

# The Elucidation of Non-equilibrium States of Catalysis by Machine Learning Aided Atomic Simulations

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### A. OVERVIEW

C. METHODOLOGY & PRELIMINARY (PUBLISHED) RESULTS

Atomic-level description of non-equilibrium states of catalysis are investigated by machine learning aided-atomic simulations.

Multi-scale simulation enable big length-scale and long time-scale with first-principles accuracy.

Machine learning is used as a bridge between the first-principles calculations and higher scale simulations.

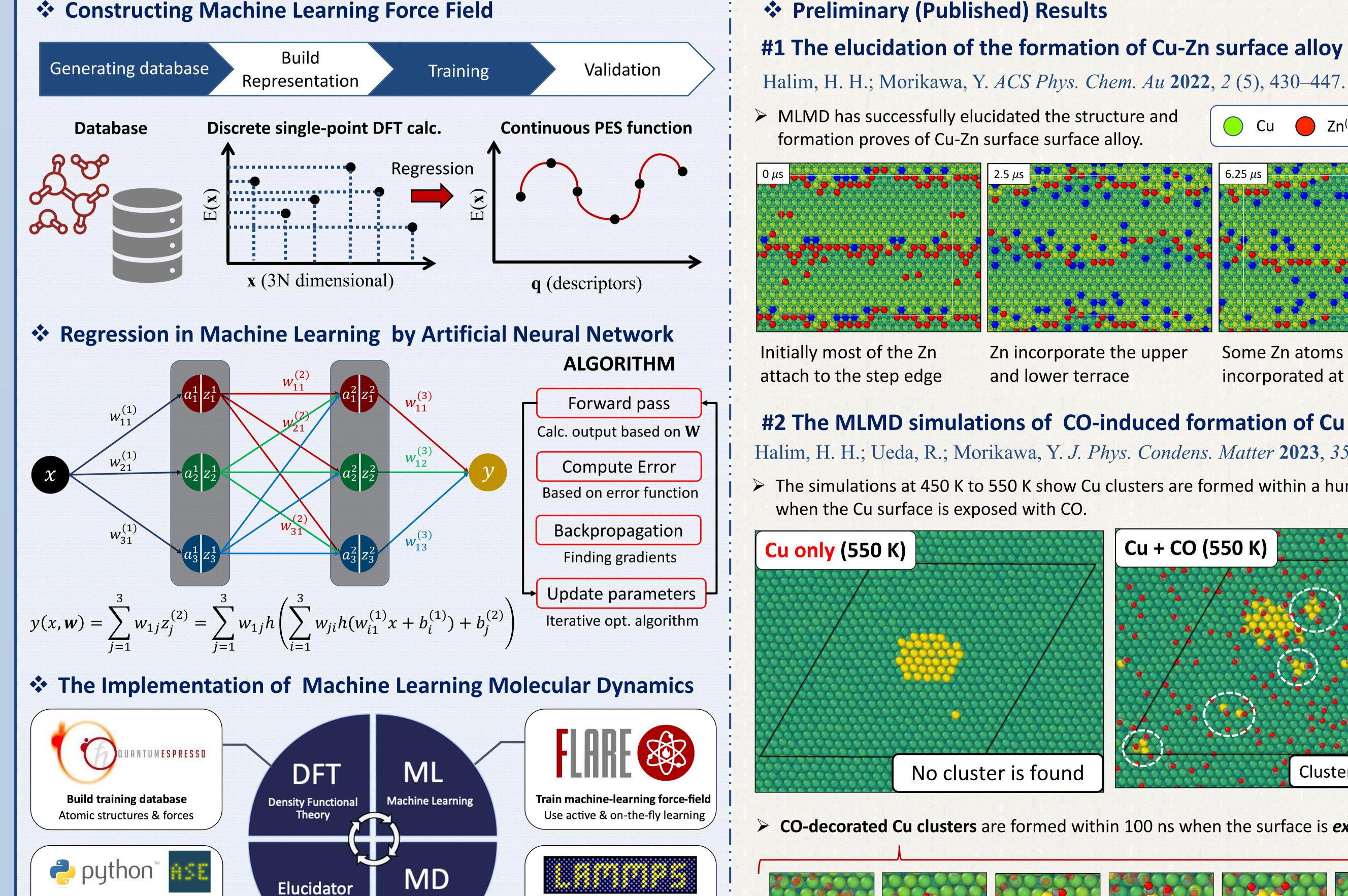
The simulations combines physics, chemistry, material science, chemical engineering, and data science.

#### **B. BACKGROUND** Catalysis is chemical reactions facilitated by with cat external material known as "catalyst". CH<sub>3</sub>OH **Heterogenous** → multi-phases are CO **Product** $CO_2$ $H_2$ involved (e.g., gas and solids) (gas) Reactant **CO<sub>2</sub> Hydrogenation to Methanol** (gas) Non-equilibrium states Adsorption Cu/ZnO/Al<sub>2</sub>O<sub>3</sub> Methanol Synthetic Gas $(CO / CO_2 / H_2)$ 200 – 300 °C Catalyst surface (CH<sub>3</sub>OH)(solid) **Reaction Pathway** Better understanding in catalysis well contributes in energy & environments.

#### B. BACKGROUND (continued) The challenge of the non-equilibrium states of catalysis Simulation tools ➤ Surface Evolution <</p> "The alloying . Closer to surface defect" effect" Element Non-equilibrium MC/KMC states Acchiacy **Adsorbate-adsorbate Surface-adsorbate** Interaction Interaction "Adsorbate-induced "The co-adsorption effect" surface transformation"

#### Machine Learning Aided Multi-scale Simulation **Machine Learning Force Field DFT Calculation Atomic forces** Force field Initial positions "Bridge" Verlet Alg. High scale simulation New positions ✓ First-principles level of accuracy ✓ Efficient for large system and long time scale

#### Objective: elucidate the behavior of catalysis at non-equilibrium states The Research Plan in Elucidating Non-equilibrium States **Train ML to Build Launch Simulation** Analyze the results **Build Training** Database (DB) Interatomic -1. Use the 1. Run Molecular **Potential** 1. Build DB for the simulation result as Dynamics (MD) feedback to clean surface. Simulation based on 1. Use Gaussian improve DB. Process and **ML** Potential 2. Build DB for Neural Network. surface + 2. Validate the 2. Extract the 2. Run active and adsorbates. accuracy of the properties of nonon-the-fly learning equilibrium states simulation scheme. of catalysis



## Zn incorporate the upper Some Zn atoms are incorporated at middle terrace and lower terrace **#2** The MLMD simulations of CO-induced formation of Cu clusters Halim, H. H.; Ueda, R.; Morikawa, Y. J. Phys. Condens. Matter 2023, 35 (49), 495001. The simulations at 450 K to 550 K show Cu clusters are formed within a hundred of ns when the Cu surface is exposed with CO. Cu + CO (550 K)No cluster is found Clusters are **found**! > CO-decorated Cu clusters are formed within 100 ns when the surface is exposed to CO. $Cu_3(CO)_3$ $Cu_6(CO)_5$ $Cu_4(CO)_4$ $Cu_5(CO)_5$ $Cu_2(CO)_2$ $Cu_7(CO)_6$

## D. ONGOING WORK & FUTURE PLAN

**Perform Machine Learning** 

**Molecular Dynamics (MLMD)** 

Get trajectories of atoms

- **❖ Improve the database** to include the other species relevant to methanol synthesis: CO₂, HCOO, HCOOH, CH₃OH, H₂O, etc.
- Perform long-time and large-scale MLMD simulations to provide explicit "molecular movie" of the catalysis.

**Analysis tools** 

Analyze the non-equilibrium states

> Elucidate the reaction networks

Search most effective active sites

Measure the reaction rates, etc.

- Connect the MLMD to higher scale simulations such as **Kinetic Monte Carlo** to enable **better comparison to experiments**.
- Design a new catalyst for the methanol synthesis based on the knowledge obtained from the multi-scale simulations.

Molecular

Dynamics

## E. REFERENCES

[QE] Giannozi. P., et.al, J. Phys. Condens. Matter, 21 (2009) 39550. [FLARE] Vandermause. J., et.al, npj Comput Mater, 6 (2020) 20. [LAMMPS] Thompson, A.P., et al., Comp Phys Comm, 271 (2022) 10817. [ASE] Larsen A. H., et al., J. Phys.: Condens. Matter. 29 (2017) 273002.