



Extreme Environment Materials - Data Analytics

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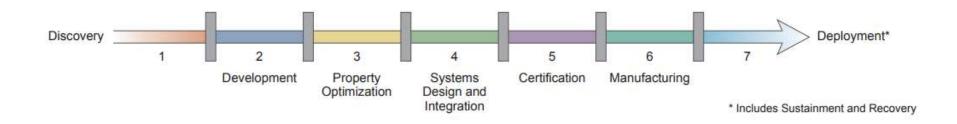








Traditional empirical materials development



Traditional materials development takes 10-20 years (source: OSTP MGI White Paper, 2011)

Empirical lifetime prediction is unreliable and not transferable to new alloys.

Solution: Use data management and analytics to integrate materials development.













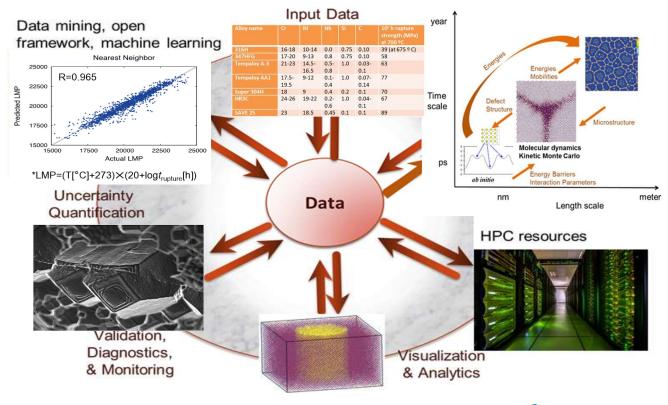




Task 2

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Aim: Use data management and analytics to reduce the time and cost for alloy development and predict lifetime reliably.





Task 4













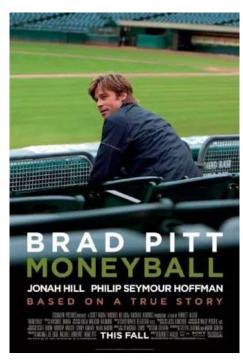
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Playing 'Money Ball' with materials is challenging.

Issues	Baseball	Materials Science
Data availability	Reliable and readily available	Scattered, hidden (proprietary), or unpublished.
Standards	Uniform	No data standards
Variability	Unambiguous: Hits, RBI, HR etc.	Uncertainty can be large; variability between groups
Relations	Rules, positions etc. well defined.	Processing-microstructure- property relations nonexistent.
Stability	Rules don't change during the season	Material microstructure changes during processing and service; surface degrades.





















Alloy data analysis challenges

- Data is sparse and expensive to obtain.
- Metadata and provenance are missing.
- Existing frameworks focus on 0 K properties.
- Complex descriptors (e.g., microstructure)
- Going beyond confirmation of one's biases
- Interpretability of models is essential.





















Creep-resistant alloy development issues

- Lack of composition-processing-structure-property relations
- Lack of validated physics-based models (especially processing)
- Gaps in microstructural and thermodynamic data
- Alloy development knowledge and data are not widely shared
- Parameter space is large (minor alloying element optimization)
- Extrapolation from short-term tests to long term life estimation
- Doing this by experiment alone would be very long and expensive





















Scope of Task 3: Data Management and Analytics

- Subtask 3.1. Data assessment
 - Collect existing data on austenitic steels and identify gaps for extreme environments
 - Composition, microstructure, mechanical properties, thermodynamics and kinetics
- Subtask 3.2. Data management
 - Develop open standards and formats, curate data, and include metadata
 - Develop robust and flexible user interface to integrate with simulation and analysis tools
 - Integrate and enhance existing frameworks to support collaboration; Sustain data long term
- Subtask 3.3: Data analytics, machine learning, and rapid simulation tools
 - Identify and evaluate available data analytics tools and gaps
 - Couple machine learning with rapid simulation tools (Thermocalc, DICTRA, etc.)
 - Develop data-driven models, integrate with physics-based models, and visualize data
 - Predict lifetime in extreme environments (chromia-forming), validate results, and refine models
 - **Design a new alumina-forming alloy for extreme environments**















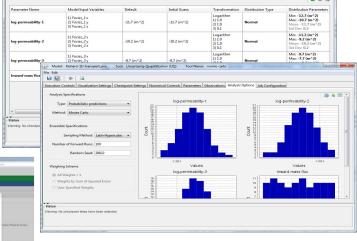
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3.2 Data Infrastructure Attributes

- Customizable and powerful web portal-based user interface (UI)
- Tool integration including client-based UIs via web browser
- Simulation management (HPC job launching/monitoring)
- Hierarchical data organization with role-based access control
- Standards-based security and authentication
- Support for structured data
- Local and cloud-based data storage with version control
- Bulk and large file uploads (e.g., microstructure data)
- Open source or no license fees for software/data
- Local deployment behind company firewalls
- Metadata and provenance
- Visualization
- **Publishing**





Ensemble Job Launching













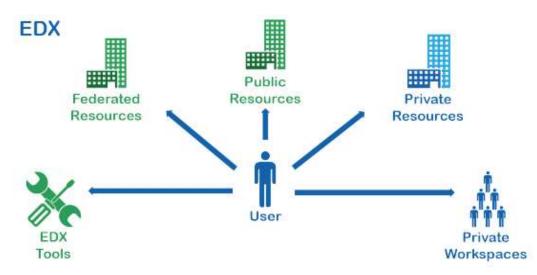


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3.2 Energy Data eXchange (EDX)

- EDX is a data management and R&D platform for DOE FE.
- It is a secure, online coordination and collaboration platform that supports energy research, knowledge transfer and data needs.
- Reliable access to historic and current R&D data, data driven products, and tools
- Both public and secure, private functionalities
- Enables knowledge transfer, data preservation, reuse and discovery.



Built by researchers for research













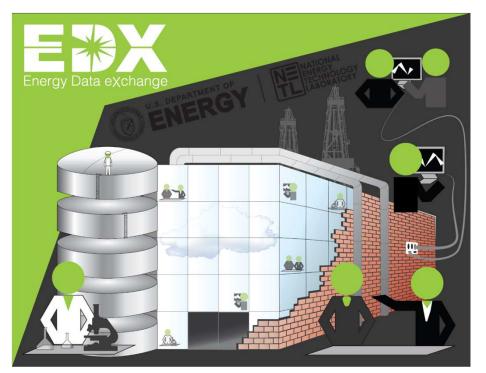


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3.2 Energy Data eXchange (EDX)

- All data is contributed by registered EDX users
- Data can be contributed as public resources or private resources shared with a user defined research team (Collaborative Workspaces)
- Over 50,000 EDX Resources (16,299 public, 35,282 private)
- Advanced data discovery and search functionality
- Custom Smart Search Tool and Related Resources functionality
- Enhanced Search within data itself (v3.0)

















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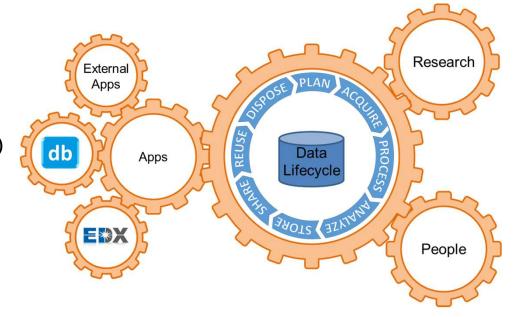
Integrating EDX with Collaborative Frameworks and Repositories

EDX

- Access/search outside data sources
- Data mining
- Collaboration beyond data (forums, calendar)
- DataBook (smart lab notebook)
- Metadata capture/search
- Smart/living database (structured data support)

Open collaborative framework

- Tool integration including client-based
- Simulation management
- Provenance support (tying tools to data)
- Local data storage and deployment









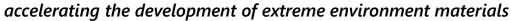






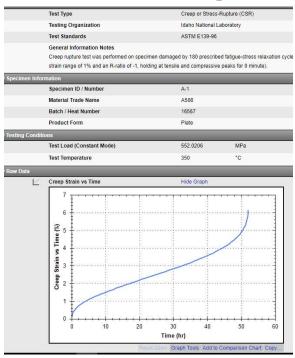




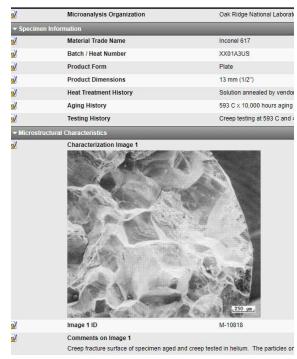




Accommodating Different Data Types with Materials Handbook



Component	Component Nar	ne Component Assem	Came	onent Function		Linking	an.
ID		Location	uny County			value	
		•	*		٠	(Component	11
B1	Graphite Brick B	X+0, Y+Top of B2				ID)	۳
82	Graphite Brick 87					B1 B2	
A-G01-X1	Acceleration Sen					A-G01-X1	
	Acceleration Sen			iring acceleration signa			
A-G01-Y1				iring acceleration signa		A-G01-Y1	
1R	Strain Gauge 1R				radial and tangent directions		ľ
16T	Strain Gauge 16	F B16 Dowel 2, 270° d			radial and tangent directions		4
V-G01-T-01	Carnera 01		Meast	iring the displacement of	of brick B1 and base plate.	V-G01-T-01	ı
Test Procedur	105	н	ide table				
Procedure ID		d Case (Boundary edition)	Direction	Excitation Type	Excitation Amplitude	Einking v	alluc
Test Proce		- Top and Side Springs	×	White Noise	0.05	1,1	
Test Proce	dure LC1 P2 LC1	- Top and Side Springs	Y	White Noise	0.05	1.2	
Test Droze	dure LC2 P1 LC2	- Side Springs	×	White Noise	0.05	2.1	
	Source	1 Data Source Edi	tor Name		R. W. SWINDEMA	AN	
	Source	e 1 Data Package Fi	le 1		8092297 ann 16n	nm plate FILE	E.x
	Source	e 1 Data Package Fi	le 2		8092297 mill ann	16mm plate	FIL
	Source	Source 1 Data Package File 3 316 test summa			/.xlsx		
Record Ma	nagement Inl	formation					
	Handb	ook Record ID			316SS 8092297 A	Ann Plate Ter	nsil
	Record Contributing Signatory			DOE United States			
	Information Category			Background Public Information			
	Record Distribution Scope				Unlimited		
	Record Edited by			Lianshan LIN and Weiju REN			
	Digitiz	ation Status			In Progress		
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	• Gener	ic Alloys for this Da					
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Materials data along with pedigree, chemical and physical properties, specimen information, technical specification etc.



















3.3 Inputs and Outputs for Data Analytics

Alloys

Chromia-forming

316H

347

347H

Alumina-forming

AFA-HP

AFA-low Ni

Nickel-based

Descriptors/Features

Thermochemistry

Elemental Composition

Phase Stability

Diffusion Kinetics

Atomic Mobility

Crystalography

Lattice Parameters

Polyhedra

Atomistic

Atomic Radius

Electronegativity

Properties/Performance

Physical Properties

Mechanical Strength

Creep Rupture Time

Chemical Properties

Corrosion/Oxidation

Open Circuit Voltage

Thermal Properties

Thermal Conductivity

 ΔH_f , ΔS_f , C_p















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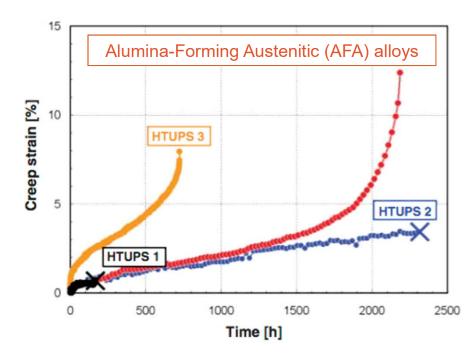


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High-Dimensional Optimization

Co	mpositions	(Wt %))
PS 1	HTUPS 2	HTUF	٥

	Compositions (wt 76)				
Elements	HTUPS	HTUPS 1	HTUPS 2	HTUPS 3	ORNL AFA
Fe	64.27	60.25	57.73	56.58	57.78
Ni	16	19.97	20	19.98	19.95
Cr	14	14.15	14.2	14.21	14.19
Al	-	-	2.4	3.67	2.48
Si	0.15	0.15	0.15	0.1	0.15
Mn	2	1.95	1.95	1.92	1.95
Мо	2.5	2.47	2.46	2.46	2.46
Nb	0.15	0.14	0.14	0.14	0.86
Ti	0.3	0.28	0.31	0.31	-
V	0.5	0.49	0.5	0.49	-
С	0.08	0.068	0.076	0.079	0.075
В	0.01	0.007	0.011	0.011	0.01
<u>P</u>	0.04	0.042	0.044	0.04	0.043



Yamamoto et al., Science 316:322, 2007.

Complex high-dimensional statistics problem (>10 elements) to optimize/maximize target properties















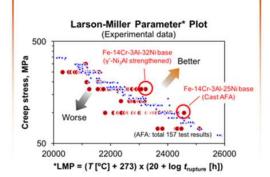
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Fitting High-Dimensional Datasets

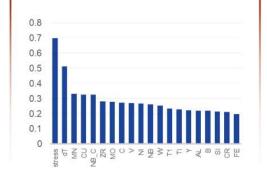
Data Collection/Population

- · Need consistent experimental data
- · What do we want to predict?
 - · Strength? Corrosion?
- · Material descriptors
 - · Composition
 - Thermodynamics and kinetics
 - · Microstructure etc.



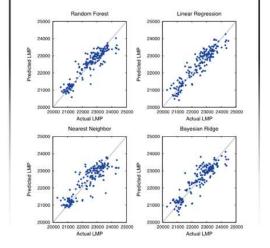
Correlation Analysis

- · Feature selection
- · High ranking descriptors
- · Superficial vs scientific descriptors
- · Participation of domain experts
- Iterative process



Machine Learning

- 'Just fit' the curve...
- · Different ML models













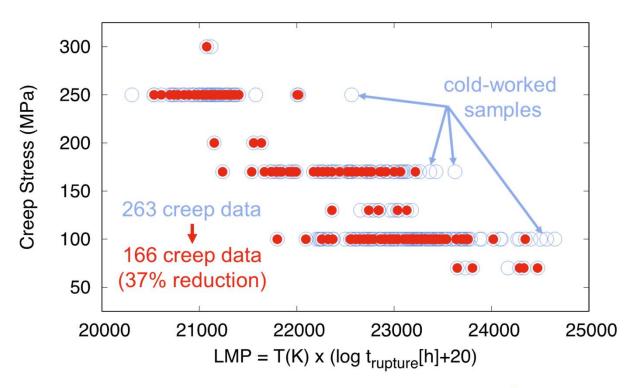








Knowing Pedigree of Data is Crucial to Develop Reliable Models

















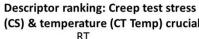


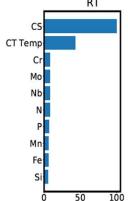


Analysis of Rupture Time for NETL 9Cr Data Set

We have constructed good ML models that could be used to predict chemistry with targeted rupture time.

(CS) & temperature (CT Temp) crucial

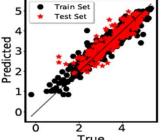


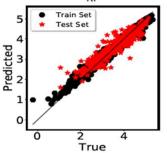


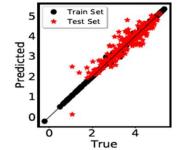
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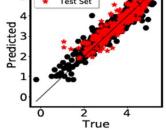




1248 data size, 26 descriptors

- Alloys compositions (21): Fe, C, Cr, Mn, Si, Ni, Co, Mo, W, Nb, Al, P, Cu, Ta, Hf, Re, V, B, N, O, S
- Temperatures (4): Homogenization heat treatment temp (Homo), Normalization temp (Normal), Heat treatment temp1 (Temper1), Creep Test Temp (CT Temp)
- Stress (1): Creep test stress (CS)





Idaho National Laboratory





Ultimate Goal of the Data Management and Analytics Task

		Access	ible	Datah	ases
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Open standard, sharable database formats with curated eXtremeMAT data Flexible interface for access control and simulation/analytics job launching Connectivity to existing open databases (energy materials network standards) Use data to develop reduced order models and link modeling scales

☐ Materials properties data for extreme environments

Structure, volume fractions of phases, and phase diagrams

New range of compositions beyond current standards

Thermomechanical processing history

Performance data: corrosion, fatigue, creep, UTS, LCF

Metastable data: time and temperature, aging

Uncertainty quantification

■ Analytical Tools

Novel tools to predict time to failure (incipient or not) in a chromia-forming alloy Design of a new alumina-forming alloy using the data and tools of eXtremeMAT



















Ultimate Goal of the Data Management and Analytics Task

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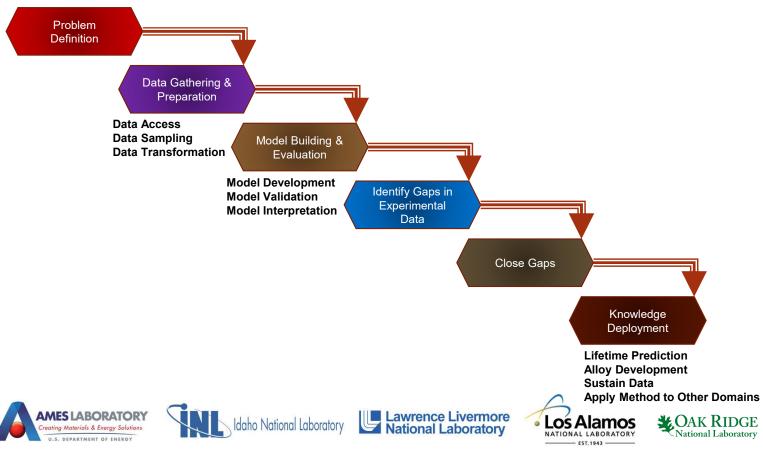






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Effective Integration Across Labs and Tasks









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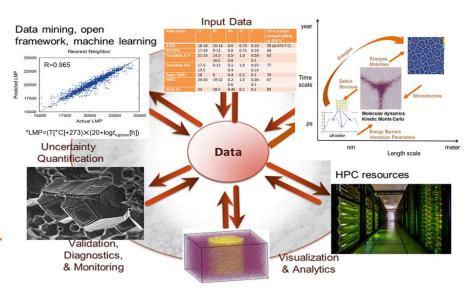


Questions?

We will use machine learning to develop datadriven models, develop linkages between physical models (Task 2)and connect them to experimental validation (Task 4).

These tools will reduce the time and cost for alloy development and lifetime prediction.

Task 4

















Task 2





Extra slides

- Variability is a huge issue
 - Composition and performance of the same alloy made by different teams could vary.
- Brute force simulations may not get us to our goal
- Embed data analytics and VV & UQ at every stage
- Need to decide on data and tools platform
 - · Framework should integrate metadata recording, job submission, publication, visualization, access control etc.
 - Get past IP concerns and open source tools
 - Access control and security; File versioning; Metadata and Provenance
 - Bulk uploads, large files (microstructure; 10s of GB)
 - Job launching (simulation management)
 - Support for other repositories
 - User interface must be intuitive for power and infrequent users















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- Need to put some thought into machine learning
 - ML often confirms your biases
 - Need ML that develops new and unanticipated insights
 - Genetic programs to develop constitutive laws on the fly
 - New analytic forms without prior assumptions
- Modeling should focus on relevant conditions
 - Previous alloy development was for room temp (no microstructural evolution)
 - Bond region in heat exchanger (don't model bulk for this)
- Multi scale models: Coarsening may throw out key data or features.
 - Don't throw the baby out with the bath water. Use human expertise with ML.
- CALPHAD is an inadequate database
- Classical thermodynamic data does not have a length scale (can't predict microstructure evolution)
- Identify relevant descriptors
 - Multiple descriptors; go beyond simple descriptors















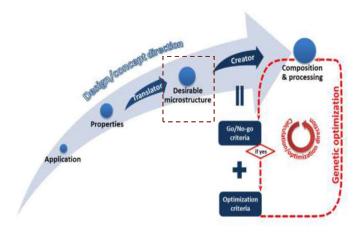


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- Data is available for composition and mechanical properties, but not for microstructure.
- Microstructure is treated as a black box between chemistry and properties.
- Microstructure changes during service.
- Need to develop key descriptors of microstructure for quantification.





Q. Lu et al, J. Mat. Sci. Tech, 2017







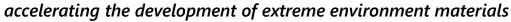






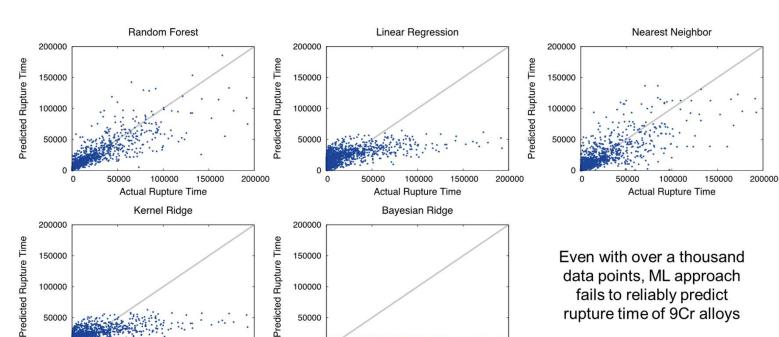








Preliminary analysis of NETL 9Cr alloy data







100000

Actual Rupture Time

150000





150000

100000

Actual Rupture Time











Preliminary analysis of NETL 9Cr alloy data

