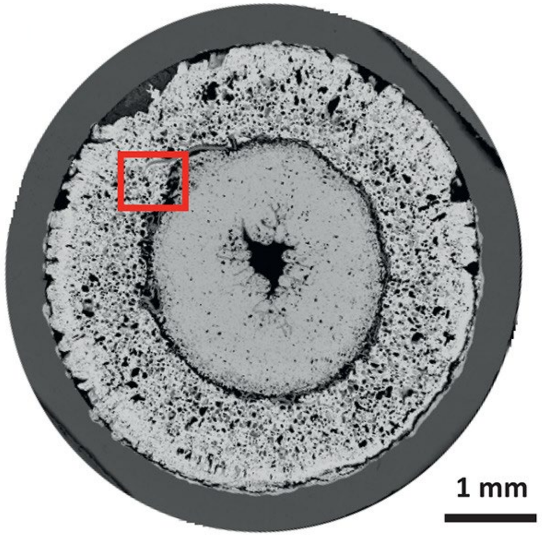


Manual bubble label

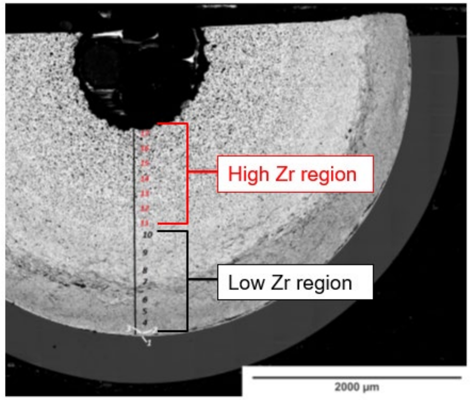


Porosity: 50.3%

Microstructure Comparison

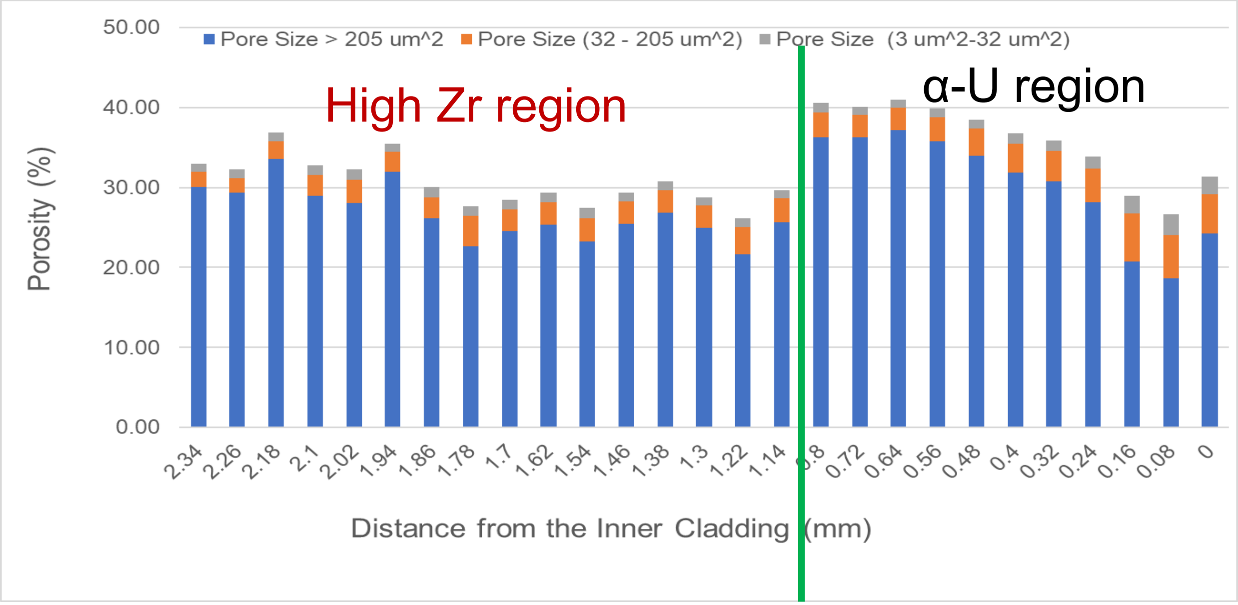


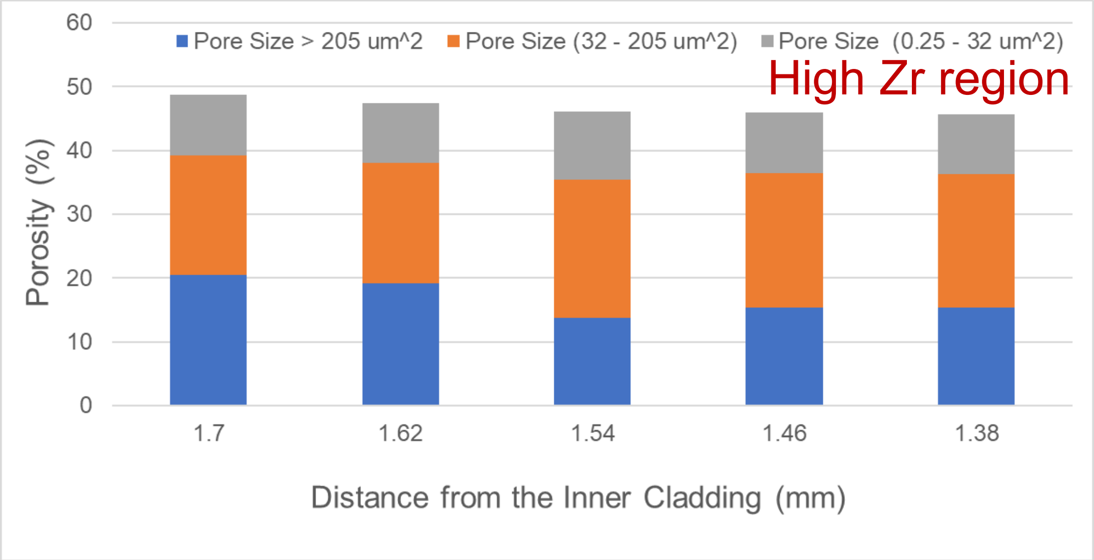
21X



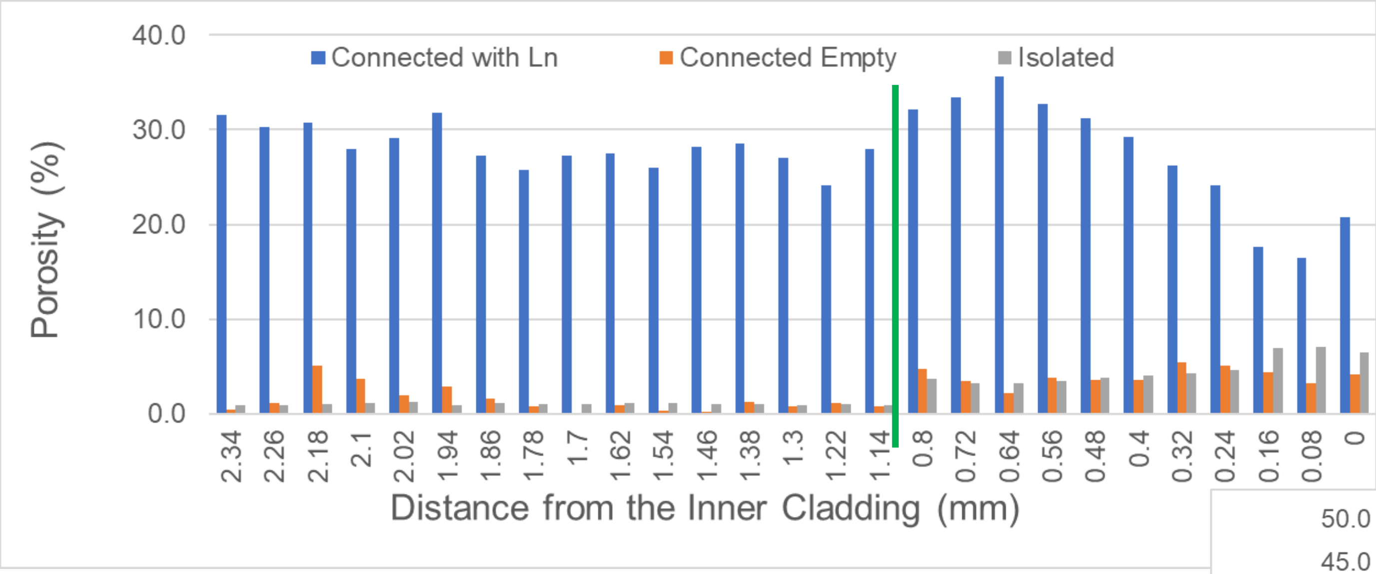
AFC-3D R1 (U-10Zr, 55% SD, annular, He, 4.3%FIMA, 600 C)

83B

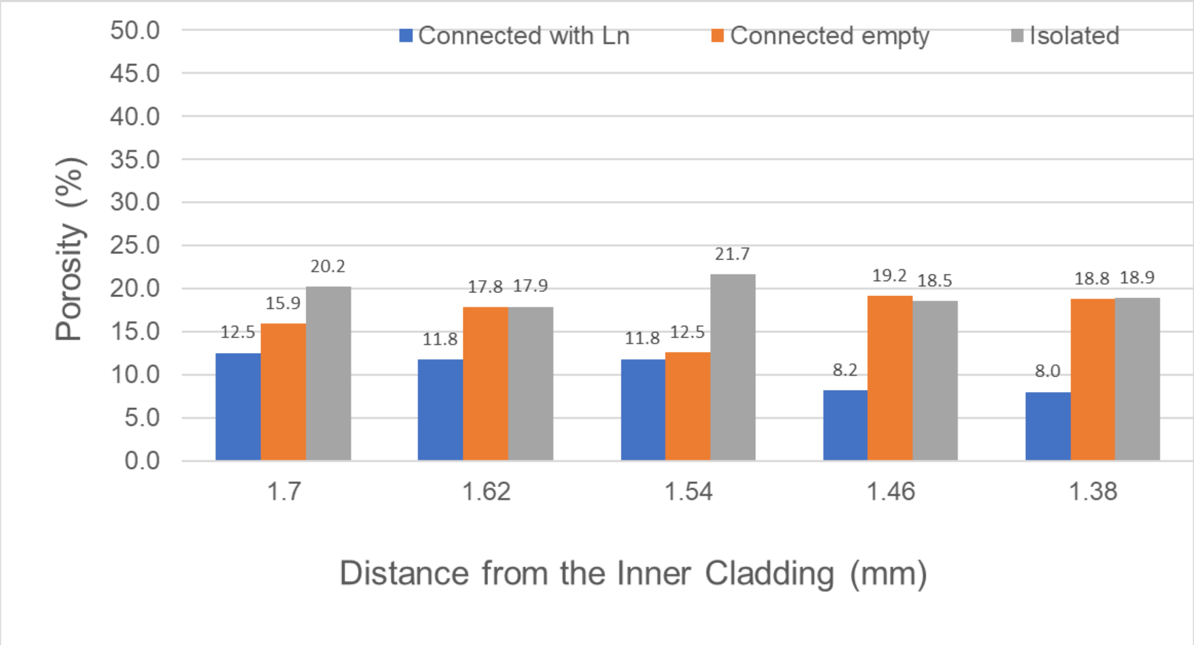




Microstructure – bubble classification

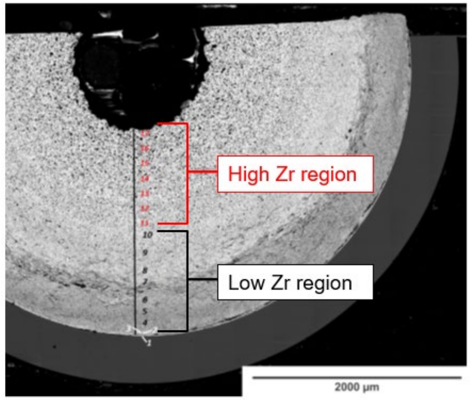


21X



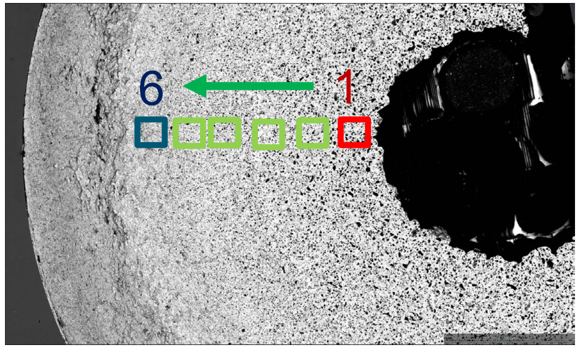
High Zr region

83B

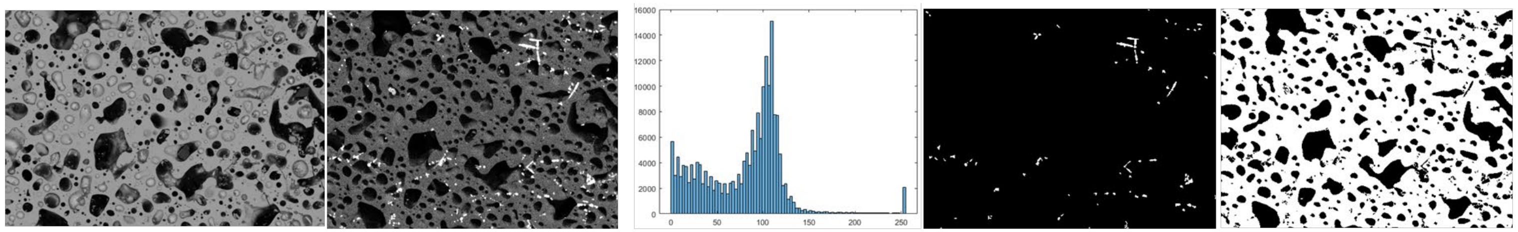


AFC-3D R1 (U-10Zr, 55% SD, annular, He, 4.3%FIMA, 600 C)

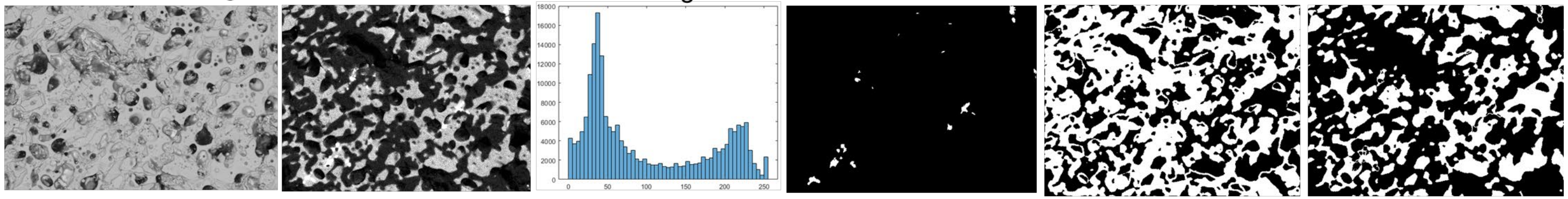
Phase Identification on 83B



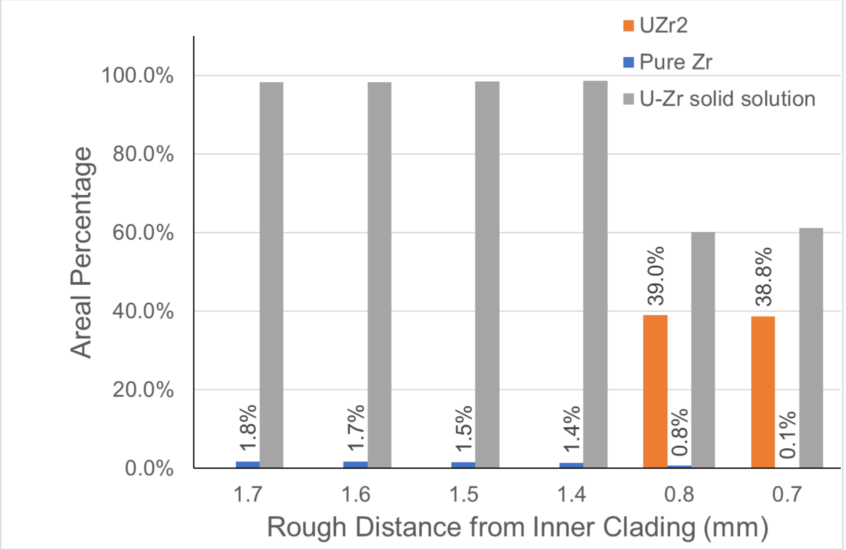
6 sample regions



Close to **center** region | Zr EDS | Zr Histogram | Pure Zr | (U, Zr) matrix



Close to **cladding** region | Zr EDS | Zr Histogram | Pure Zr | (U, Zr) matrix | UZr_2



Conclusion

Why machine learning

Complex problem
Huge dataset
Avoid human preference
Quantitative data for analysis

- Porosity distribution
- Bubble types/distribution
- Phase identification/distribution

Better understanding and prediction of fuel performance

Accelerate fuel qualification and licensing

Thank you for your attention