

Cite this: *Energy Adv.*, 2023,  
2, 1781

# Advancements in computational approaches for rapid metal site discovery in carbon-based materials for electrocatalysis

Somayeh Faraji,<sup>†</sup> Zhiyu Wang,<sup>†</sup> Paola Lopez-Rivera and Mingjie Liu<sup>†</sup>\*

Heterogeneous electrocatalysts exhibit immense potential for advancing energy technologies. However, the constraints associated with noble metals have sparked a surge of interest in the exploration of single-atom catalysts and metal–carbon hybrids as alternative options. Designing metal sites in carbon-based materials has demonstrated high activity, selectivity, stability, and cost-effectiveness in various electrochemical reactions. In spite of these advantages, the intricate nature of the designed structures and the expansive design space encompassing potential metal site structures pose formidable challenges in terms of experimental characterization and optimization. To address these challenges, computational approaches have emerged as powerful tools to accelerate the discovery of new metal sites in carbon-based materials and understand the structure–catalytic property relationships for electrocatalysis. In this review paper, we provide an overview of the state-of-the-art computational approaches from reported modeled structures, theoretical foundations of computational methods in modeling electrochemical reactions, to the data-driven approaches to accelerate new catalyst design. We summarize the utilization of structure-binding energy relationships, virtual high-throughput screening methods, and machine learning techniques to explore a wide range of metal site structures and identify promising candidates for experimental validation. Furthermore, the review highlights the importance of considering the solvent effect and the impact of spin/oxidation states on extra electron transfer to enhance the accuracy of predicting binding energies. Finally, we summarize the current challenges and offer a brief perspective on future opportunities in the field of computational acceleration for carbon-based catalyst development.

Received 8th July 2023,  
Accepted 6th September 2023

DOI: 10.1039/d3ya00321c

rsc.li/energy-advances

## 1 Introduction

Electrochemical reactions are critical for sustainable energy and environment, as they form the basis of numerous essential technologies like batteries, fuel cells, and electrocatalysis.<sup>1</sup> Heterogeneous electrocatalysts facilitate electrochemical reactions; thus, developing effective heterogeneous electrocatalysts is crucial for advancing these technologies and promoting sustainable energy and environmental practices. The bulk metals exhibit striking electrocatalytic properties for small molecule activation, for example, Pt for oxygen reduction reaction (ORR) and hydrogen evolution reaction (HER),<sup>2,3</sup> Cu for CO<sub>2</sub> RR,<sup>4,5</sup> and Ru, Pd, and Ag for NRR.<sup>6–9</sup> However, most of them are either noble metals or exhibit poor stability, selectivity, and activity. These limitations emphasize the necessity of developing new electrocatalysts to overcome these challenges.

Carbon materials, such as graphene and carbon nanotubes (CNT), hold great promise for electrocatalysis due to their high surface area, excellent electric conductivity, and remarkable thermal stability. Moreover, carbon is abundant and environmentally friendly, and has a multitude of allotropes that offer a diverse range of tunable properties through structural variations. The shortcoming of chemical inertness can be addressed by introducing defects and dopants which can act as active sites while the carbon materials behave as the substrate or host materials. For example, single atom catalysts (SACs) as one of the emerging heterogeneous catalysts consist of isolated metal atoms dispersed on a support material (*e.g.*, graphitic carbon, metals or metal oxides).<sup>10</sup> Numerous studies have demonstrated that carbon-based SACs and other metal–carbon hybrid structures (metal clusters on graphene or CNTs) are promising as the next-generation electrocatalysts for various electrochemical reactions, for example, water splitting, CO<sub>2</sub> RR, ORR, and NRR, with the potential to replace precious metal catalysts.<sup>11–13</sup> Therefore, the development of metal-doped carbon-based electrocatalysts has gained significant attention in recent decades

Department of Chemistry, University of Florida, Gainesville, FL 32611, USA.

E-mail: mingjieliu@ufl.edu

<sup>†</sup> These authors contributed equally to this work.

In this review, our main focus is the application of modeling and computation to expedite the design of carbon-based materials with carefully engineered metal sites. We first overview the well-studied modeled systems and summarize the quantum simulation-based approaches to understand the properties related to the electrochemical reactions (Section 2). Although these approaches can offer detailed insights into the structure–property relationships, enabling the design of efficient catalytic sites, the main challenge lies in the extensive design space and the inherent limitations in accuracy associated with these methods. To tackle these challenges, data-driven approaches such as high-throughput screening and machine learning models are employed. In the next two sections, we review the utilization of data-driven approaches to accelerate the exploration of the extensive design space (Section 3) and the ongoing endeavors to improve the accuracy of the computational models (Section 4). At last, we envision future opportunities from the computational perspective, poised to expedite the development of metal sites in carbon-based materials (Section 5).

## 2.1 Overview of well-explored structures

In addition to M-N<sub>4</sub>, the general M-N<sub>x</sub> moieties in the graphene lattice have also been explored. The number of coordinated nitrogen atoms varying from 1 to 6 can be modeled

Investigations have also been conducted on alternative coordinated atoms, apart from nitrogen. The most common alternatives are oxygen,<sup>76</sup> sulfur,<sup>77–80</sup> boron,<sup>81</sup> and phosphorus<sup>82,83</sup> with conclusions that some of the dopants coordinated with metal can show better catalytic activity than nitrogen<sup>76,79,83</sup> but the stability may decrease.<sup>77</sup> Dual metals<sup>84</sup> and metal trimers<sup>85</sup> are also investigated on graphene and graphdiyne. However, the metal clusters beyond that are barely explored due to the ambiguous metal cluster structures. Experimentally, the dual metal catalysts have been synthesized with Cu<sub>2</sub>, CuNi,<sup>86</sup> FeNi,<sup>87–89</sup> and FeCo<sup>90</sup> and the improved performance for CO<sub>2</sub>RR and ORR is explained by synergistic electronic modulation effects.<sup>89–91</sup>

Computational approaches based on DFT simulations provide an atomistic understanding of catalytic reactivity and stability. In the next two subsections, we will provide a brief overview of the approaches and their application in understanding these properties.

**2.2.1 DFT-based electrochemical modeling.** In electrochemical reactions, a series of intermediate steps occur, and each step involves the transfer of electrons and protons. In heterogeneous catalysts, the electrochemical process happens at the electrode/electrolyte interface, where the electrode/electrolyte serves as the conductor for electron/proton respectively. Under equilibrium, an electrochemical system is a grand canonical ensemble as it can exchange electrons with the electrode, while the standard DFT is performed in the canonical ensemble where the charge of the system is fixed. Hence, it is challenging to accurately describe the practical reactivity dependence on the electrode potential with DFT. Here, we focus on reviewing two most commonly used computational methods for modeling electrochemical reactions: the computational hydrogen

**2.2.2 Stability assessment.** Besides catalytic reactivity, structural stability is another crucial property. In SACs, the metal atom forms strong covalent bonds with the surrounding atoms, known as the covalent metal-support interaction (CMSI),<sup>103</sup> which plays a vital role in stabilizing the metal site within the carbon lattice. However, studies have also shown that certain metals, such as Fe<sup>104</sup> and Cu,<sup>105–107</sup> undergo aggregation in graphene. This mobility and structural transformations make the initially designed structure or active site unstable, consequently affecting the catalytic activity under experimental conditions. Therefore, it is imperative to meticulously evaluate the stability of the catalyst, especially under operando conditions, in order to facilitate a rational computational design and acquire a comprehensive understanding of the durability of these materials. Computationally, there are several common approaches to evaluate the stability, which can be categorized as thermal stability, thermodynamic stability, and electrochemical stability. Thermal stability is commonly examined using molecular dynamics (MD) simulations, which allow for the analysis of the structural changes at varying temperatures.<sup>62,85,108,109</sup> While the assessment of thermal stability is relatively straightforward, we will now provide more

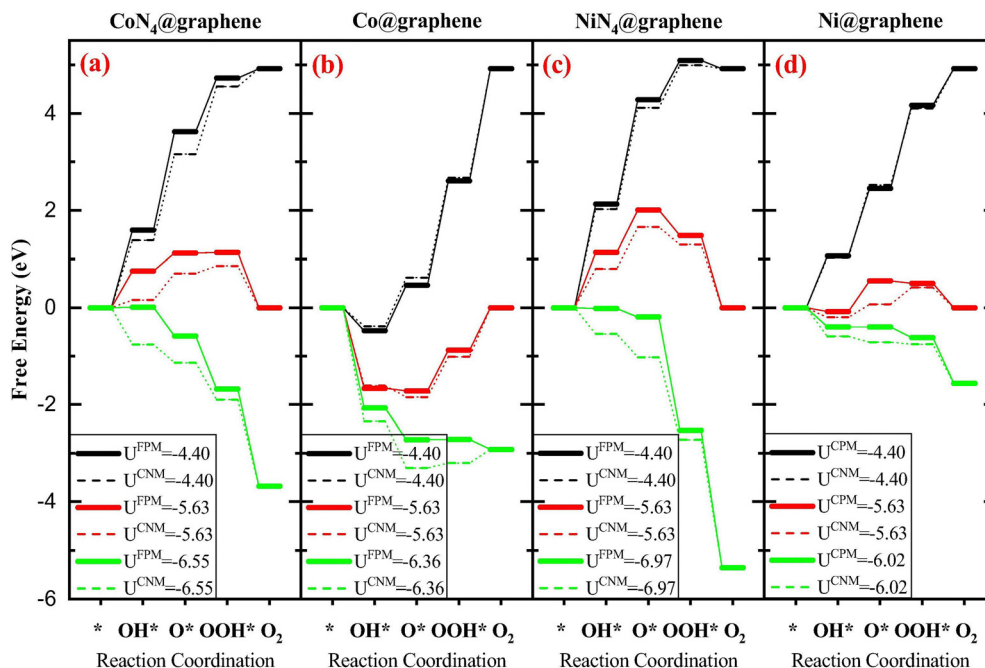


Fig. 1 The free energy diagrams associated with the OER on four different systems: (a) CoN<sub>4</sub>@graphene, (b) Co@graphene, (c) NiN<sub>4</sub>@graphene, and (d) Ni@graphene. FPM is GCDFT and CNM is CHE. Reprinted with permission from ref. 101. Copyright 2020 Elsevier.

details regarding thermodynamic stability and electrochemical stability.

**Thermodynamic stability.** To quantify the thermodynamic stability, the binding energy ( $E_b$ ), formation energy ( $E_f$ ), and diffusion barriers are usually calculated as criteria. The first criterion,  $E_b$ , is defined as

$$E_b = E_{M@sub} - (E_{sub} + E_M), \quad (2)$$

where  $E_{M@sub}$  and  $E_{sub}$  are the total energies of the substrate with and without the metal atom, and  $E_M$  is the energy of the isolated metal atom. According to this definition, a negative  $E_b$  indicates that the structure is thermodynamically favorable (the more negative the  $E_b$ , the more stable the structure).

The second criterion,  $E_f$ , employs a different reference energy of atoms to estimate the thermodynamics stability of the structure. For example, in the case of one metal anchored in the divacancy of N-doped graphene, the metal atom is coordinated with four atoms (*i.e.*,  $M@N_xC_{4-x}$ ), where the metal atom is bonded with  $x$  nitrogen atoms ( $x \leq 4$ ) and  $4 - x$  carbon atoms. The value of  $E_f$  can be calculated using the following equation:

$$E_f = E_{M@N_xC_{4-x}} + (x + 2)E_C - (E_{psub} + xE_N + E_{M^0}). \quad (3)$$

Here,  $E_{M@N_xC_{4-x}}$  and  $E_{psub}$  are the total energies of the system and the pristine substrate, and  $E_C$ ,  $E_N$ , and  $E_{M^0}$  are the energies of one carbon atom, one nitrogen atom, and one metal atom. The energy of atoms can be obtained from the most stable phase of each atom (*e.g.*,  $E_C$  as the carbon atom in graphene,  $E_N$  as the nitrogen atom in N<sub>2</sub>, and  $E_{M^0}$  as the metal atom in the bulk phase). The formation energy, depending on the reference

states of the atoms, represents the energy required to form the designed structures from the stable phases of those atoms.

It is also important to consider the stability of the metal atoms against aggregation. This could be examined by comparing the  $E_b$  of the metal in the carbon substrate and the metal bulk cohesive energy ( $E_{coh}$ ) which is defined as  $E_{coh} = E_{M^0} - E_M$ . Therefore, satisfying both conditions of  $E_b < 0$  and  $E_b > E_{coh}$  indicates the metal atom's propensity to aggregate. The mobility of the metal atoms in the carbon substrate has been employed as a means to assess their stability from a kinetic perspective. The diffusion barrier of the metal atom migrating in the substrate can be obtained by searching the transition states in the migration path. The lower the diffusion barrier, the easier the metal can migrate, potentially leading to favorable aggregation.

The mentioned criteria were employed in various studies. Some studies have only considered  $E_f$  for the stability.<sup>55,110</sup> Others have employed a combination of those criteria.<sup>34,85,108</sup> For example, the stability of Fe-N-C and Mn-N-C can be assessed based on  $E_f$ ,  $E_b$ , diffusion barriers, and  $E_{coh}$ .<sup>38,111</sup>

**Electrochemical stability.** The limitations of thermal and thermodynamic stability lies in their failure to consider the impact of electrode potential, pH, or electrolyte in actual catalytic reactions. In contrast, the evaluation of electrochemical stability specifically takes these factors into account. In the following, we will briefly discuss some attempts to address the electrochemical stability.

One way to evaluate the electrochemical stability is to consider whether the embedded metal atom will dissolve in



solution. This can be examined by the dissolution potential  $U_{\text{diss}}$  (relative to the SHE),<sup>112</sup> which is calculated as

$$U_{\text{diss}} = U_{\text{diss}}^0(\text{metal, bulk}) - (E_{\text{f}}/nq). \quad (4)$$

Here  $U_{\text{diss}}^0(\text{metal, bulk})$  is the standard dissolution potential (pH = 0) of the bulk metal, experimentally determined for pure metals in an aqueous solution;  $n$  is the number of electrons transferred during dissolution, which depends on the specific chemical reaction that takes place; and  $q$  is the electron charge. According to this definition, a more positive  $U_{\text{diss}}$  relative to the equilibrium potential indicates that the metal atom binds the substrate strongly, and the dissolution of metal atoms can be avoided under electrochemical conditions. The approach was initially proposed for surface alloys and then applied to SACs in N-doped carbon materials for catalytic reactions such as HER and OER,<sup>113</sup> CO<sub>2</sub>RR<sup>114</sup> and ORR.<sup>110,115</sup>

Another way to examine the electrochemical stability under operando conditions is through the Pourbaix diagram. The Pourbaix diagram depicts the thermodynamics stability regions of different chemical species in an aqueous solution as a function of electrode potential and pH.<sup>116</sup> Examples of constructing Pourbaix plots for SACs can be found in the literature.<sup>117–120</sup> For example, Holby *et al.*<sup>120</sup> proposed an approach based on DFT-calculated properties to explore the electrochemical stability of Fe–N<sub>4</sub> in bilayer graphene. The presented methodology can take reaction environment variables into account, such as pH, electrode potential, and reaction intermediates. Experimental observations regarding relative stability in acid vs alkaline environments, dissolution of Fe at low potential, and the possible role of O<sub>2</sub> can be well interpreted within the presented framework. There are also some other proposed approaches to incorporate environmental conditions to make results comparable with experiments. For example, experimentally reported reversible transformation between Cu single atoms and clusters under the realistic reaction conditions<sup>105,107</sup> can be explained by the constant potential hybrid-solvation dynamic model.<sup>121</sup>

The computational frameworks offer a unique approach to comprehending the structure–property relationship at an atomistic scale. By combining DFT-based simulations with fundamental physical principles, these frameworks can provide valuable design principles to guide experimental synthesis. The current focus in designing metal sites with carbon materials primarily revolves around manipulating the coordination environment surrounding single or dual metal sites within graphitic carbon structures. Through a combination of experimental synthesis and characterization, the incorporation of metal atoms into carbon-based materials exhibits tremendous potential for electrocatalysis. Given the diverse methods available to engineer the molecular interactions between metals and carbon during materials design, as well as the intricacies of electrochemical processes, the development of data-driven and accuracy-driven models has emerged as a solution to address challenges and expedite catalyst design. In the subsequent sections, we will delve into the exploration of these two aspects

separately, specifically in relation to the design of atomic metal sites in carbon-based materials.

We aim to provide an overview of recent successful applications of data-driven models in the field of designing metal atomic sites in carbon catalysts, encompassing high throughput screening, machine learning, and identification of key descriptors. In order to enhance the accuracy of computational modeling, we also review approaches for incorporating solvation effects, as well as electron and proton transfer mechanisms, spin states, and oxidation states into the models.

### 3 Structure–binding energy relationship

Catalysts are composed of various elements and combinations, which result in a high-dimensional composition space to be explored for specific catalytic reactions. In addition, catalytic reactions often involve multiple intermediates and reaction pathways which make the mechanism complex. Besides, catalyst properties depend on different factors such as surface morphology and electronic properties. Therefore, performing *ab initio* calculations for all possibilities becomes very challenging because of the high computational cost. The data-driven approaches to address these challenges will be discussed in this section.

#### 3.1 Linear scaling relationship and BEP relationship

The scaling relationship is a fundamental principle in catalyst design. It simplifies complex catalytic reactions which involve multiple reaction steps by finding relationships between those steps. There are two well-accepted scaling relationships for catalyst design: the linear scaling relationship and the Bell–Evans–Polanyi (BEP) relationship. The linear scaling relationship refers to the relationship between the adsorption energies of intermediates that bind to the catalyst surface through the same atom. For example, in CO<sub>2</sub> RR, the possible intermediates are \*COOH, \*CO, \*CHO, \*COH, \*CH<sub>2</sub>O, \*OH, and \*OCH (\* denotes the adsorption site). DFT studies revealed a linear relationship between  $E_{\text{ads}}[\text{CH}_2\text{O}]$ ,  $E_{\text{ads}}[\text{CHO}]$ , and  $E_{\text{ads}}[\text{COOH}]$  against  $E_{\text{ads}}[\text{CO}]$  on transition-metal surfaces.<sup>122</sup> Based on the scaling relationship, the complete free energy profile can be depicted by considering the adsorption energy of one (or a few) intermediate(s) on the same adsorption site. From these adsorption energies, the activity and selectivity can be inferred.<sup>123–125</sup> The linear scaling relationship can be explained through the bond order conservation theory.<sup>126–128</sup>

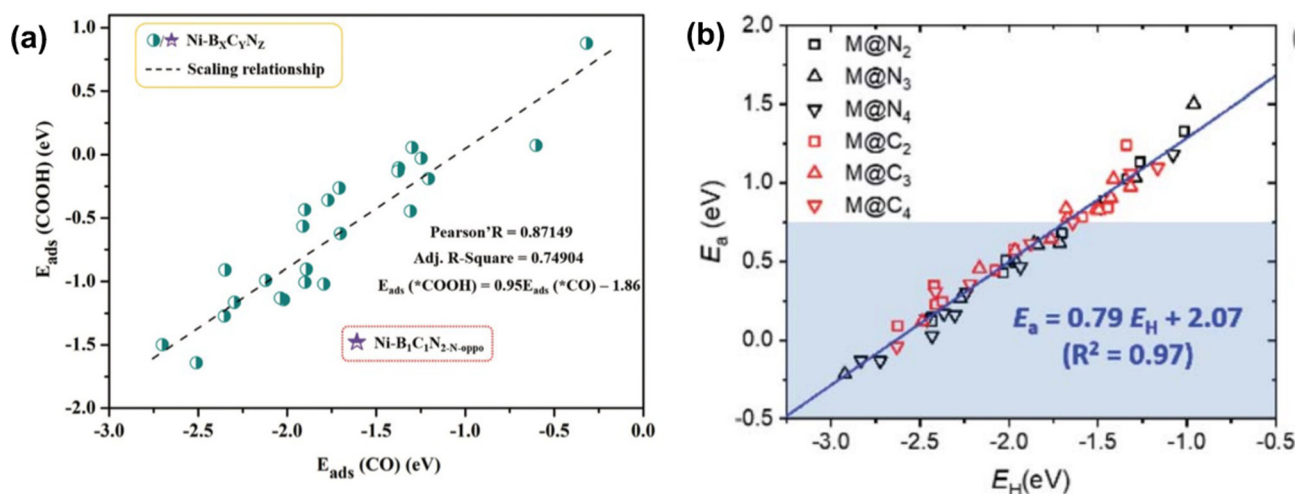
The BEP relationship establishes a connection between the activation energy (energy of the transition state) and reaction enthalpy (the enthalpy change in an elementary reaction). It states that these two quantities are proportional to each other. This idea was first demonstrated by Evans and Polanyi in 1937, who showed that an increase of reaction enthalpy causes a decrease in activation energy in classic molecular reactions.<sup>131</sup> After that, Michaelides *et al.* found that the linear relationship between activation energy change and enthalpy change was



Both scaling relationships have been examined in carbon-based SACs for various reactions. For example, in SACs on N-doped graphene and  $C_2N$ , the scaling relationship was established between the intermediates of ORR where  $\Delta E_{\text{ads}}$  between  $^*\text{OH}$  and  $^*\text{O}$  exhibited a slope close to 2, and  $^*\text{OH}$  and  $^*\text{OOH}$  showed slopes close to 1.<sup>60,136–138</sup> For  $\text{CO}_2$  RR, a linear relationship with a slope close to 1 was observed between the adsorption energy of  $^*\text{CO}$  and  $^*\text{COOH}$  or  $^*\text{CHO}$  on a single metal site with C-, N-, or B-doped graphene and  $C_2N$  (Fig. 2(a)).<sup>59,83,129</sup> For NRR, a scaling relationship was established between the adsorption energy of  $\text{N}_2\text{H}^*$  and  $\text{NH}_2$  with a slope close to 0.8<sup>139–141</sup> on metal (M) in single porphyrin sites and N-doped graphene ( $M = \text{Cr}, \text{Mn}, \text{Fe}, \text{Co}$ ). The BEP relationship was also examined for SACs in carbon-based materials. For example, to examine the activation energy for the transition state in ORR reaction, Wang *et al.* investigated the BEP relationship on zigzag, armchair, and basal plane of graphene and graphene oxide. A clear linear relationship was observed between the energy of the transition state and the chemisorption energy of the O atom with different functional groups.<sup>142</sup> Similar results were also observed in carbon-based SAC systems. Choi *et al.* studied 13 transition metals coordinated with N and C in graphene (denoted as  $M@N_xC_y$ ) for C–H bond activation. The

With the scaling relationships demonstrated for metal-carbon materials, the parameters that tune the adsorption energies of the key species can be used to screen new catalysts or catalytic sites that provide the best reactivity. However, it should be noted that the scaling relationships only apply to adsorbates that are adsorbed on the same site through the same type of atom that forms the chemical bonds with the site. Therefore, the application of linear relationships for catalyst design should be complemented by a thorough identification of active sites.<sup>143</sup> Compared to transition metal catalysts, the active sites in metal-carbon materials exhibit greater diversity. The scaling relationship, as a consequence, can be modified if different adsorption sites are introduced.<sup>91,144,145</sup> For example, both metal and non-metal as adsorption sites were observed in  $M@N_4C_4$  moieties ( $M = Fe, Co, Ni$ ) for ORR.  $*O$  and  $*OH$  were found to preferentially adsorb on the carbon site, while  $*OOH$  favored the metal site, circumventing the scaling relationship between their adsorption energies.<sup>14</sup> Similar strategies have also been used for NRR and  $CO_2$  RR on the  $C_3N$  monolayer and  $PC_6$ .<sup>139,144,146</sup>

One of the applications of the scaling relationships is virtual high-throughput screening (VHTS). The VHTS can rapidly screen and evaluate a large number of materials and active sites, and thus the process of catalyst discovery and optimization can be accelerated. In metal-carbon materials, both metal and carbon substrates can be tuned through various strategies. For instance, optimizing the activity can be achieved by using



© 2023 The Author(s). Published by the Royal Society of Chemistry

different metals,<sup>100,136</sup> different host materials,<sup>147</sup> and different coordination environments.<sup>55,56,65,66,68</sup>

Such flexibility in metal–carbon electrocatalysts was probed by Guo *et al.* They screened a total of 210 carbon-based SACs for ORR<sup>110</sup> by exploring 30 different transition metals in combination with various coordination and substrate materials, including defective graphene, N-doped graphene, and phthalocyanine (Pc). Among them, 31 SACs have the potential to break the scaling relationship, and high activity and selectivity can be achieved towards hydroperoxide by screening the adsorption energy of O\* (Fig. 3(a) and (b)). In their study, 7 SACs showed higher activity and selectivity than the benchmark PtHg<sub>4</sub> in acidic media. Zn@Pc–N<sub>4</sub> was recognized as the best catalyst with a small overpotential of 0.15 V, which was supported by experiments.<sup>148</sup> In NRR, multi-step screening strategies have been used to search for the optimized catalysts.<sup>139,149,150</sup> Ling *et al.* screened 540 SACs in nitrogen-doped graphene by varying metal coordinated atoms and single metal species. They found that W<sub>1</sub>C<sub>3</sub> site exhibited the most outstanding performance with an extremely low onset potential of 0.25 V.<sup>150</sup> In contrast, fewer VHTS have been applied for CO<sub>2</sub>RR.<sup>100,144</sup> Guo *et al.* explored 72 candidates of 12 metals with 6 different coordination environments. By screening the  $\Delta E_{\text{ads}}$  of \*CO, \*COOH and competing adsorption of \*H, they found that Fe–N<sub>4</sub>, Ni–N<sub>4</sub>, Cu–N<sub>4</sub>, Pd–N<sub>4</sub>, and Pd–N<sub>4</sub> are the most selective sites for CO<sub>2</sub>RR against HER.

In addition to the energetic screening for the adsorbents, stability has also been considered in the screening process.<sup>68,100,110</sup> In a previous example,<sup>110</sup> before screening the adsorption energy of O\*, the structures were first screened regarding the thermodynamic and electrochemical stability. The criterion for stability was  $U_{\text{diss}} > 0$  and  $\Delta E_{\text{f}} < 0$  as we explained in Section 2.2.2. Based on the examination of stability, the substrates such as BN, Pc–N<sub>4</sub>, and Py–N<sub>4</sub> are found to be good supports to host metal atoms. In terms of metal species, transition metals from group 8–12 are more likely to be stabilized under reaction conditions. In total, 146 SACs out of 210 were screened out (Fig. 3c), and Zn@Pc–N<sub>4</sub> is verified as the best candidate for both stability and high activity for 2-electron ORR. As a support, these active moieties also have been synthesized successfully including Ni–N<sub>4</sub>–C, Fe–N<sub>4</sub>–C, and Co–N<sub>4</sub>–C.<sup>14</sup>

VHTS is a powerful tool that greatly reduces the effort required for conducting experiments. This approach enables the exploration of various tuning parameters simultaneously. However, performing a large number of DFT calculations is still computationally expensive. Machine learning-assisted high-throughput screening can be further leveraged to accelerate the VHTS.

### 3.3 Machine learning for adsorption energies

As discussed, the energetic descriptor such as  $\Delta E_{\text{ads}}$  can be used as the property in VHTS to screen new catalysts; however, calculating the energetic property from DFT to explore the vast design space is time-consuming. A surrogate model based on machine learning methods provides a faster way to predict

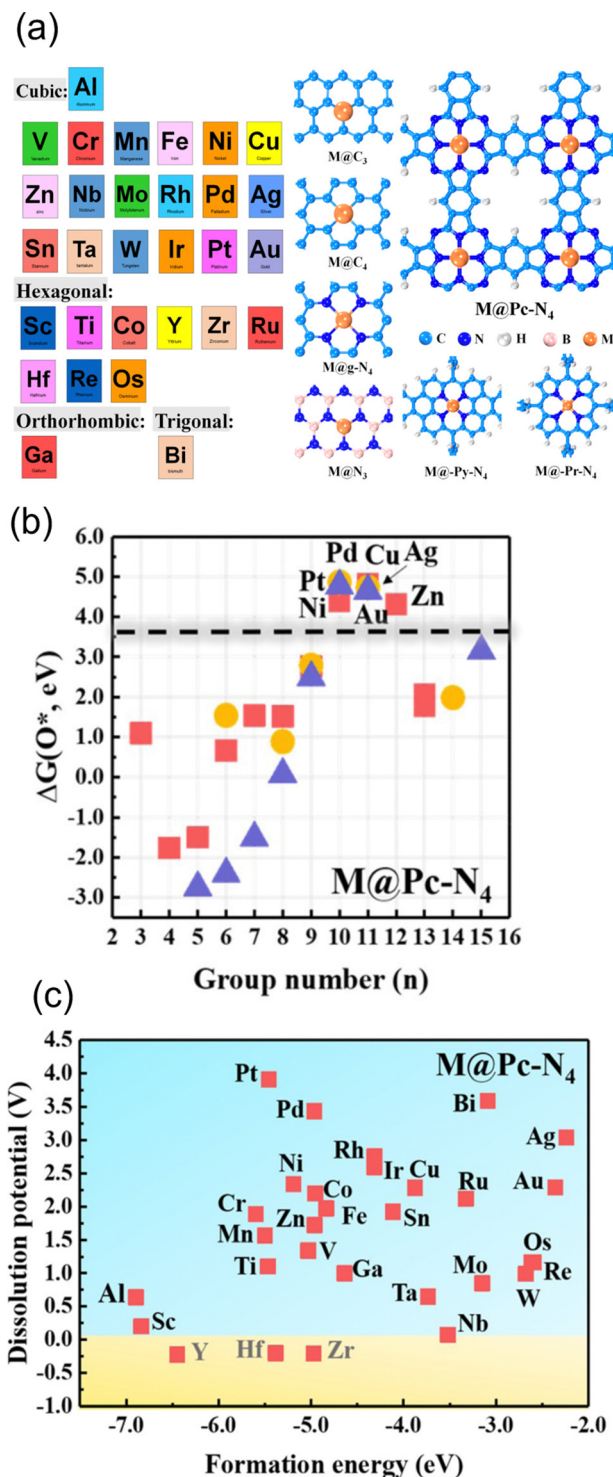


Fig. 3 (a) Schematic illustration of screened metal atoms with their most stable bulk structure and all considered substrates. (b) The O\* adsorption energy screening of metal from group 3–15 on Pc–N<sub>4</sub> configuration. Squares, circles, and triangles represent Al, 3d transition metal, 4d transition metal, and 5d transition metal, respectively. (c) The stability screen for metal on Pc–N<sub>4</sub> configuration. Reprinted with permission from ref. 110. Copyright 2019 American Society of Chemistry.

$\Delta E_{\text{ads}}$ .<sup>151</sup> The properties that machine learning model get trained to predict adsorption energy are known as features.

By selecting key features, machine learning models can not only predict accurate  $\Delta E_{\text{ads}}$  but also provide insights into the underlying mechanisms and design principles. In SACs, several machine learning models have been explored, including deep neural network (DNN),<sup>152</sup> random forest regression (RFR),<sup>60,153</sup> support vector machine (SVM),<sup>154</sup> gradient boosted regression (GBR)<sup>68,155,156</sup> and sure-independence screening and sparsifying operator (SISSO).<sup>157,158</sup> The training data for these models range from ten to thousands. For example, Kaspe *et al.* combined DFT simulations and machine learning models to predict the  $\Delta E_{\text{ads}}$  of \*OH in carbon-based materials for ORR.<sup>154</sup> They explored 2500 sites in 0D (graphene flakes), 1D (graphene nanoribbons), and 2D (graphene) doped with S, P, SO<sub>2</sub> and PO<sub>2</sub>, and applied six machine learning models with 13 electronic and structural features. The SVM achieved the best performance in testing, with an  $R^2$  coefficient of determination of 0.87, followed by multiple linear regressor ( $R^2 = 0.84$ ),  $K$ -nearest neighbor (KNN) ( $R^2 = 0.84$ ), RFR ( $R^2 = 0.83$ ), Extreme Gradient Boosting Regressor ( $R^2 = 0.79$ ), and Decision Tree Regressor ( $R^2 = 0.78$ ). Fischer *et al.* studied 1700 transition metals doped in defective N-doped graphene by varying the metal species, the number of dopants, and the number of vacancies for the adsorption energies of O and H adsorbate species. The best performance was given by the RFR model with MAE = 0.31 eV for testing in predicting the  $\Delta E_{\text{ads}}$  of \*O compared to SVM with MAE = 0.32 eV. Umer *et al.* screened 364 SACs by anchoring 3d–5d single metal atoms on various substrates. A combined DFT-machine learning framework found that mono- or dual-type

non-metal (B, N, and P) doping in g-C<sub>3</sub>N<sub>4</sub>, two-dimensional  $\pi$ -conjugated polymer, graphene and hexagonal boron nitride can substantially improve HER activity and stability. For predicting the adsorption energy for H\*, Light Gradient Boosting Machine (LGBM), Histogram-based Gradient Boosting Regressor (HGBR), Extremely Randomized Trees (ERT), Gradient Boosting (GB), Bagging, XGBoost regressor (XGBR), RFR and AdaBoost regressor (ABR) are used. The top three performances are given by LGBR with RMSE = 0.20 eV, HGBR with RMSE = 0.24 eV and ERT with RMSE = 0.26 eV (Fig. 4(a)).

Besides predicting  $\Delta E_{\text{ads}}$ , machine learning models have also been used to reveal the structure–property–performance relationship where there are multiple properties that could influence the catalytic performance. For instance, Zhu *et al.*<sup>155</sup> employed DFT and machine learning to study ORR on dual-metal site catalysts (DMSCs) in the carbon substrate and provide a comprehensive depiction of the relationship between intrinsic properties of these catalysts and their catalytic activity. They found that electron affinity, van der Waals radius, and electronegativity of two metal sites are important properties related to the adsorption energy of OH\*. In another example, Deng *et al.* employed a DFT-machine learning study to understand the origin of the activity of bi-atom catalysts on N-doped graphene for ORR. They considered 20 electronic and geometric features in an RFR model, and the ranking of feature importance directly translated from the weight of each feature. Two dominant features, M–M (distance of two metals) and M–N (average distance between the metal and coordinated N atoms),

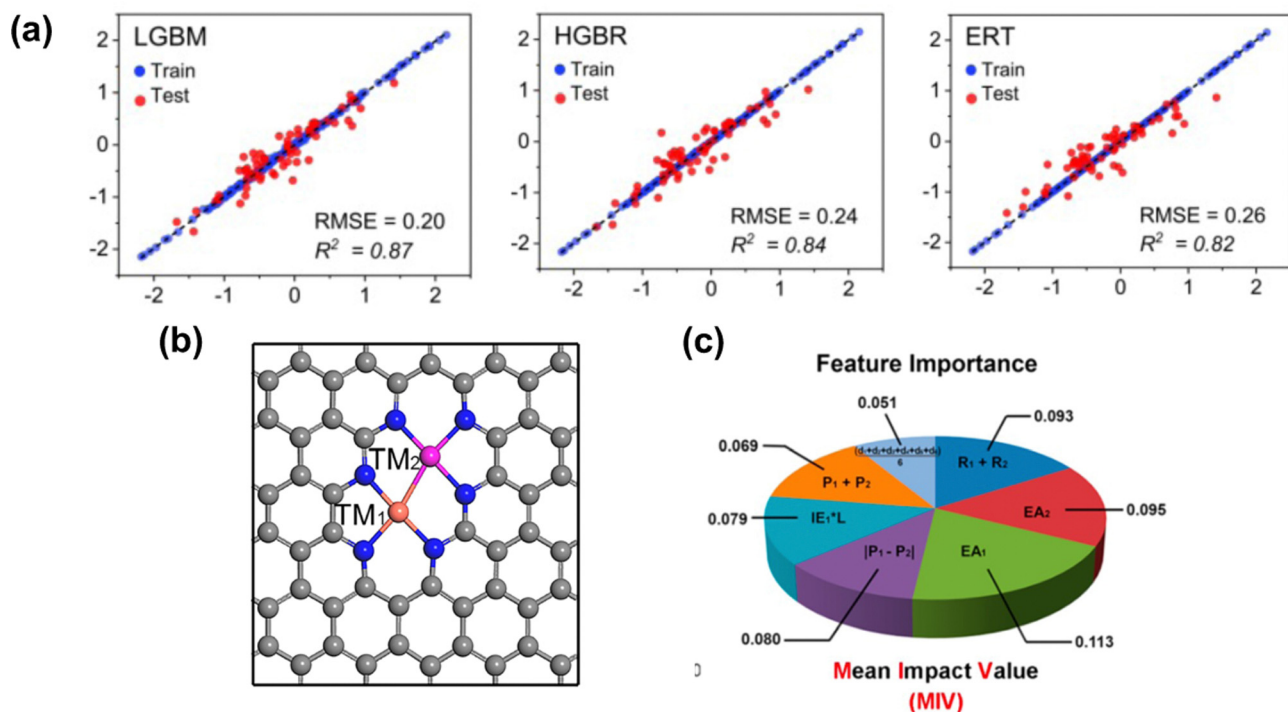


Fig. 4 (a) Machine learning model performance for predicting the adsorption energy of H\* on 2D carbon materials. (b) Schematic illustration of the bi-metal site on graphene. (c) Mean impact value (MIV) employed for considering feature importance. Reprinted with permission from ref. 159. Copyright 2022 Royal Society of Chemistry.

rates the number of d electrons of a metal atom ( $V_M$ ), the electronegativity of the metal atom ( $X_M$ ), its nearest atom ( $X_L$ ), adsorbate C ( $X_C$ ) or O ( $X_O$ ) atom connected to the metal atom, and the bond length between the metal atom and its nearest neighbor atom (d). This descriptor accurately describes the  $\Delta E_{\text{ads}}[\text{*CHO}]$  for CO<sub>2</sub> RR on M-N<sub>4</sub>-C SACs, as determined in

| Category               | $\phi$                                                                                                                                                                                        | Property                                                                        | System                          | Reaction                     | Ref. |
|------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------|---------------------------------|------------------------------|------|
| Physical-based         | d-Band center                                                                                                                                                                                 | $\Delta E_{\text{ads}} \propto$ d-band                                          |                                 |                              | 160  |
|                        | $\theta_{\text{d}} \times E_{\text{TM}}$                                                                                                                                                      | $\Delta E_{\text{ads}}[\text{OH}^*]$                                            | g-C <sub>3</sub> N <sub>4</sub> | ORR                          | 163  |
|                        | $k(S_{\text{v}}^{-2}/\chi^{\beta}) + b$                                                                                                                                                       | $\Delta E_{\text{ads}}$                                                         | Various substrates              | CO <sub>2</sub> RR, NRR, ORR | 164  |
|                        | $\theta_{\text{p}}$                                                                                                                                                                           | $\Delta E_{\text{ads}}[\text{OH}^*]$ ,<br>$\Delta E_{\text{ads}}[\text{OOH}^*]$ | N-Doped CNT,<br>B-doped CNT     | ORR                          | 165  |
| Fitting-based          | $\theta_{\text{d}} \times \frac{E_{\text{M}} + \alpha \times (n_{\text{N}} \times E_{\text{N}} + n_{\text{C}} \times E_{\text{C}})}{E_{\text{O/H}}}$                                          | Activity, $\Delta G[\text{OH}^*]$ ,<br>$\Delta G[\text{H}^*]$                   | N-Doped gra-<br>phene SACs      | ORR, OER, HER                | 166  |
|                        | $\frac{V_{\text{M}} \left[ X_{\text{M}} \left( \prod_{L=1}^N \frac{1}{d^L} X_L \right) \right]^{1/(N+1)}}{X_{\text{C/O}}}$                                                                    | $\Delta E_{\text{ads}}[\text{*CHO}]$                                            | M-N <sub>4</sub> -C             | CO <sub>2</sub> RR           | 114  |
|                        | $(4 \times V_{\text{M}_1} \times (E_{\text{M}_1} + E_{\text{N/O}})/E_{\text{N/O}} + V_{\text{M}_2} \times (E_{\text{M}_2} + E_{\text{N/O}})/E_{\text{N/O}}) \times L_{\text{M}_1-\text{N/O}}$ | Catalytic activity                                                              | Bimetallic 2D<br>MOFs           | CO <sub>2</sub> RR           | 167  |
| Machine learning-based | $-1.032 \times (e_{\text{d}}/q) + 13.424 \times (1/r_{\text{cov}}) + 1.726 \times (e_{\text{d}} \times \text{EN}) - 0.045 \times d_{\text{occ}}^2 - 9.241$                                    | $\Delta G[\text{H}^*]$                                                          | N-Doped gra-<br>phene SACs      | HER                          | 157  |
|                        | $0.69 + 0.00029\sqrt{\text{EA}_1} + 0.15\text{EA}_1 - 0.067\sqrt{\text{EA}_2} + 0.0076\text{EA}_2$                                                                                            | $\Delta G[\text{OH}^*]$                                                         | Dual-metal<br>catalysts         | ORR                          | 155  |
|                        | $-0.012(R_1 + R_2) - 1.19 P_1 - P_2 ^2$                                                                                                                                                       |                                                                                 |                                 |                              |      |

Electrocatalytic processes occur in aqueous solutions; hence, there are more complex interactions and other physical parameters involved in the actual reaction that have not been fully considered. Besides, in metal-carbon systems, the spin and



Some studies consider only the role of different spin states and demonstrate how these states alter the reaction pathway of catalytic reactions.<sup>104,203–206</sup> For example, spectroscopic studies of Fe–N–C systems consider two distinct moieties, namely high-spin FeN<sub>4</sub>C<sub>12</sub> and low/intermediate-spin FeN<sub>4</sub>C<sub>10</sub>.<sup>104</sup> The results show that both sites initially contribute to the ORR activity but only the low/intermediate-spin moiety substantially contributes after 50 hours of operation. This experimental evidence motivated the examination of oxidation and spin states in computational catalysis. For example, DFT studies on the (salen)Mn(III)-catalyzed epoxidation reaction mechanism reveal that competing channels have different spin states.<sup>203</sup> DFT results on M–N<sub>4</sub>–C (M = Mn, Fe, and Co) systems for ORR show that Mn–N<sub>4</sub> and Fe–N<sub>4</sub> centers in graphene exhibit the lowest O<sub>2</sub> dissociation energies across three spin channels,

while for Co-N<sub>4</sub> they find two spin channels require the same dissociation energy.<sup>204</sup> Additionally, a study on Fe-N-C systems for ORR indicates that the change of electronic spin moments of Fe and O<sub>2</sub> due to molecular-catalyst adsorption scales with the amount of electron transfer from Fe to O<sub>2</sub>, as shown in Fig. 6, promoting the catalytic activity of C<sub>2</sub>N-Fe for driving ORR.<sup>206</sup> Based on the relationship between catalytic activity and spin moment variation, they suggested that the electronic spin moment could be a promising catalytic descriptor for Fe SACs.

Some studies consider the effect of both oxidation and spin states in the catalysts.<sup>207,208</sup> For example, an experimental study on Fe-N-C for selective oxidation of C-H bonds provides evidence that among different FeN<sub>x</sub> ( $x = 4-6$ ), the medium-spin Fe(III)N<sub>5</sub> affords the highest turnover frequency (6455 h<sup>-1</sup>), and is at least 1 order of magnitude more active than the high-spin and low-spin Fe(III)N<sub>6</sub> structures and 3 times more active than the Fe(II)N<sub>4</sub> structure, although its relative concentration in the catalysts is much lower than that of the Fe(III)N<sub>6</sub> structures.<sup>205</sup> Yang *et al.*<sup>207</sup> investigated dual-metal atomically dispersed Fe, Mn/N-C catalysts and found that the O<sub>2</sub> reduction preferentially takes place on Fe(III) in the FeN<sub>4</sub>/C system with the intermediate spin state which possesses one e<sub>g</sub> electron (t<sub>2g</sub><sup>4</sup>e<sub>g</sub><sup>1</sup>) readily penetrating the antibonding  $\pi$ -orbital of oxygen. Both magnetic measurements and the theoretical calculation reveal that the adjacent atomically dispersed Mn-N moieties can effectively activate the FeIII sites by both spin-state transition and electronic modulation, rendering the excellent ORR performances of Fe,Mn/N-C in both alkaline and acidic media. Gong *et al.*<sup>208</sup> developed a facile strategy to manipulate the cobalt spin state over COF-367-Co by changing the oxidation state of Co, resulting in the regulation of the photocatalytic performance for CO<sub>2</sub>RR and enhanced selectivity to HCOOH. According to their DFT calculations and experimental results, Co(II) and Co(III) are embedded in COF-367 with  $s = \frac{1}{2}$  and 0 spin ground states, respectively.

In electrocatalysis, the transfer of electrons and protons between the electrode, catalyst, and reactants is important. Proton transfer is often coupled with electron transfer in a process known as proton-coupled electron transfer (PCET), which can modulate the pathway that the reactants follow. Therefore, this coupled motion of electrons and protons plays a critical role in a wide range of electrochemical processes such as CO<sub>2</sub>RR, ORR, and N<sub>2</sub>RR in carbon and carbon-metal systems.<sup>134,209-214</sup> Fig. 7 provides a representative example demonstrating how electron transfer (ET), proton transfer (PT) and PCET affect the reaction mechanism during the four-electron ORR on nitridated carbon (NC) catalysts. Generally, PCET describes the mechanism of electron and proton transfer from atom to atom, which is also important for catalyst design. As described in Section 2.2, CHE predicts the thermodynamics properties of electrochemical reactions. Thus, PCET reactions can be evaluated using CHE which uses gas phase H<sub>2</sub> formed from H<sup>+</sup> and e<sup>-</sup> as a reference reaction. This intrinsically connects the PCET step to the standard hydrogen electrode (SHE) scale. To understand PCET at interfaces, where there are spatially inhomogeneous internal electric fields and electrostatic potentials within the active site, we need modeling strategies to explore PCET thermodynamics and further develop molecular active sites. Recent works have attempted to provide atomic-scale insight into interfacial PCET reactions, which are key steps in catalyst design. For instance, Hammes-Schiffer *et al.*<sup>215</sup> provide a first-principles modeling strategy based on DFT calculations. They illustrated that investigating the interfacial PCET at graphite-conjugated catalysts (GCC) bearing organic acid moieties explains the absence of a cyclic voltammetry peak. This combined theoretical-experimental study not only demonstrates the critical role of continuous conjugation and strong electronic coupling between the GCC acid sites and the graphite in enabling PCET at acid sites, but also emphasizes the importance of understanding the connection between the atomic structure of the surfaces and the

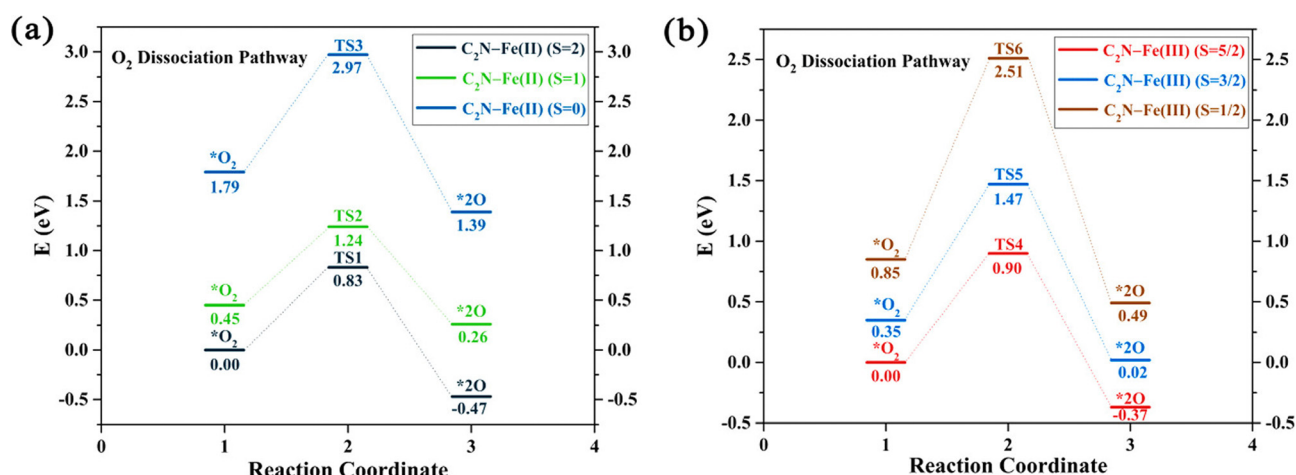
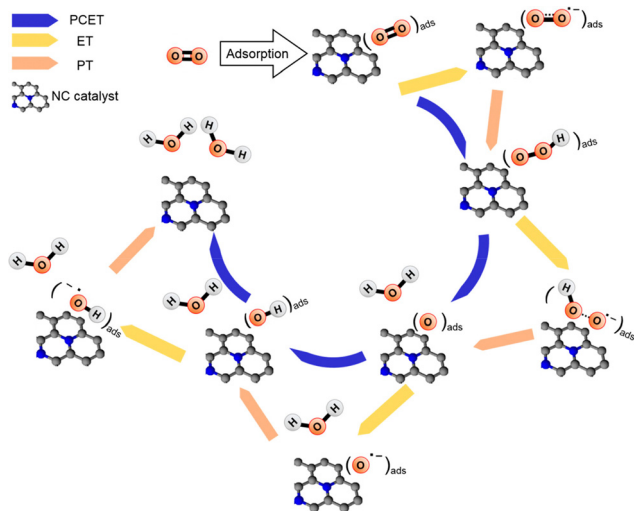


Fig. 6 The potential energy profiles for the O<sub>2</sub> dissociation pathway calculated for two systems: (a) C<sub>2</sub>N-Fe(II) with spin states  $S = 2, 1$ , and  $0$ , and (b) C<sub>2</sub>N-Fe(III) with spin states  $S = 5/2, 3/2$ , and  $1/2$ . The relative energies represented in the profiles correspond to Gibbs free energies, with the energies of the spin ground states set as a reference point at  $0$  eV. Reprinted with permission from ref. 206. Copyright 2021 American Chemical Society.



**Fig. 7** Representative possible elementary steps during four-electron ORR ( $\text{O}_2 + 4\text{H}^+ + 4\text{e}^- \rightarrow 2\text{H}_2\text{O}$ ) on carbon-based electrocatalysts. Black and blue balls represent carbon and nitrogen atoms, respectively. Reprinted with permission from ref. 210. Copyright 2018 American Chemical Society.

interfacial electrostatic potentials and fields that govern PCET thermochemistry. Furthermore, the study of these GCC catalysts in the presence of defects, such as heteroatom dopants in the graphitic surface, reveals that the lowest unoccupied electronic states can serve as a descriptor for changes in PCET thermodynamics.<sup>216</sup> Such studies highlight the need to consider PCET mechanisms in the computational screening of SACs.

The above-mentioned case studies provide evidence that oxidation states, spin states, and interfacial PCET are critical issues that cannot be ignored in catalyst design. However, providing computationally accurate results for such properties is challenging. For instance, it has been shown that the choice of DFT exchange–correlation functional can highly affect the binding energy of CO on TM atoms embedded on nitrogen-doped graphene.<sup>217</sup> Similarly, the absolute value of the spin magnetic moment of Fe, the spin magnetic moment of  $^*O_2$  ( $M^*O_2$ ), and the d-band center gap of spin states can also be affected.<sup>218</sup> For the (salen)Mn(III)-catalyzed epoxidation reaction mechanism, Abachkin *et al.* clearly showed how the choice of DFT functional and model can dramatically change the results.<sup>203</sup> Hence, these challenges can generally be addressed for specific systems with careful treatment of each effect. Nevertheless, the solution is still computationally expensive and not feasible for widely applying in large structural space search.

## 5 Perspectives and future opportunities

In Section 2.1, we have summarized the computational work on single atom and multiple metal sites in carbon-based materials, covering the exploration of coordination configurations, carbon

substrate structures, alternative dopants, and their influences on catalytic activity and stability. However, to find an optimal  $M-X_x$  ( $X = N, P, S, B, \text{etc.}$ ) moiety that possesses high activity, selectivity and stability remains demanding and not straightforward, particularly in the exploration of moieties in different graphitic carbon structures to host  $M-X$  sites. Additionally, the curvature of the carbon substrates can also affect the properties of the electrocatalysts. Unfortunately, most modeled structures are primarily based on flat graphene substrates, with only a few studies demonstrating the importance of the curvature effects. For example, fullerenes which exhibit reactivity changes due to their curvatures<sup>219</sup> are rarely explored. In contrast, studies on N-doped fullerenes indicate the potential of such structures as cathode catalysts for hydrogen fuel cells,<sup>220</sup> CO oxidation,<sup>221,222</sup> and ORR.<sup>223</sup> In light of the challenges encountered in the exploration of optimal configurations for metal embedded in carbon-based catalysts, there are compelling opportunities to advance the field through the development of innovative computational tools and collaborative initiatives. One such opportunity lies in the creation of automated virtual high-throughput screening workflows that would be capable of swiftly exploring the huge design space. The workflows that can automatically generate diverse structures, efficiently perform DFT simulations, and subsequently conduct data-driven assessments would revolutionize the search for stable moieties that exhibit enhanced catalytic stability and selectivity.

Furthermore, accurately describing the reactivity through DFT simulations presents another significant challenge. A benchmark from the comparison with experimental data to assess the accuracy of different computational models is needed. Also, modeling the catalysts under operando conditions by considering the solvent effects, electrode potential, and structural evolution during reactions increases both the complexity of the model and the computational costs dramatically. As a consequence, attaining high accuracy in virtual high-throughput screening continues to be a persistent challenge. One potential solution is to train an accurate machine learning model to replace the computationally expensive DFT simulations. The machine learning models are expected to be trained based on the database that would be obtained from simulations with high accuracy. The establishment of such database plays a pivotal role in accelerating the research in the field. The database could serve as a repository with valuable information on structural, electronic and catalytic properties regarding the metal embedded in carbon-based materials.

Overall, computational approaches such as DFT simulations and data-driven models have been extensively leveraged in discovering sustainable, cost-effective, and highly reactive electrocatalysts derived from metal-carbon materials. However, there is still a need for efficient and predictive machine learning models. Training those models requires automated virtual high-throughput screening tools as well as accessible databases, which serve as crucial components in advancing the field. In conclusion, the continued advancement and integration of computational techniques, coupled with experimental efforts, hold tremendous promise for accelerating the

development and optimization of metal sites in carbon-based materials for electrocatalysis, propelling us closer to realizing efficient and scalable energy technologies.

## Author contributions

Somayeh Faraji: literature curation, formal analysis, investigation, methodology, writing – original draft, writing – review and editing; Zhiyu Wang: literature curation, formal analysis, investigation, methodology, writing – original draft, writing – review and editing; Paola Lopez-Rivera: literature curation; Mingjie Liu: conceptualization, supervision, writing – review and editing.

## Conflicts of interest

There are no conflicts to declare.

## Acknowledgements

This work was financially supported by the University of Florida's new faculty start-up funding.

## Notes and references

- 1 V. R. Stamenkovic, D. Strmcnik, P. P. Lopes and N. M. Markovic, *Nat. Mater.*, 2017, **16**, 57–69.
- 2 Y. Bing, H. Liu, L. Zhang, D. Ghosh and J. Zhang, *Chem. Soc. Rev.*, 2010, **39**, 2184–2202.
- 3 C. Li and J.-B. Baek, *ACS Omega*, 2019, **5**, 31–40.
- 4 Y. Hori, R. Takahashi, Y. Yoshinami and A. Murata, *J. Phys. Chem. B*, 1997, **101**, 7075–7081.
- 5 J. Resasco and A. T. Bell, *Trends Chem.*, 2020, **2**, 825–836.
- 6 A. J. Medford, A. Vojvodic, J. S. Hummelshøj, J. Voss, F. Abild-Pedersen, F. Studt, T. Bligaard, A. Nilsson and J. K. Nørskov, *J. Catal.*, 2015, **328**, 36–42.
- 7 H. Tao, C. Choi, L.-X. Ding, Z. Jiang, Z. Han, M. Jia, Q. Fan, Y. Gao, H. Wang and A. W. Robertson, *et al.*, *Chem*, 2019, **5**, 204–214.
- 8 G. Deng, T. Wang, A. A. Alshehri, K. A. Alzahrani, Y. Wang, H. Ye, Y. Luo and X. Sun, *J. Mater. Chem. A*, 2019, **7**, 21674–21677.
- 9 H. Huang, L. Xia, X. Shi, A. M. Asiri and X. Sun, *Chem. Commun.*, 2018, **54**, 11427–11430.
- 10 S. K. Kaiser, Z. Chen, D. Faust Akl, S. Mitchell and J. Perez-Ramirez, *Chem. Rev.*, 2020, **120**, 11703–11809.
- 11 Y. Wang, H. Su, Y. He, L. Li, S. Zhu, H. Shen, P. Xie, X. Fu, G. Zhou and C. Feng, *et al.*, *Chem. Rev.*, 2020, **120**, 12217–12314.
- 12 Y. Chen, L. Wang, Z. Yao, L. Hao, X. Tan, J. Masa, A. W. Robertson and Z. Sun, *Acta Phys.-Chim. Sin.*, 2022, **38**, 2206020.
- 13 D. Yu and J. Wang, *Chin. J. Struct. Chem.*, 2022, **41**, 2207002.
- 14 W. Chu and C. Wu, *et al.*, *J. Am. Chem. Soc.*, 2017, **139**, 14889–14892.
- 15 Y. Yang, J. Li, C. Zhang, Z. Yang, P. Sun, S. Liu and Q. Cao, *J. Phys. Chem. C*, 2022, **126**, 4338–4346.
- 16 P. Brimley, H. Almajed, Y. Alsunni, A. W. Alherz, Z. J. Bare, W. A. Smith and C. B. Musgrave, *ACS Catal.*, 2022, **12**, 10161–10171.
- 17 W. Ju, A. Bagger, G.-P. Hao, A. S. Varela, I. Sinev, V. Bon, B. Roldan Cuenya, S. Kaskel, J. Rossmeisl and P. Strasser, *Nat. Commun.*, 2017, **8**, 1–9.
- 18 A. Kumar, S. Ibraheem, T. A. Nguyen, R. K. Gupta, T. Maiyalagan and G. Yasin, *Coord. Chem. Rev.*, 2021, **446**, 214122.
- 19 K. L. Svane, M. Reda, T. Vegge and H. A. Hansen, *ChemSusChem*, 2019, **12**, 5133–5141.
- 20 C. Yin, H. Tang, K. Li, Y. Yuan and Z. Wu, *New J. Chem.*, 2018, **42**, 9620–9625.
- 21 Z. Jiang, X. Zhang, H.-S. Chen, X. Hu and P. Yang, *ChemCatChem*, 2019, **11**, 4558–4567.
- 22 W. Shan and G. Wang, *J. Phys. Chem. C*, 2021, **125**, 16004–16012.
- 23 C. Choi, S. Back, N.-Y. Kim, J. Lim, Y.-H. Kim and Y. Jung, *ACS Catal.*, 2018, **8**, 7517–7525.
- 24 H. Yang, R. Shi, L. Shang and T. Zhang, *Small Struct.*, 2021, **2**, 2100007.
- 25 G. Gao, S. Bottle and A. Du, *Catal. Sci. Technol.*, 2018, **8**, 996–1001.
- 26 Y. Zhou, G. Gao, Y. Li, W. Chu and L.-W. Wang, *Phys. Chem. Chem. Phys.*, 2019, **21**, 3024–3032.



- Energy Adv., 2023,
- 2**
- , 1781-1799 | 1797



- 202 K. Lakshmanan, W.-H. Huang, S. A. Chala, B. W. Taklu, E. A. Moges, J.-F. Lee, P.-Y. Huang, Y.-C. Lee, M.-C. Tsai and W.-N. Su, *et al.*, *Adv. Funct. Mater.*, 2022, **32**, 2109310.
- 203 Y. G. Abashkin, J. R. Collins and S. K. Burt, *Inorg. Chem.*, 2001, **40**, 4040–4048.
- 204 W. Orellana, *J. Phys. Chem. C*, 2013, **117**, 9812–9818.
- 205 W. Liu, L. Zhang, X. Liu, X. Liu, X. Yang, S. Miao, W. Wang, A. Wang and T. Zhang, *J. Am. Chem. Soc.*, 2017, **139**, 10790–10798.
- 206 W. Zhong, Y. Qiu, H. Shen, X. Wang, J. Yuan, C. Jia, S. Bi and J. Jiang, *J. Am. Chem. Soc.*, 2021, **143**, 4405–4413.
- 207 G. Yang, J. Zhu, P. Yuan, Y. Hu, G. Qu, B.-A. Lu, X. Xue, H. Yin, W. Cheng and J. Cheng, *et al.*, *Nat. Commun.*, 2021, **12**, 1734.
- 208 Y.-N. Gong, W. Zhong, Y. Li, Y. Qiu, L. Zheng, J. Jiang and H.-L. Jiang, *J. Am. Chem. Soc.*, 2020, **142**, 16723–16731.
- 209 A. M. Verma, K. Honkala and M. M. Melander, *Front. Energy Res.*, 2021, **388**, 606742.
- 210 K. Sakaushi, M. Eckardt, A. Lyalin, T. Taketsugu, R. J. Behm and K. Uosaki, *ACS Catal.*, 2018, **8**, 8162–8176.
- 211 Y. Li, Z. Qiao, Y. Cao, H. Wang, H. Liang, H. Yu and F. Peng, *ChemSusChem*, 2019, **12**, 1133–1138.
- 212 K. Sun, W. Xu, X. Lin, S. Tian, W.-F. Lin, D. Zhou and X. Sun, *Adv. Mater. Interfaces*, 2021, **8**, 2001360.
- 213 Y. Li, S. Zhang, J. Yu, Q. Wang, Q. Sun and P. Jena, *Nano Res.*, 2015, **8**, 2901–2912.
- 214 J. C. Peters, *Faraday Discuss.*, 2023, **243**, 450–472.
- 215 R. E. Warburton, P. Hutchison, M. N. Jackson, M. L. Pegis, Y. Surendranath and S. Hammes-Schiffer, *J. Am. Chem. Soc.*, 2020, **142**, 20855–20864.
- 216 P. Hutchison, R. E. Warburton, Y. Surendranath and S. Hammes-Schiffer, *J. Phys. Chem. Lett.*, 2022, **13**, 11216–11222.
- 217 Q. Wu, G. Wang and M. Liu, *ChemPhysChem*, 2022, **23**, e202100787.
- 218 K. Liu, J. Fu, Y. Lin, T. Luo, G. Ni, H. Li, Z. Lin and M. Liu, *Nat. Commun.*, 2022, **13**, 2075.
- 219 T. Lin, W.-D. Zhang, J. Huang and C. He, *J. Phys. Chem. B*, 2005, **109**, 13755–13760.
- 220 F. Gao, G.-L. Zhao, S. Yang and J. J. Spivey, *J. Am. Chem. Soc.*, 2013, **135**, 3315–3318.
- 221 I.-H. Lin, Y.-H. Lu and H.-T. Chen, *J. Comput. Chem.*, 2017, **38**, 2041–2046.
- 222 E. Shakerzadeh, H. Hamadi and M. D. Esrafil, *Inorg. Chem. Commun.*, 2019, **106**, 190–196.
- 223 B. Modak, K. Srinivasu and S. K. Ghosh, *Int. J. Hydrogen Energy*, 2017, **42**, 2278–2287.

