Supporting Information for

A machine learning-assisted study of the formation of oxygen vacancies in anatase titanium dioxide

Dan Wang,^{+,a} Ronghua Zan, ^{+,b} Xiaorong Zhu,^{*,c} Yuwei Zhang, ^a Yu Wang, ^a Yanhui Gu,^{*,b} and Yafei Li^{*,a}

^aJiangsu Key Laboratory of New Power Batteries, Jiangsu Collaborative Innovation Centre of Biomedical Functional Materials, School of Chemistry and Materials Science, Nanjing Normal University, Nanjing, 210023, P. R. China

^bSchool of Computer Science and Technology, Nanjing Normal University, Nanjing 210023, P. R. China

^cCollege of Chemistry and Chemical Engineering, Nantong University, Nantong 226019, P. R. China



Figure S1. The O vacancy formation energy of the uppermost layer of O atoms on TiO_2 (110), under CO, H₂ and NO atmosphere when set the reaction temperature to be 298 K.



Figure S2. The O vacancy formation energy of the uppermost layer of O atoms on TiO_2 (211), under CO, H_2 and NO atmosphere when set the reaction temperature to be 298 K.



Figure S3. The O vacancy formation energy of the uppermost layer of O atoms on TiO_2 (110), under CO, H_2 and NO atmosphere when set the reaction temperature to be 500 K.



Figure S4. The O vacancy formation energy of the uppermost layer of O atoms on TiO_2 (211), under CO, H_2 and NO atmosphere when set the reaction temperature to be 500 K.



Figure S5. The compassion between DFT calculated $E_{\rm f}$ and (a)KNN, (b) RFR, (c)SVR, (d)MLP predicted values on TiO₂(100), TiO₂(110), TiO₂(211).



Figure S6. The compassion between DFT calculated $E_{\rm f}$ and (a)OLS, (b)ridge predicted values on TiO₂(100), TiO₂(110), TiO₂(211).



Figure S7. Comparison between the E_f of the second O layer predicted by the ML based on the RFR model and the results calculated by DFT for (a) TiO₂(211), (b) TiO₂(110), and (c) TiO₂(100) surfaces. The purple, yellow, red, blue, and green dots represent the partial pressure ratio of 1, 10, 15, 20, and 30, respectively.

Features	Equation	RMSE
$n, p, T, \gamma, \mu_1, \mu_2, \mu_3$	$E_f = (0.943(p+n) - 0.640(p \times \gamma)) \left(\frac{\mu_3}{n}\right) - 0.301 \frac{p \times \mu_3}{n \times \gamma} + 9.154$	0.7106 eV
$n, T, \gamma,$ μ_1, μ_2, μ_3	$E_f = \left(2.973\mu_3 - 2.049(\mu_3 \times \gamma) - 3.164\frac{\gamma}{n}\right)\gamma + 9.356$	0.7112 eV
$n, T, \gamma,$ μ_2, μ_3	$E_f = \left(2.973\mu_3 - 2.049(\mu_3 \times \gamma) - 3.164\frac{\gamma}{n}\right)\gamma + 9.356$	0.7112 eV
n, γ, μ_2, μ_3	$E_f = \left(2.973\mu_3 - 2.049(\mu_3 \times \gamma) - 3.164\frac{\gamma}{n}\right)\gamma + 9.356$	0.7112 eV
γ, μ_2, μ_3	$E_f = (0.035\mu_3 + 4.024 - 2.525\gamma)(\mu_3 \times \gamma) + 11.367$	0.8003 eV
γ, μ ₃	$E_f = 7.832\mu_3 + 2597.384\frac{1}{\mu_3} + 8401.311\frac{1}{{\mu_3}^2} + 254.794$	1.0002 eV

Table S1. The SISSO algorithm uses different numbers of features to construct equations for $E_{\rm f}$.