

Machine Learning and Supercomputing to Predict Corrosion/Oxidation of High-Performance Valve Alloys

Dongwon Shin (shind@ornl.gov)

Oak Ridge National Laboratory

June 13th, 2019

Project ID# 162

ORNL is managed by UT-Battelle, LLC
for the US Department of Energy

This presentation does not contain
any proprietary, confidential, or
otherwise restricted information

Overview

Timeline

- Project start: Oct 2018
- Project end: Sep 2021
- Percent complete: 15%

Budget

- Total project funding: \$1,935K
 - DOE share: \$1,500K
 - Cost share: \$ 435K
- Awarded for 3 years (FY19-FY21)
- FY 2019: \$500K

Barriers

- Absence of physics-based model to predict high-temperature alloy oxidation
- Lack of fundamental alloy oxidation data (e.g., atomic mobilities in oxides, oxygen permeability)

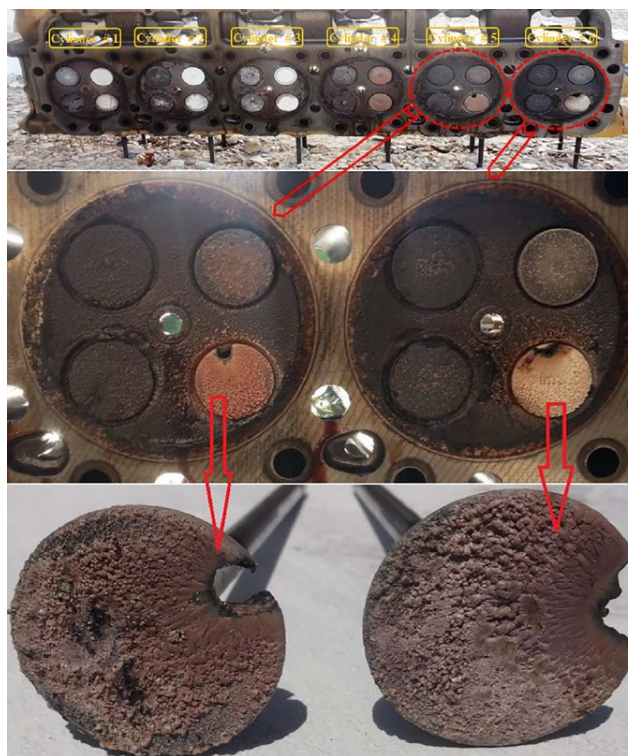
Partners

- ASM International
- Penn State University
- Federal-Mogul Powertrain

Increased exhaust temperature for engine efficiency will require advanced corrosion/oxidation-resistant alloys



Oxidation damage in IN751 valves at $\sim 850^{\circ}\text{C}$ *



*estimated

M.I. Khan et al. Engineering Failure Analysis 85 (2018) 77–88

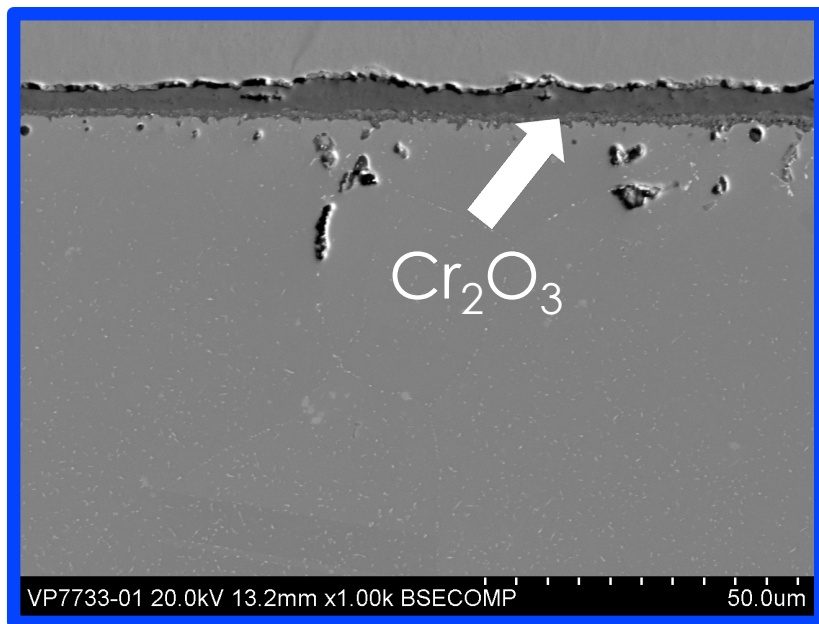
Natural gas engine operated for 10,000 h

Strategy to mitigate high-temperature oxidation?

Thermally grown thin and coherent oxide scales to protect alloys from extreme environments

Sanicro25

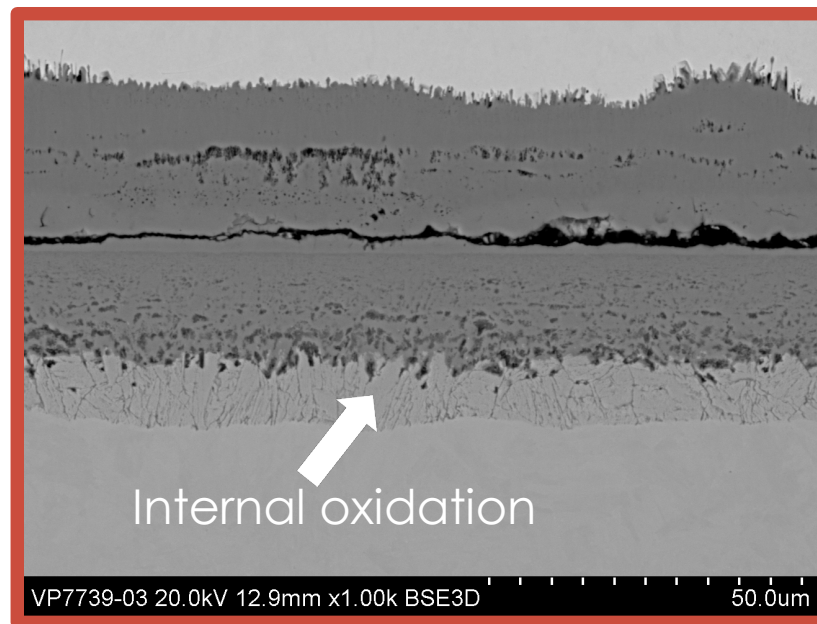
22Cr25NiWCoCu stainless steel



Good

Gr91

9Cr1Mo steel



Bad

Is it possible to predict high-temperature alloy oxidation?

First-principles bottom-up design of oxidation-resistant multi-component alloy is not yet possible



Alloy thermodynamics

- alloy phase diagrams

Alloy diffusion kinetics

- precipitate coarsening

Oxide thermodynamics

- oxide phase diagrams



Oxide diffusion kinetics

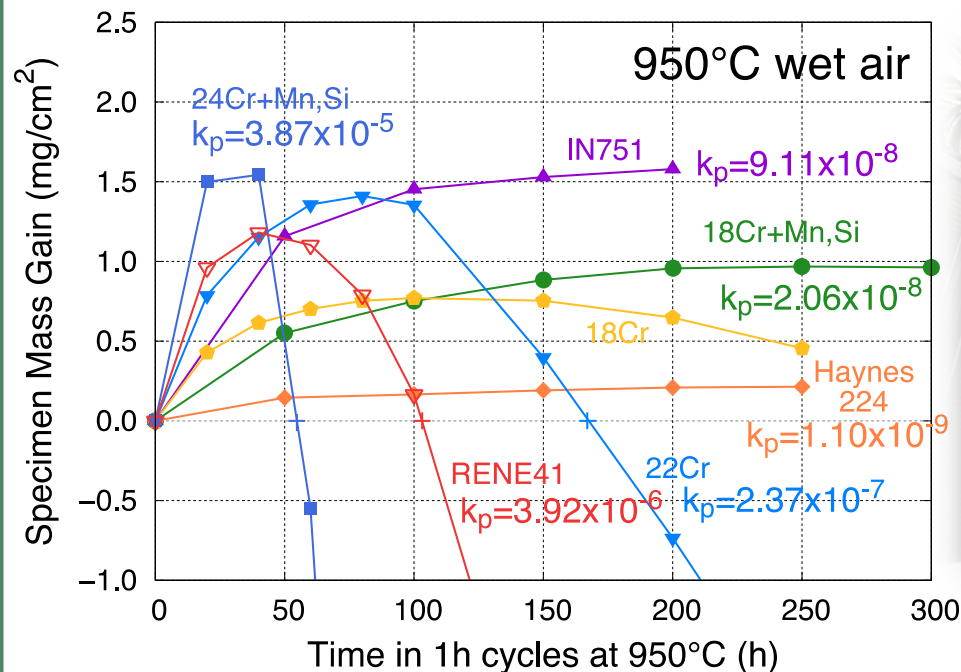
- metal cation mobilities
- grain boundary diffusion

Alloy thermodynamics with oxygen

- oxygen permeability
- oxygen mobilities

Predictive models for alloy oxidation are not available due to the lack of fundamental experimental data

Leveraging ORNL's high-quality experimental oxidation data with modern supercomputing



This project aims to develop predictive models as accurate as cyclic oxidation experiments relevant to automotive applications

ORNL's 20yrs+ high-quality experimental data coupled with advanced scientific alloy features



**Augment raw
experimental
data**

composition profile oxygen permeability
1D microstructure metal cation mobility
defect chemistry oxygen mobility

High-throughput
CALPHAD

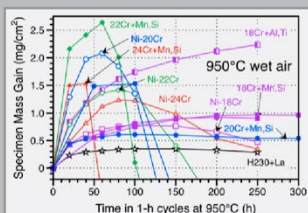
Reactive
Force Field

**Advanced features
via supercomputing**

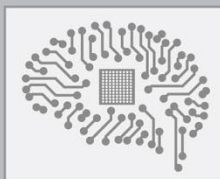


ORNL Summit

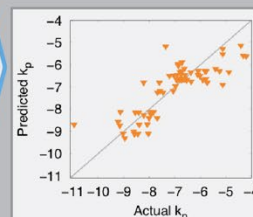
**ORNL alloy
oxidation data**



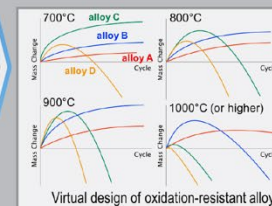
**Machine
Learning**



Training



Prediction

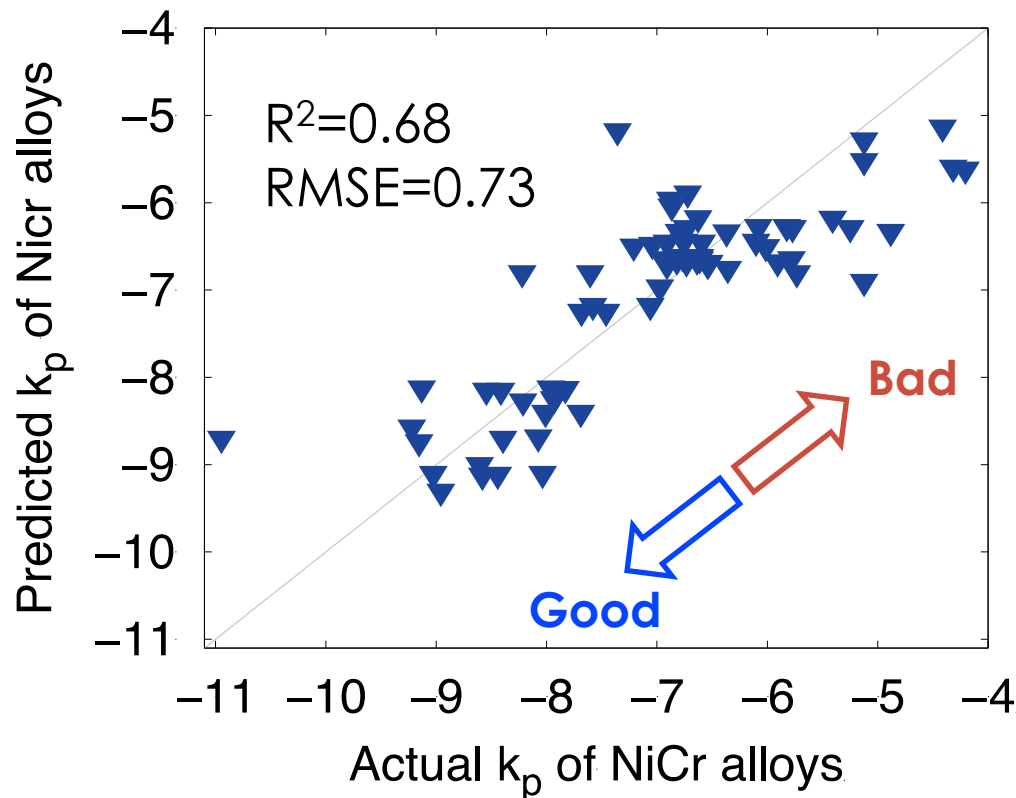


Validation

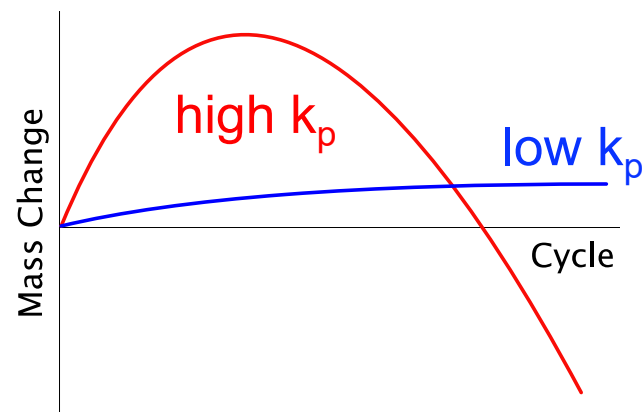
**Proposed workflow is anticipated to go beyond Ni-Cr alloys
(e.g., stainless steel and Ni-Al alloys)**

Successful training of preliminary machine learning models to predict rate constant (k_p)

78 Ni-Cr alloys at 950°C (10% H₂O)



- input: alloy chemistry (Ni, Cr, Co, Mo, Mn, Fe, ...)
- output: alloy oxidation rate constant (k_p)



Predictive, but features other than compositions are needed to better understand fundamental alloy oxidation mechanisms



Computational
Thermodynamics/
Diffusion Kinetics

Data Analytics and
Supercomputing



Data
Repository

**World-class research
teams to develop
alloy oxidation model
with 20+ years data
and supercomputer**

Atomistic
Simulations



PennState



Finite Element
Analysis

**Monthly all-hands conference call,
biweekly subtask team meetings**

Project will focus on generating alloy features to be correlated with ORNL's high-quality experimental data

High-throughput CALPHAD

- Populate scientific alloy features
 - Depletion of major elements (e.g., Cr)
 - Dissolution of key strengthening precipitates
 - Temperature excursion



High-fidelity Atomistic Simulations

- Generate fundamental oxidation data via Reactive Force Field (ReaxFF) simulations
 - Oxygen permeability
 - Grain boundary diffusion

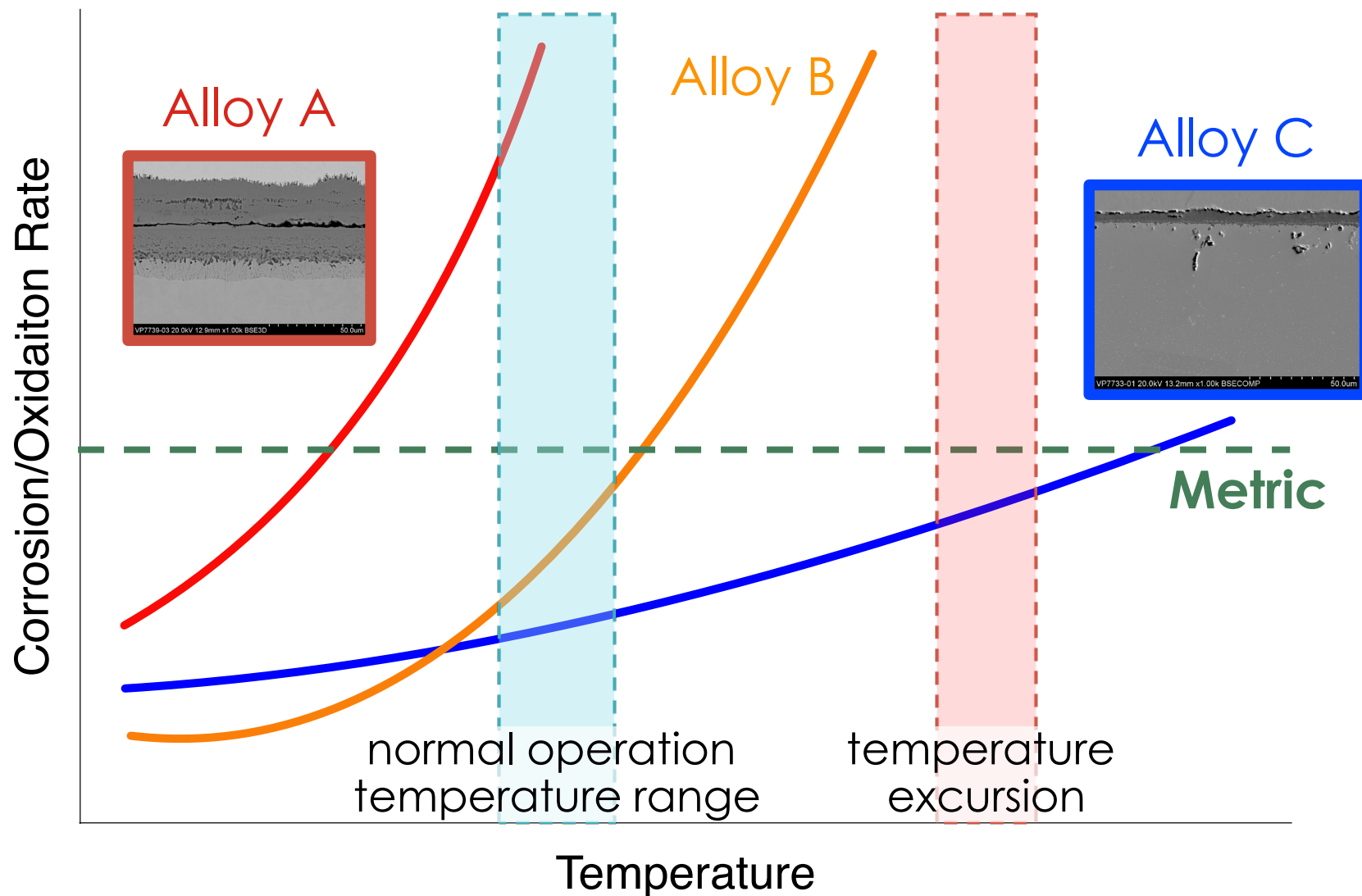


Data analytics

- Analyze correlation between input features and alloy oxidation
- Train machine learning models with identified key features

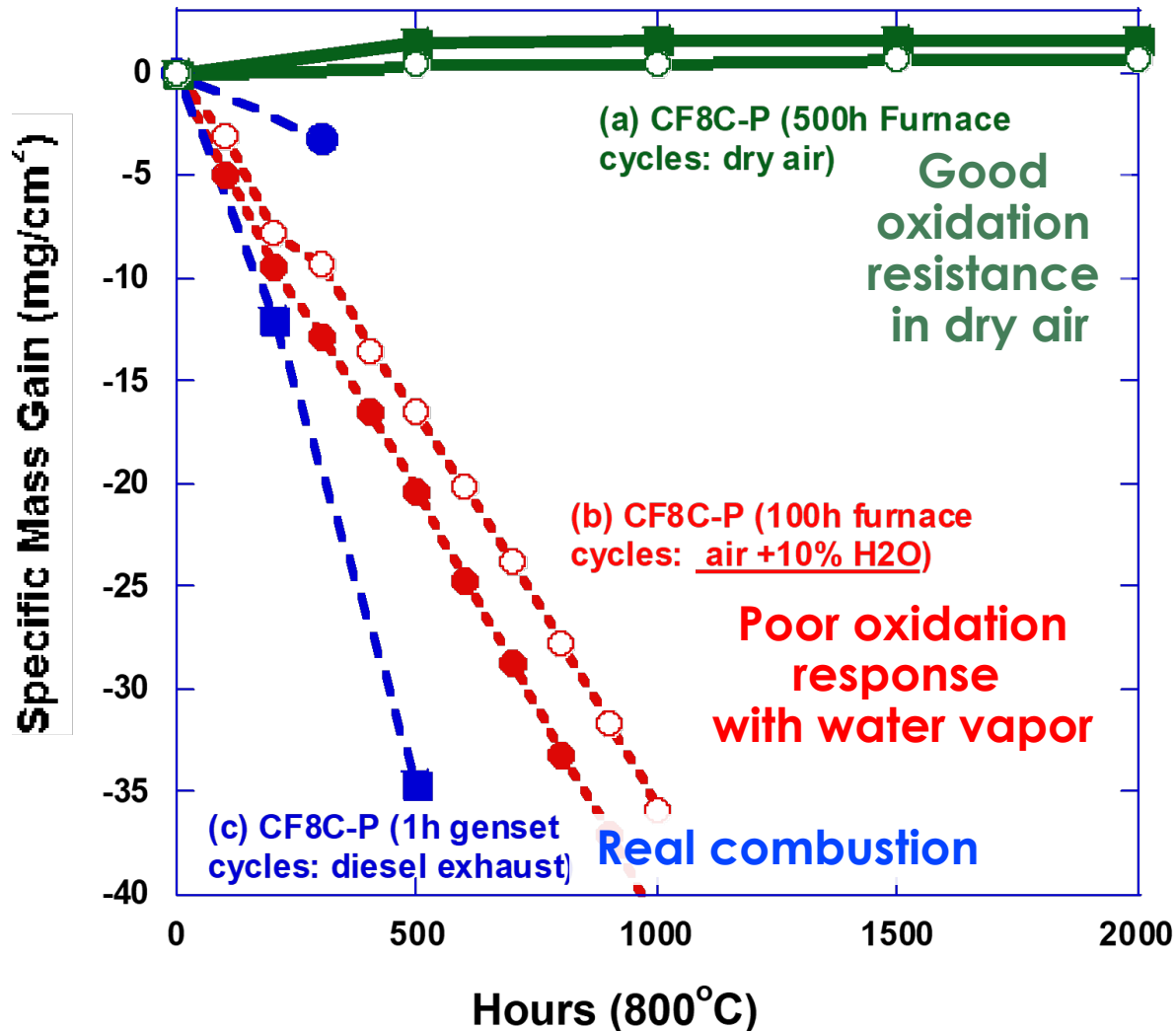


Develop practical alloy oxidation model with 20yrs+ ORNL data, machine learning and supercomputing

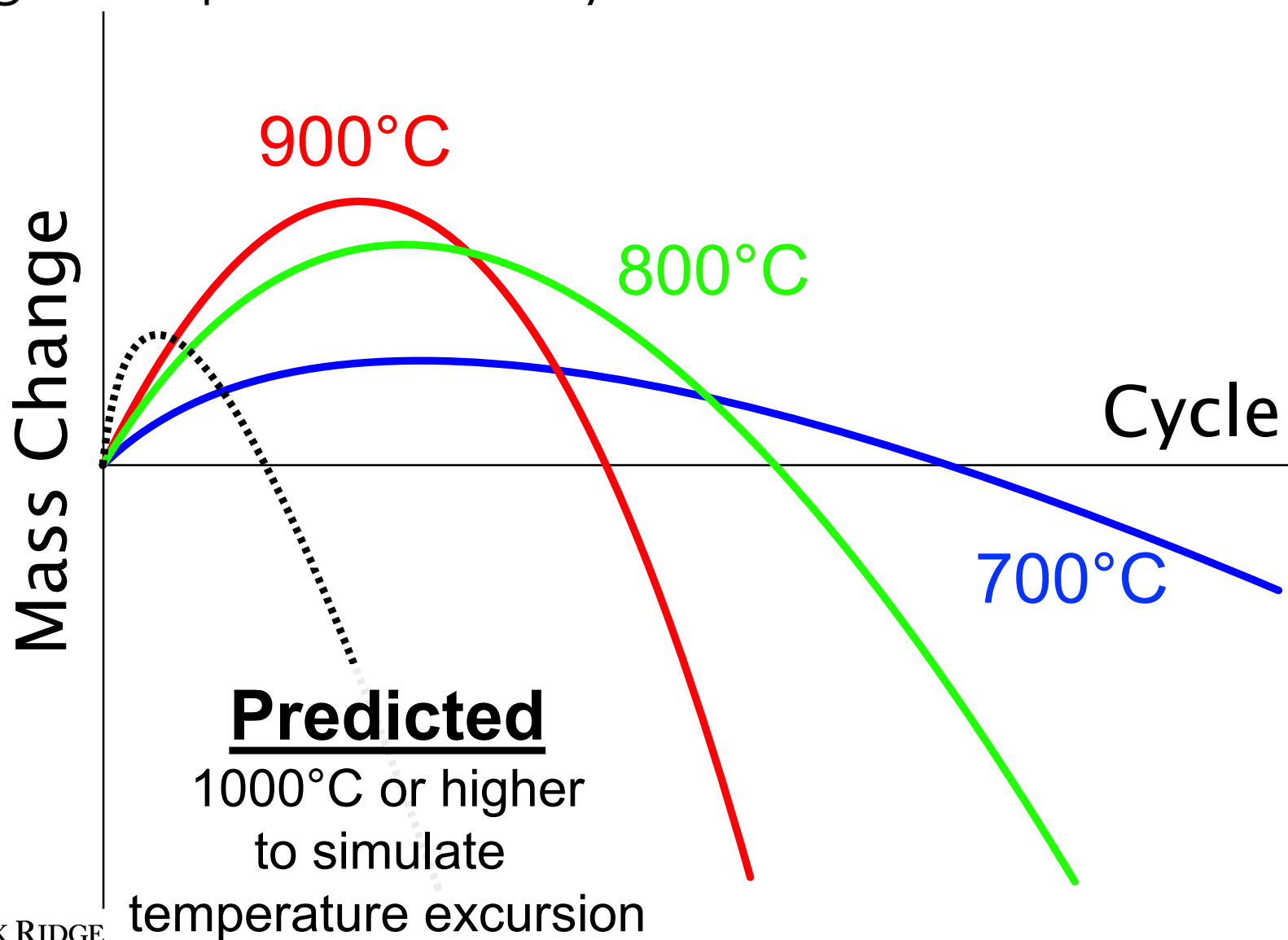


Technical Backup

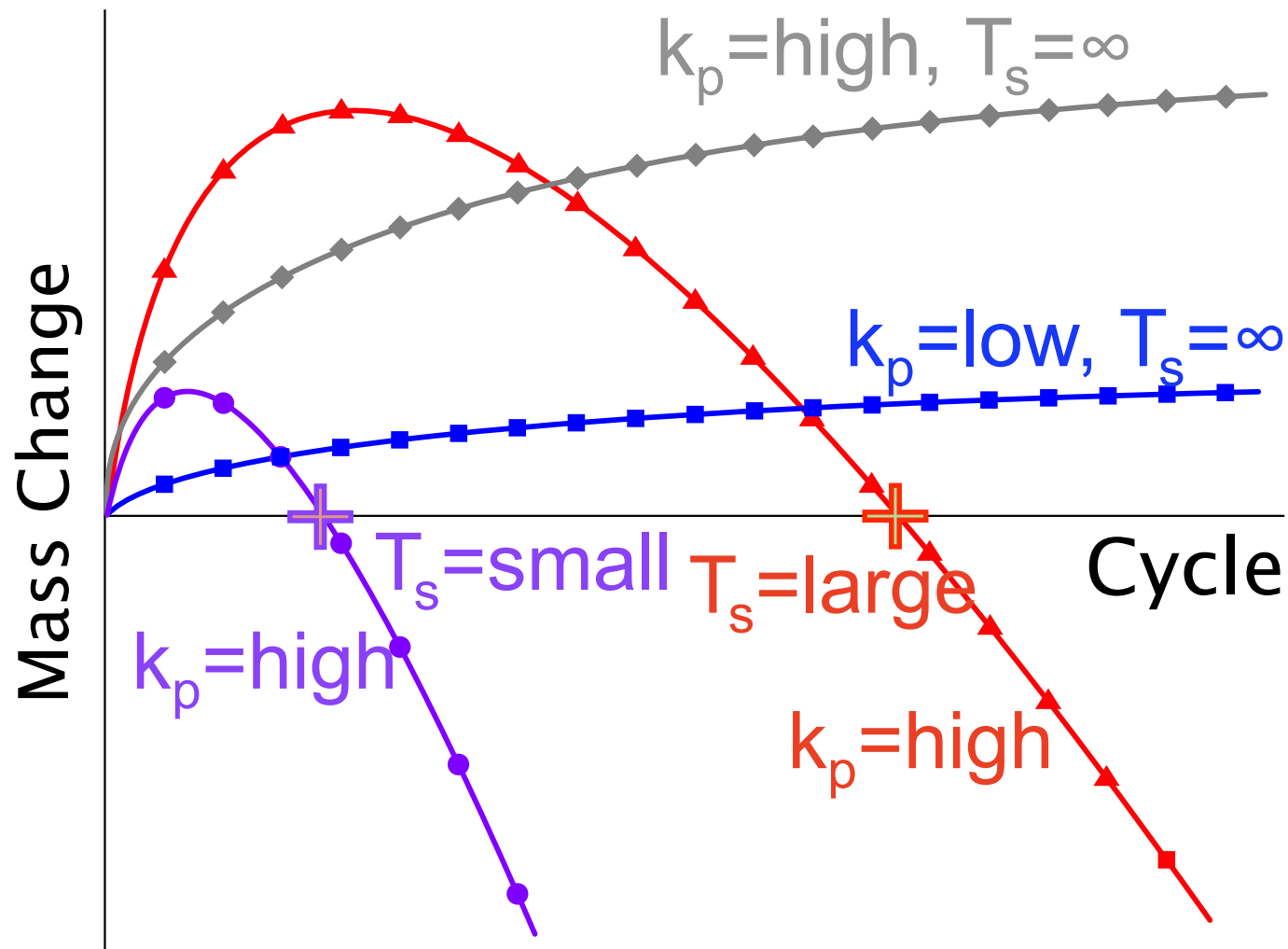
Laboratory simulated 10% water vapor testing can mimic real combustion environment



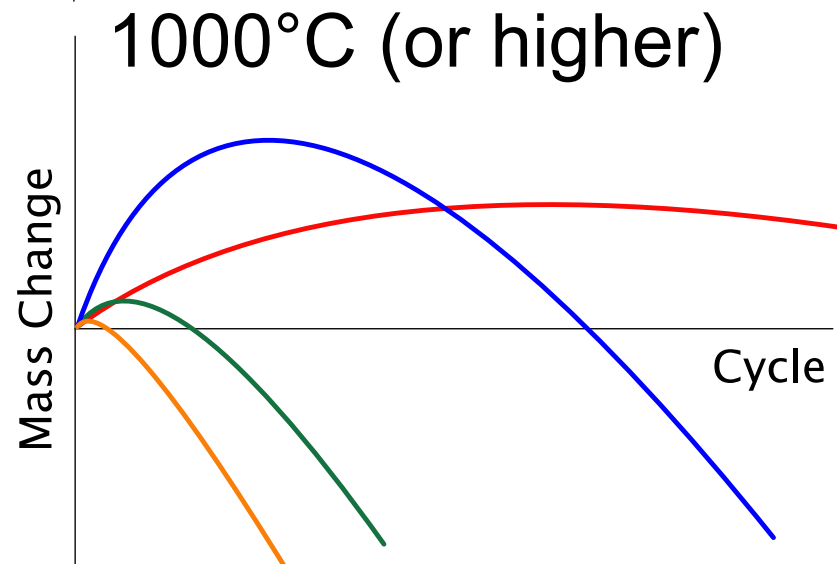
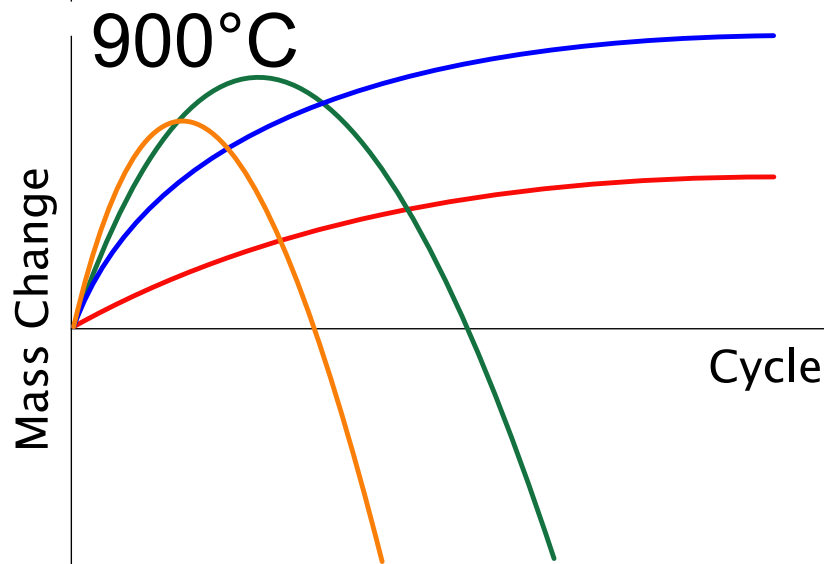
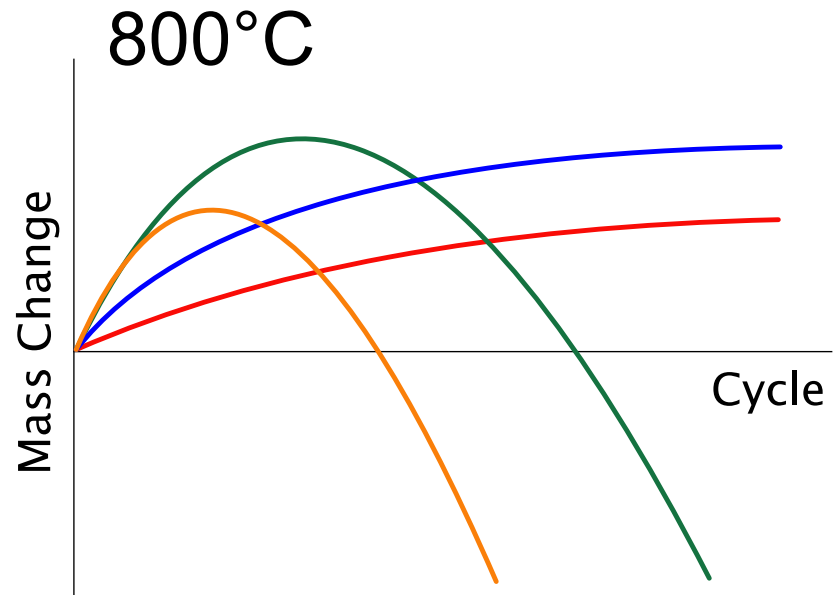
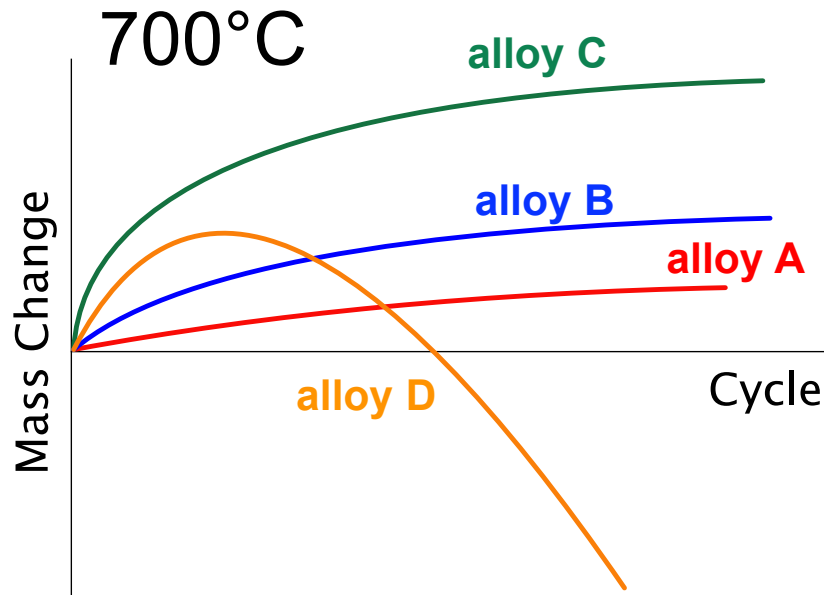
Temperature effect on oxidation behavior of high-temperature alloys



We propose using k_p (rate constant) and T_s (time/cycle to spall) to represent oxidation behavior of alloys



Alloy chemistry and temperature dependent k_p and T_s prediction



Catalog of ORNL's experimental data for 10% H₂O cyclic oxidation NiCr alloys: total 337 data

Temp (°C)	Model alloys	Commercial alloy data*	
800	32		
850	23	15	N80, N90, 31V & 751 (2~4) R41 & WASPalloy (1)
900	40	45	247 (21), 751, 214, 31V, R41, 282, N80 & WASPalloy (2~4), U520, U720, 230, N90 (1)
950	18	64	751 (11), N80 (9), U520 (6), 247 (5), R41 (5), 214, N90, 246, 713, 282 & U720 (2~4) 230 & WASPalloy (1)
1000		8	246, 247 & 713 (2~3), N90 (1)
1050	4		
1100	16	42	247 (42)
1150	15	12	247, 214, 224 & 230 (2~4), 713 (1)
1200		6	247 (6)

*() – individual data count