# Augmented Experiments in Material Engineering Using Machine Learning

Aomar Osmani <sup>1</sup>, **Massinissa Hamidi** <sup>1</sup>, and Salah Bouhouche <sup>2</sup>

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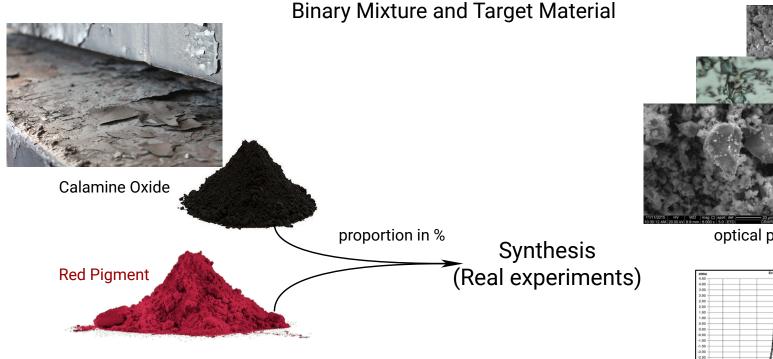
<sup>2</sup> Research Center in Industrial Technologies, CRTI

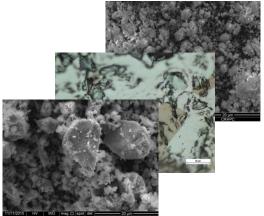




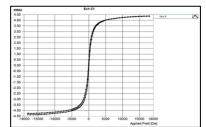


# Synthesis of New Materials in Industry



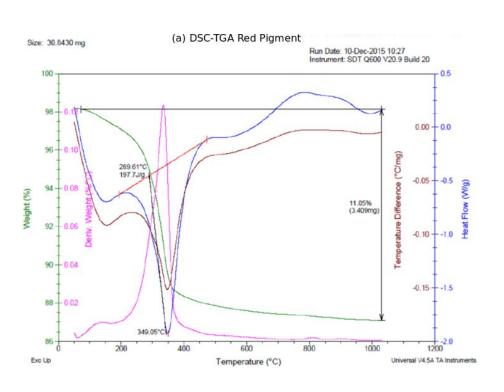


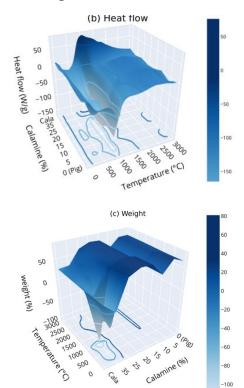
optical properties



ferromagnetic properties

#### **Thermal & Mass Loss Analysis**

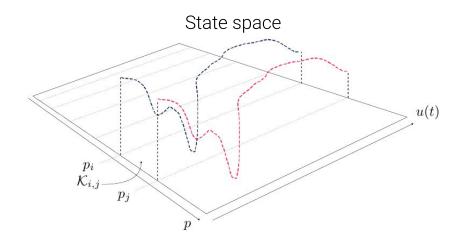




#### **State Space Partitioning & Evaluation Protocol**

#### Reconstruction models:

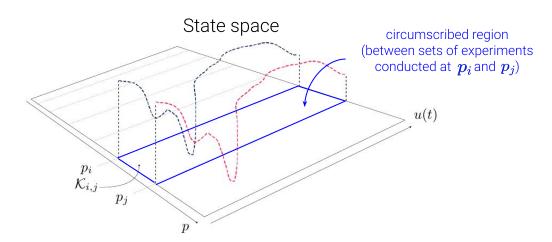
- Inside circumscribed regions;
- Outside circumscribed regions



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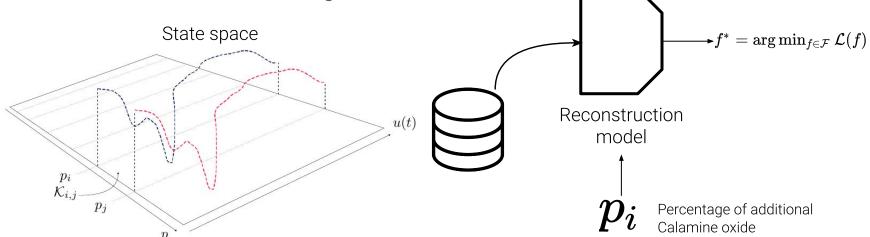
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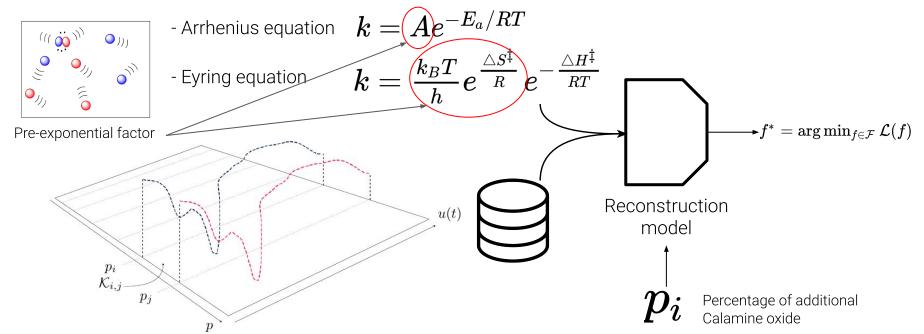
- Inside circumscribed regions;
- Outside circumscribed regions



# Combining Domain Models & Empirical Data

## **Combining Analytical Models and Real Experiments**

Rate of the reaction  $rac{\partial lpha}{\partial t} = k(1-lpha)^n$ 

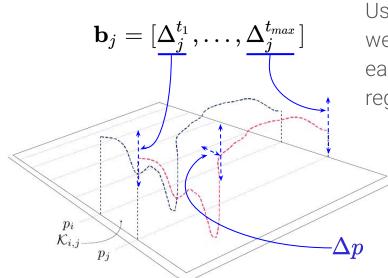


Laidler, Keith J. Journal of chemical Education 61.6 (1984): 494. Lasaga, Antonio C. Rev. Mineral. 8 (1981).

#### **Kinetic-Based Regularization**

u(t)

$$f^* = rg \min_{f \in \mathcal{F}} \mathcal{L}(f) + \lambda R(f)$$

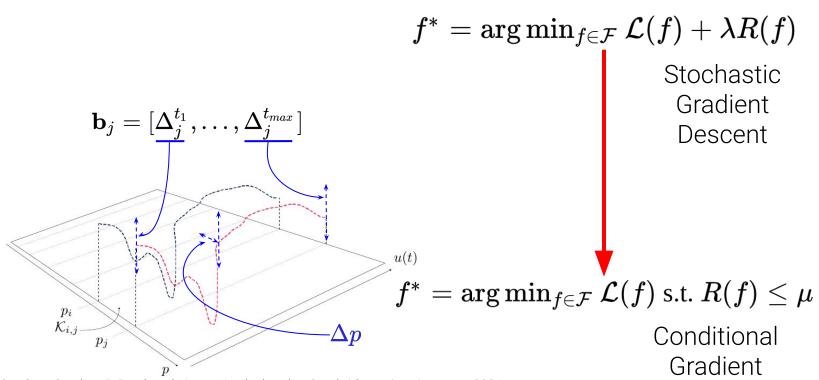


Using the neighboring points  $p_i + \Delta p, p_i + 2\Delta p, p_i + 3\Delta p$  we derive a series of penalty bounds  $\mathbf{b}_j = [\Delta_j^{t_1}, \ldots, \Delta_j^{t_{max}}]$  at each applied temperature  $t_1, \ldots, t_{max}$ . The regularization-like term becomes

$$R(f) = rac{1}{P} \sum_{j=1}^P 1\{|f(p_i + j\Delta p) - \mathbf{b}_j| > \epsilon\}$$

Boyd, Stephen, Stephen P. Boyd, and Lieven Vandenberghe. Cambridge university press, 2004. Ravi, Sathya N., et al. *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 33. 2019.

#### **Finding Pareto-Optimal Solutions**



Boyd, Stephen, Stephen P. Boyd, and Lieven Vandenberghe. Cambridge university press, 2004. Ravi, Sathya N., et al. *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 33. 2019.

# Experiments

#### **Experimental Setup**

#### - Dataset

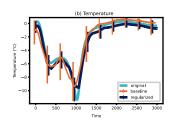
- SDT-Q600 from TA-instruments version 20.9 build 20;
- Monitored signals: temperature (°C), weight (mg), heat flow (mW), temperature difference(µV), sample purge flow (mL/min), etc.;
- 3000 measurement points at a sampling rate of 2 Hz;
- Real experiments conducted at 5, 10, 15, 20, 25, and 35 % of additional calamine oxide

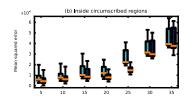
#### - Training details

- Stacking of Conv1d/ReLU/MaxPool blocks (Tensorflow);
- Hyperparameter optimization (scikit-optimize/Microsoft NNI);
- Kinetics regularization-like terms derived analytically (chempy)

#### **Experimental Evaluation**

(i) Reconstruction Process





(ii) Distance between Training and Validation Experiments

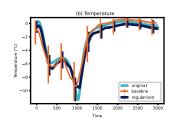
(iii) Reconstruction at specific percentages

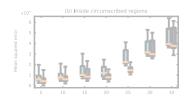
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Eyring (E)	$0.57 \pm .0145$ (10)	$0.385 \pm .0031$ (5)	$0.228 \pm .0079$ (10)	$0.587 \pm .0037$ (20)
pig (P)	$2.408 \pm .0034$ (10)	$0.408 \pm .015$ (5)	$1.188 \pm .0061$ (5)	$2.408 \pm .0042$ (10)
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(iv) Trade-off between real experiments and analytical models

#### **Experimental Evaluation**

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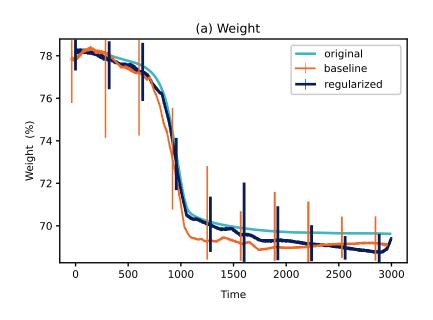
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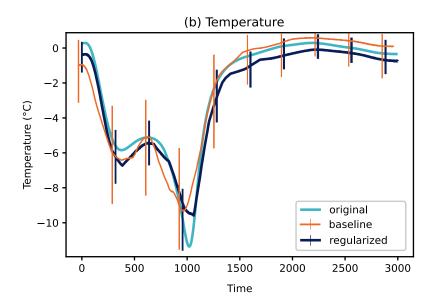
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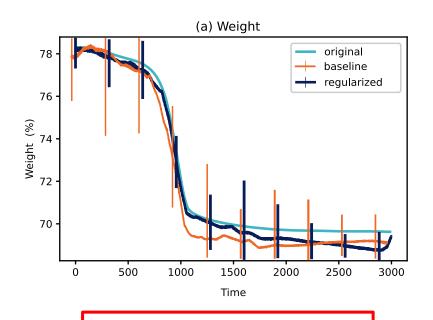
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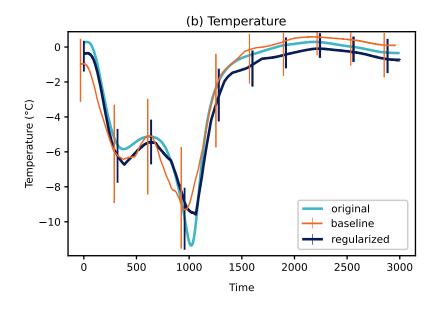
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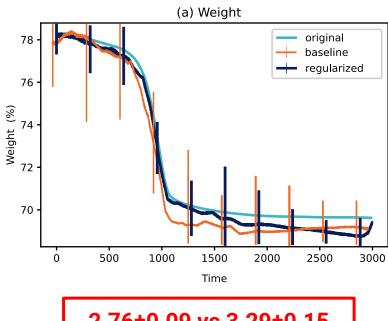
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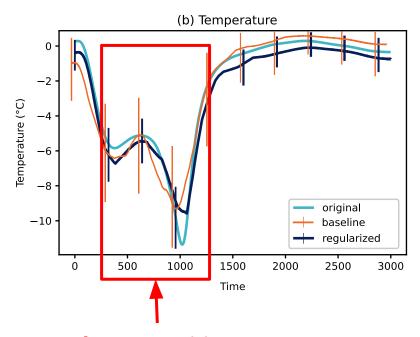


2.76±0.09 vs 3.29±0.15

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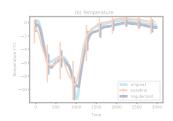
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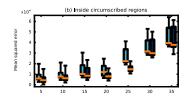


Phase transitions between ~ 250°C and 1250°C

#### **Experimental Evaluation**

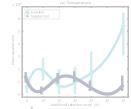
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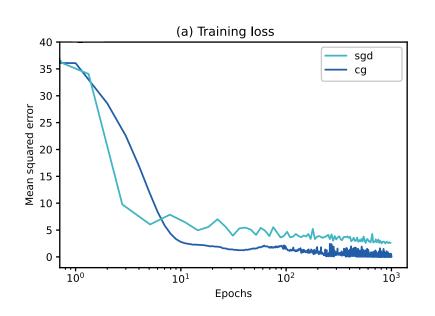
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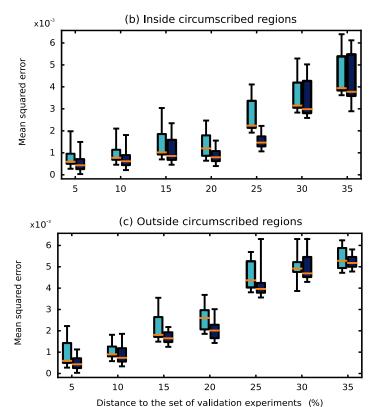


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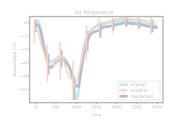
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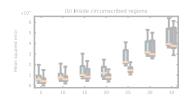




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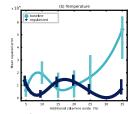
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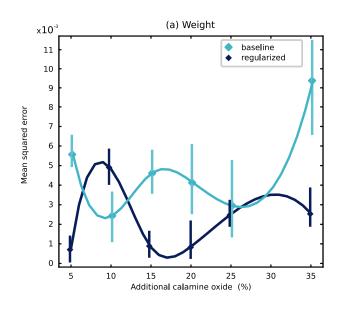
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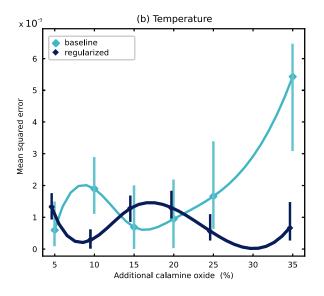


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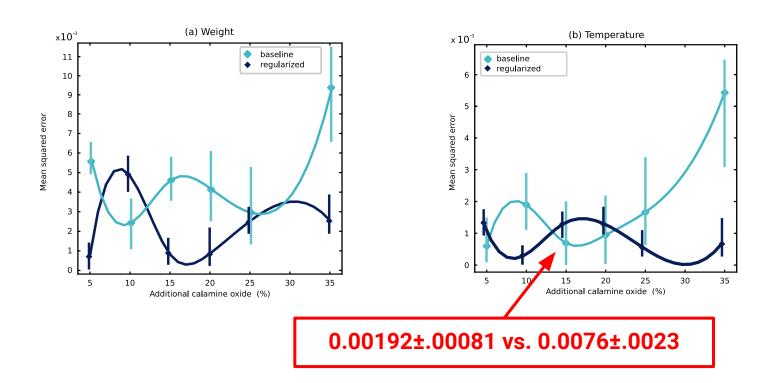
(iv) Trade-off between real experiments and analytical models

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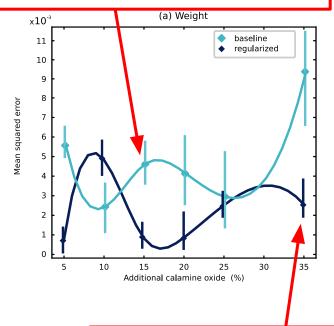


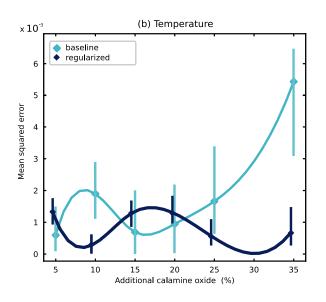
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0.00087±.00122 vs. 0.00477±.0021

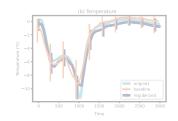


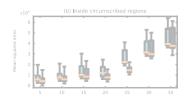


0.00246±.002 vs. 0.00932±.0056

#### **Experimental Evaluation**

(i) Reconstruction Process





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#### **Summary**

- Evaluation of a real-world application of material engineering;
- Incorporation of domain analytical models via regularization-like terms;
- Converge to Pareto-optimal solutions using conditional gradient descent;
- Extensive experimental analysis reveal remarkable efficiency improvement;

Aomar Osmani <sup>1</sup>, **Massinissa Hamidi** <sup>1</sup>, and Salah Bouhouche <sup>2</sup>

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