Predicting Hydrogen Storage in MOFs *via* Machine Learning

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ABSTRACT: The H₂ storage capacities of a diverse set of 918,734 metal-organic frameworks (MOFs) sourced from 19 databases is predicted via machine learning (ML). Using only 7 structural features as input, ML identifies 8,282 MOFs with the potential to exceed the capacities of state-of-the-art materials under physisorptive conditions. The identified MOFs are predominantly hypothetical compounds having low densities ($<0.31 \text{ g cm}^{-3}$) in combination with high surface areas ($> 5,300 \text{ m}^2 \text{ g}^{-1}$), void fractions (~ 0.90), and pore volumes ($> 3.3 \text{ cm}^3 \text{ g}^{-1}$). In addition, the relative importance of the input features are characterized, and dependencies on the ML algorithm and training set size are quantified. The single most important features for predicting H₂ uptake are pore volume (for gravimetric capacity) and void fraction (for volumetric capacity). The ML models are available for use via the web, allowing for rapid and accurate predictions of usable hydrogen capacities for MOFs with only minimal structural data as input; for the simplest models only a single input feature is required.

KEYWORDS: Energy storage fuel cells; MOFs; hydrogen storage; machine learning

INTRODUCTION

Hydrogen (H₂) is considered to be a future automotive fuel.^{1–6} This potential reflects its high specific energy compared to competing fuels such as natural gas and gasoline, and the ability of H₂ to be produced renewably and consumed without CO₂ emissions.^{2,7} Nevertheless, the adoption of hydrogen in mobile applications such as fuel cell (FC) vehicles has been limited by its low volumetric energy density.^{2,6,7} Consequently, the design of low-cost H₂ storage systems that overcome these volumetric limitations has been the focus of recent research.^{4,8–12} At present, FC vehicles employ storage systems based on gaseous H₂ compressed to pressures up to 700 bar.¹³ This approach is costly and can incur limitations in driving range.^{7,11,13,14}

Storage based on adsorption in porous hosts is an alternative to high-pressure compression.¹⁵ Due to their high gravimetric densities, fast kinetics, and reversibility, metal-organic frameworks (MOFs) have emerged as one of the most promising classes of hydrogen sorbents.^{2,7} MOFs are crystalline materials formed by the self-assembly of inorganic metal clusters and organic linkers.^{16–22} By virtue of their building-block structure and the large number of potential components, the number of MOFs is potentially limitless.^{21–25} Further modifications to MOF chemistry can be achieved by introducing functional groups, substituting different metals, and by mixing metals and/or linkers.^{26–28}

Despite these many possibilities, a relatively small fraction of MOFs have been synthesized.^{29,30} While the crystal structures of these ‘real’ MOFs are available in the Cambridge Structural Database (CSD),^{29,30} many exhibit disorder, missing atoms, or have negligible porosity; consequently, these materials are not immediately amenable to assessment via computational modeling.^{29,31–35}

One way to bypass these complications is through computational design. To date, nearly a million ‘hypothetical’ MOFs have been reported,^{1,36,45,46,37–44} and it is reasonable to expect that many more materials will be proposed.^{47–51} High-throughput screening using Grand Canonical Monte Carlo (GCMC)^{52–56} has been successful

in identifying promising candidates with superior gas storage capacities on sub-sets of these catalogs.^{36,38,39,46,50,57–60} Nevertheless, given the large number of possibilities, a systematic search across all of these materials is challenging even with high-throughput techniques.^{1,61} Furthermore, differences in the implementation (i.e., use of different temperature/pressure conditions or interatomic potentials) can complicate comparisons between screening studies. Thus, more efficient and consistent screening approaches are desirable for predicting the gas storage properties of MOFs in existing and future databases.

Machine learning (ML) could provide a path forward.^{62–65} For ML to be helpful, access to high-quality training data is essential. Unfortunately, training on experimental H₂ storage data in MOFs is non-trivial:^{1,2,6,66–68} experimental uptake data is generally restricted to a relatively small number of MOFs, and can depend sensitively upon the experimental conditions and the purity of the sample.^{2,67,69} Employing a dataset based on a consistent set of computational predictions may be a better choice.^{62,63}

Earlier work has demonstrated that accurate isotherms for H₂ uptake in MOFs can be predicted using the pseudo-Feynman-Hibbs potential (to describe H₂) combined with general interatomic potentials to describe the MOF.^{1,2,6,70} This approach was used to screen a database of 5,309 real MOFs, from which IRMOF-20 was identified and experimentally demonstrated to have a favorable balance of high gravimetric and volumetric H₂ density.² In a follow-on study a larger database of 495,305 MOFs was compiled from several publicly-available databases (see Table S1 for details).^{1,29,31,33,36–40,45} Following a pre-screen based on crystallographic properties and empirical correlations, the H₂ capacities of a subset of 43,777 MOFs were evaluated using GCMC. Three additional MOFs – SNU-70, UMCM-9, and PCN-610/NU-100 – were identified and shown experimentally to out-perform the leading MOF candidate, IRMOF-20.¹

Table 1: Summary of recent studies that use machine learning (ML) to predict H₂ adsorption in MOFs. ρ_{crys} , vf, vsa, mpd, lcd represent single crystal density, void fraction, volumetric surface area, maximum pore diameter, and largest cavity diameter, respectively. R², AUE, and RMSE represent the coefficient of determination, average unsigned error, and root-mean-square error, respectively.

Study	ML Features	ML Method	Properties Predicted	Accuracy
Anderson et al. (2019) ⁴⁵	Epsilon, temperature, pressure, ρ_{crys} , vf, vsa, mpd, lcd, alchemical catecholate site density, unit cell volume	Neural network ⁷⁷	Total volumetric H ₂ for pressures 0.1, 1, 5, 35, 65, and 100 bar at 77, 160, and 295 K	AUE = 0.75 - 2.93 g-H ₂ L ⁻¹
Bucior et al. (2019) ⁸²	Energetics of MOF-guest interactions	Multilinear regression with LASSO ⁷⁷	Deliverable H ₂ storage capacity between 2-100 bar at 77 K	R ² = 0.96; MAE = 1.4 - 3.4 g-H ₂ L ⁻¹ ; RMSE = 3.1 - 4.4 g-H ₂ L ⁻¹
Borboudakis et al. (2017) ⁶³	92 binary features based on linker, metal cluster, and 12 functional groups	Ridge linear regression and support vector machine with polynomial/Gaussian kernel ^{77,79,80}	Total H ₂ storage capacity at 1 bar and 77 K	AUE = 0.47 (ridge regression), 0.50 (SVM) g-H ₂ g ⁻¹ -MOF
Thornton et al. (2017) ⁷⁸	Adsorption energy, ρ_{crys} , vf, gsa, vsa, lcd	Neural network ⁷²	Net H ₂ capacity for pressure swing between 1 and 100 bar at 77 and 298 K	R ² = 0.88; RMSE = 3.6 g-H ₂ L ⁻¹

The database of MOF properties⁷¹ generated in these prior studies presents an opportunity to develop ML models that can predict H₂ uptake across even larger MOF datasets.^{1,71} Table 1 summarizes prior ML studies of H₂ storage in MOFs. (Reports employing ML for other adsorbates such as CH₄,^{72,73} CO₂,^{74,75} N₂,^{74,75} are summarized in Table S2.) To the best of our knowledge, ML was first used to predict H₂ uptake in compounds from the Nanoporous Materials Genome.⁷⁶ A neural network (NN)⁷⁷ was used to predict usable capacities on a test set of ~1000 compounds, including MOFs.⁷⁸ In the same year, Borboudakis et al.⁶³ predicated H₂ capacities in 100 MOFs using 92 binary features related to a MOF's linker, metal cluster, and functional group(s). Ridge linear regression (RR)^{77,79,80} and support vector machine (SVM)^{77,81} algorithms were used to predict gravimetric capacity. Later, Bucior et al.⁸² predicted the H₂ capacities of 50,000 MOFs extracted from the CSD using multi-linear regression (MLR).⁷⁷ The models were trained using the energetics of H₂-MOF interactions and the usable volumetric capacities predicted by GCMC. More recently, ML was used to predict H₂ storage capacities in 105 hypothetical MOFs constructed from 17 different topologies, 4 distinct metal clusters, and 5 unique organic linkers.⁴³ NN⁷⁷ models employing 11 features were trained to predict total volumetric uptake at various temperatures and pressures.⁴³

Expanding upon these prior reports, the present study applies ML to explore a large database of 918,734 known and proposed MOFs. The database was assembled from a diverse collection of publicly-available MOF repositories,^{1,29,41-45,83,84,31,33,34,36-40} and allows for a wide-ranging and consistent assessment of H₂ uptake in MOFs.

Here the extremely randomized trees (ERT)^{77,85} algorithm was identified as the most accurate ML model for predicting H₂ uptake. A training set comprising 24,674 MOFs was sufficient to enable accurate predictions of usable capacities across 820,039 unseen compounds.⁷¹ These predictions were made using a small set of seven crystallographic features as input: single-crystal density, pore volume, gravimetric & volumetric surface area, void fraction, largest cavity diameter, and pore limiting diameter. Importantly, ML identified 8,282 MOFs – 8,187 appropriate for pressure swing operation and 95 for temperature/pressure swing use – with the potential to exceed both the gravimetric and volumetric capacities of state-of-

the-art materials. These compounds are comprised predominantly of hypothetical MOFs, and exhibit low densities (<0.31 g cm⁻³) in combination with high surface areas (> 5,300 m² g⁻¹), void fractions (~0.90), and pore volumes (>3.3 cm³ g⁻¹). In addition to identifying high-capacity MOFs, the relative importance of the input features is quantified; dependencies on the ML algorithm and training set size and are also assessed. The single most important features for predicting H₂ uptake are pore volume (for gravimetric capacity) and void fraction (for volumetric capacity). A simplified model using only two input features is demonstrated to predict capacities with high accuracy – within 0.2 wt.% and 1.4 g g-H₂ L⁻¹ of more expensive Monte Carlo calculations. The ML models are available for use via the web,⁸⁶ allowing for rapid and accurate predictions of hydrogen capacities with only a small amount of structural data required as input.

METHODOLOGY

MOF database. A database of crystal structures for 918,734 MOFs was created by combining 19 existing databases.^{1,29,41-45,83,84,31,33,34,36-40} Table 2 summarizes the source databases and the number of MOFs contained in each. Out of these 19 databases, only the UM,³¹ CSD,^{29,30} and CoRE^{33,34} databases contain data on MOFs that have been previously synthesized. (MOFs listed in these datasets are referred to as ‘real’ MOFs.) The remaining databases contain data for proposed, or ‘hypothetical,’ MOFs. The combined database includes data for seven crystallographic properties that were calculated using the zeo++ code.^{25,87-90} These properties include: single crystal density (d), pore volume (pv), gravimetric surface area (gsa), volumetric surface area (vsa), void fraction (vf), largest cavity diameter (lcd), and pore limiting diameter (pld).

A prior study examined a subset of the present database, wherein the hydrogen uptake in 495,305 MOFs was estimated using the Chahine rule.^{71,1,2} Subsequently, usable uptake in a portion of this subset comprising 43,777 MOFs predicted to be promising based on

Table 2. MOF datasets employed in this study.

Source	Number of MOFs
Real MOFs:	
UM ³¹ +CoRE ³³ +CSD ^{29,30}	15,235
CoRE 2019 ³⁴	14,142
*CSD 2017 additional ^{29,30}	48,696
Mail-order ³⁸	112
In-silico deliverable ⁴⁶	2,816
In-silico surface ³⁹	8,885
MOF-74 analogs ⁴⁰	61
ToBaCCo ⁵⁹	13,512
Zr-MOFs ⁴⁵	204
Northwestern ³⁶	137,000
**Univ. of Ottawa ^{39,91,92}	317,462
BJT MOFs ⁸³	303,793
***R-WLLFHS ^{43,93}	51,163
MTV ⁸⁴	11,555
CSM-2018-I ⁴⁴	117
CSM-2018-II ⁴⁵	32
CSM-2019-I ⁴⁶	99
In-house ¹	18
Total	918,734

*A subset of the CSD 2017 MOF dataset^{29,30} whose crystallographic properties were found to exhibit extremely low values (e.g GSA ~ 0) in a prior study.

**A recent version of this database is available publicly;^{91,92} however, the present study employs an earlier version³⁷ that was shared privately.

***A curated subset of the Northwestern³⁶ database.

the Chahine rule was evaluated using Grand Canonical Monte Carlo (GCMC). This GCMC-evaluated dataset contained a mix of real and hypothetical MOFs: 15,235 real MOFs were sourced from the UM,³¹ CoRE,³³ and Cambridge Structural Databases,^{29,30} and 28,542 hypothetical MOFs were extracted from the Mail-order,³⁸ *in silico* deliverable,⁴⁶ *in silico* surface,³⁹ MOF-74 analogs,⁴⁰ ToBaCCo,⁵⁹ Zr-MOFs,⁴⁵ Northwestern,³⁶ University of Ottawa,^{37,91,92} and in-house¹ hypothetical MOF databases (see Ref. 1 or Table S1 for details).^{1,29,31,33,36-40} Hydrogen uptake isotherms for two operating conditions were predicted: for an isothermal pressure swing (PS) at T = 77 K between 5 and 100 bar, and for a combined temperature-pressure swing (TPS) between 77 K/100 bar (filled state) and 160 K/5 bar (empty state). Usable gravimetric (UG) and volumetric (UV) capacities were then calculated based on the isotherm data.

In addition to the 43,777 MOFs examined in Ref. 1, in the present study GCMC isotherms were evaluated for an additional 54,918 MOFs. These MOFs were selected at random from the 495,305 entry HyMARC database and therefore represent a more diverse sampling of the MOF property-space. To this dataset 423,429 additional compounds were added from 7 additional datasets: BJT MOFs,⁸³ R-WLLFHS,^{41,93} MTV,⁸⁴ CSM-2018-I,⁴² CSM-2018-II,⁴³ and CSM-2019-I,⁴⁴ and selected MOFs from the CSD 2017 dataset.^{29,30} Subsequently, the capacities of the MOFs from these additional datasets were predicted by the ML models without retraining (i.e., no MOFs from these datasets were used for training or testing). In total, the dataset employed in the present study contains H₂ uptake data for 98,695 MOFs⁷¹ and crystallographic property data for 918,734 MOFs.

Machine learning model. The No Free Lunch Theorem⁹⁴ implies that the optimal choice of ML algorithm is problem-specific. The differing performance of the algorithms summarized in Tables 1 and S2 is consistent with this notion. Identifying the best algorithm for a given dataset requires comparing multiple ML methods, each with optimized hyperparameters. Unfortunately, few comparisons

Table 3. Machine learning regression algorithms employed in this work.

Machine Learning Algorithm	Abbreviation
Extremely Randomized Trees ^{77,85,104,105}	ERT
Boosted Decision Trees ^{77,102,104,105-107}	BDT
Bagging with Decision Trees ^{77,104,105,108}	B/DT
Random Forest ^{77,104,105,109}	RF
Bagging with Random Forest ^{77,104,105,108,109}	B/RF
Gradient Boosting ^{77,95,102,104,105,107}	GB
Decision Trees ^{77,104,105}	DT
Nu-Support Vector Machine with Radial Basis Function (RBF) Kernel ^{77,81,96-98,104,105}	Nu-SVM/RBF-K
Support Vector Machine Radial Basis Function (RBF) Kernel ^{77,81,96-98,104,105}	SVM/RBF-K
Support Vector Machine with Linear Kernel ^{77,81,96-99,104,105}	SVM/L-K
Linear Regression ^{77,79,80,104,105}	LR
Ridge Regression ^{77,79,80,104,105}	RR
K-Nearest Neighbors ^{77,99,101,104,105}	K-NN
AdaBoost ^{77,102,104,105-107}	AB

of ML methods for gas adsorption exist; although dozens of ML algorithms are available,^{77,79,100-109,80,81,85,95-99} only RR,^{77,79,80} MLR,⁷⁷ SVM,^{77,81} and NN⁷⁷ have been examined for predicting H₂ storage.^{43,63,78,82,108} The present study casts a wider net by comparatively assessing 14 ML algorithms (Table 3).^{77,79,100-109,80,81,85,95-99}

The crystallographic properties of MOFs are known to correlate with H₂ capacities.^{2,31,110-114} The ML models developed here exploit these correlations by adopting only crystallographic properties as input features. Moreover, the number of features was restricted to a small set comprising 7 properties: d, pv, gsa, vsa, vf, lcd, and pld. These are the same properties employed in our prior work.^{1,2,87,115} Figure S1 shows the distribution of crystallographic properties for the training, test, and unseen datasets. Also, Table S3 summarizes five descriptive (minimum, maximum, mean, median, and % of 0's) and two distribution statistics (skew and kurtosis) of all crystallographic features for the training, test, and unseen datasets. (The details regarding these statistics and the definitions of skew and kurtosis can be found in Section S3 of the SI). The maxima's and minima's of the features in the training set establish the validity ranges of the ML models developed here.

The goal of the ML models is to predict 4 output properties: UG and UV for each of PS and TPS operating conditions. This was accomplished by developing separate ML models for each of the four targeted capacities. Figure S2 illustrates the overall work-flow.

The existing dataset of 98,695 MOFs (for which both crystallographic and capacity data are available)⁷¹ was initially split into training and test sets of 74,201 and 24,674 MOFs, respectively, after shuffling the entire dataset.¹⁰⁹ ML algorithms^{95,98,99,109} (Table 3) were implemented using the scikit-learn library.¹⁰⁹ Both scaled and unscaled features were used in training ML models. 10-fold cross-validation was used to optimize the hyperparameters of each model. The performance of the ML algorithms was assessed by comparing the predicted H₂ capacities to the capacity predicted by GCMC for the MOFs in the test set. The metrics used for the performance assessment of ML models were the coefficient of determination (R²), average unsigned error (AUE), root-mean-squared error (RMSE), median absolute error (MAE), mean absolute percentage error (MAPE), and the Kendall rank correlation coefficient (τ). Additional details regarding these calculations can be found in Section S5 of the SI.

Dataset size. An obstacle to wider adoption of ML in materials science is the availability of sufficient quantities of high-quality training data.^{116,117} Unfortunately, it is not yet clear how much data is needed to construct a useful ML model for a given system. Fernandez et al.⁷³ found that a reasonable balance between accuracy ($R^2 \sim 0.85$ to 0.93) and computational expense for predicting methane storage in MOFs was achieved for a training set containing data on 10,000 MOFs with 3 features. In contrast, Fanourgakis et al.¹¹⁸ showed that a much smaller training set of ~ 1000 MOFs was sufficient to predict methane uptake when using six crystallographic fea-

The present study explores this issue further by systematically examining the effect of training set size, and the training set to test set ratio, on ML accuracy. For each of the four targeted capacity outputs, 100 independent ML models were developed by varying the size of the training set between 100 and 74,000 MOFs (see Table S4 for a list of the training set sizes). The four best-performing ERT ML algorithms identified earlier were used with 10-fold cross-validation.

Table 4. Performance of the Extremely Randomized Trees ML algorithm in predicting UG and UV H₂ capacities of MOFs under PS and TPS conditions. R², AUE, RSME, and MAE represent the coefficient of determination, average unsigned error, root-mean-squared error, and median absolute error, respectively.

Figure 2. Performance of the Extremely Randomized Trees ML algorithm with respect to GCMC calculations for predicting usable H_2 capacities in MOFs. Data is collected at 77 K for a pressure swing between 100 and 5 bar on a test set of 24,674 MOFs. Different colors represent different categories of MOFs. Top (a-c) and bottom (d-f) panels illustrate performance for usable gravimetric and volumetric capacities, respectively. (a, d): Agreement between ML and GCMC predictions. (b, e): Difference between ML and GCMC as a function of GCMC capacity. (c, f) Distribution of differences in predictions between ML and GCMC.

The resulting models were assessed using a common test set of 24,674 MOFs.

Feature importance/selection. The well-known Chahine rule proposes a linear correlation between gravimetric surface area and excess gravimetric H_2 capacity in adsorbents.^{119,120} Nevertheless, the Chahine rule overpredicts H_2 capacities for MOFs with high surface areas,¹²⁰ and has not been extended to predict usable capacities.^{1,2,6} Hence, a model for predicting H_2 uptake that is more general than the Chahine rule, yet requires limited input data, would be very helpful. In principle, ML could be used to generate such a predictive model if the features that are the most important for predicting H_2 uptake could be identified. Along these lines, Pardakhti et al. reported improved accuracy in predicting CH_4 adsorption when using a combination of (7) crystallographic and (19) chemical features.⁷² Recently, Moosavi et al. explored feature importance in predicting the synthesis of MOFs.¹²¹

The present study determines the minimum number and optimal combination of crystallographic features necessary to achieve a specified accuracy in predicting H_2 uptake. The relative importance of the input features was assessed for all possible univariate and multivariate feature combinations using ERT ML models. The number of multivariate feature combinations, M , is given by: $M(n_{tot}, n_{sub}) = \frac{n_{tot}!}{n_{sub}!(n_{tot}-n_{sub})!}$, where $n_{tot} = 7$ is the total number of available features, and $1 \leq n_{sub} \leq 7$ is the number of features used as input to a given ML model. A total of 127 feature combinations are possible. ML models were developed for each of these feature combinations for each of the 4 output capacities, result-

ing in a total of 508 distinct ML models. All models were trained using a dataset of 74,021 MOFs and tested on a common set of 24,674 MOFs. 10-fold cross-validation was used for tuning and validating the models using only the training set. Univariate feature importance was further assessed using (i) Pearson’s correlation coefficient (r),^{122–124} (ii), Breiman and Friedman’s tree-based algorithm as implemented in Scikit-learn,^{95,109} and (iii) the permutation importance method as implemented in rfpimp package.¹²⁵ Additional details regarding these methods can be found in Section 11 of the SI.

RESULTS AND DISCUSSION

Evaluating ML algorithms. Tables S5-S8 illustrate the effect of several feature scaling methods on the performance of the ML algorithms examined here. Only the SVM family of models (SVM/L-K, SVM/RBF-K, and Nu-SVM/RBF-K)^{77,95,101,103,104,109} were impacted by the choice of scaling method.

Figure 1 compares the accuracy of the ML algorithms for predicting hydrogen uptake in MOFs. R^2 and AUE were used as performance metrics. SVM variants were trained using min-max feature scaling; un-scaled features were used in training the remaining models. The performance of the algorithms as measured by 4 additional metrics – root mean square error (RMSE), explained variance (EV), MAE (median absolute error), and Kendall τ – is reported in Tables S5-8.

Overall, these data indicate that the tree-based ensemble methods are superior to the other methods examined. In particular, the Extremely Randomized Trees (ERT)^{77,85,109} algorithm exhibited the best performance overall. Boosted Decision Trees (BDT),^{77,95–}

Figure 3. Performance of Extremely Randomized Trees ML models for predicting usable (a) gravimetric and (b) volumetric H_2 capacity as a function of training set size and the ratio of training to test set size. 100 different training sets ranging in size between 100 and 74,021 MOFs were examined. A common set of 24,674 MOFs was used for testing. Performance is quantified using R^2 (left axis, black) and the average unsigned error, AUE (right axis, blue and red for UG and UV, respectively). Lines represent a power-law fit to the data.

^{97,107,109} Random Forest (RF),^{77,99,109} and Bagging algorithm variants^{77,98,109,126,127} (with tree-based base estimators) are nearly as accurate. The R values for ERT predictions exceed 0.997 for gravimetric capacities, which are equivalent to errors of ~ 0.14 wt.%. Volumetrically, the accuracy of the ERT algorithm is slightly worse than its gravimetric performance: $R^2 = 0.967$ – 0.984 , equivalent to errors of ~ 1.1 g- H_2 L $^{-1}$ on average. In general, the worst-performing algorithms were linear regression, ridge regression, and support vector machine with linear kernel. For these algorithms R^2 varies between 0.913 and 0.992 depending on the conditions (i.e., gravimetric/volumetric and PS/TPS). As expected, the linear nature of these algorithms fails to fully capture the nonlinear dependence of output capacities on the multiple input features.

Figure 1 also shows that all the algorithms tested yield more accurate predictions of UG capacities compared to those for UV. Likewise, all algorithms more accurately predict usable capacities under PS conditions than under TPS conditions. This reflects the fact that the functional relationships between output capacities (UG/UV) and input features under PS and TPS conditions are likely different, as was observed in previously reported structure(feature)-property(capacity) relationships.^{1,6,128}

Table 4 summarizes the performance of the ERT algorithm in further detail. A comparison of Tables 1 and 4 indicates that the accuracy of the present ML models surpass previously-reported models for H_2 uptake. Furthermore, the present models also appear to be an improvement over earlier models that aim to predict the adsorption capacities of MOFs for any gas species, Table S2. This improved performance can be attributed to the exploration and optimization of multiple ML algorithms, use of an appropriate feature set, and the relatively large size of the present training set.

Figure 2 illustrates the degree of agreement between ERT ML predictions and GCMC calculations of usable H_2 capacities under PS conditions as a function of MOF source database. (Fig. S3 shows similar data for TPS conditions; see also Table 4.) As mentioned

above, the present ML models more accurately predict UG capacities than UV capacities. The largest differences between ML and GCMC capacities (Fig. 2c,f & Fig. S3c,f) primarily occur for the real MOF dataset. In principle, these differences may arise either from ML overfitting or from inaccurate GCMC predictions caused by non-ideal/incomplete MOF crystal structure data (i.e., missing atoms, disorder, etc.) as mentioned in prior studies.^{1,35,129–132} ERT algorithms are fairly robust against overfitting.⁸⁵ To examine the possibility for overfitting, test set errors were compared with training set errors as shown in Fig. S4 and Table 4. These data suggest that the outliers are not a consequence of over fitting; hence, inaccuracies in the crystal structure data is proposed as the most likely source of this disagreement.^{1,35,129–132}

Effect of training set size. Figure 3 illustrates the impact of training set size on the accuracy of the ERT ML models as quantified using R^2 and AUE. (Table S4 summarizes the dataset sizes used in these plots.) For training sets containing more than 5000 MOFs R^2 and AUE vary slowly and in a monotonic fashion, with AUE decreasing and R^2 increasing. The accuracy of the models is more sensitive to the size of the training set for smaller training sets containing roughly 5,000 or fewer MOFs. Figure S5 highlights the variation in performance for these smaller training sets.

The trends AUE as a function of training set size can be fit to a power-law expression of the form $AUE(m) = \alpha m^\beta + \gamma$, where m represents the size of the training set and β is the power law exponent. Fitting this model to the data shown in Fig. 3 reveals that the AUE for UG converges faster with training set size ($\beta = -0.37$ and -0.43) than it does for UV ($\beta = -0.16$ and -0.23). A full tabulation of the power-law parameters is given in Table S9. Based on these power-law expressions, one can determine the necessary size of the training set to achieve a desired level of accuracy. For example, assuming pressure swing operation, to achieve an AUE of approximately 0.25 wt.% and 1.5 g- H_2 L $^{-1}$ requires training set sizes (for UG and UV) of less than 300 MOFs randomly selected from the diverse datasets used here.

Figure 4. Importance of seven features in predicting usable H_2 storage capacities of MOFs. Feature importance was determined by developing distinct ERT models for each individual feature. The accuracy of the resulting models was assessed using R^2 (left axis; black data set) and AUE (right axis; red data set). Models were trained on a dataset of 74,201 MOFs and tested on a set of 24,674 MOFs. pv = pore volume; d = density; vf = void fraction; gsa = gravimetric surface area; pld = pore limiting diameter; lcd = limiting cavity diameter; vsa = volumetric surface area.

Univariate feature importance. Figure 4 illustrates the relative importance of the seven crystallographic features in predicting usable hydrogen uptake in MOFs. Feature importance was determined by developing ERT models for each single feature individually. Additional details for these models are provided in the Supporting Information. Based on these models, it is evident that pore volume (pv) and void fraction (vf) are the dominant features in predicting H_2 capacity; these two properties appear as the first- or second-most important single features regardless of operating condition or capacity type. The importance of these features can be rationalized by two factors. First, based on the empirical Chahine rule, the pore volume of a MOF correlates with its excess uptake.¹³³ Second, pore volume and void fraction are related (since $pv = vf d^{-1}$) – MOFs with larger pv have larger vf, and *vice versa*.¹

Conversely, the largest cavity diameter (lcd) and volumetric surface area (vsa) are the single features whose ML models yield the lowest accuracy. The relative importance of the individual features for predicting UG capacities is: $pv > d > vf > gsa > pld > lcd > vsa$. This ordering is the same for PS and TPS conditions. In contrast, the importance ordering for UV capacities differs based on the operating condition. Nevertheless, vf and pv remain the two most important single features for both UV conditions, in that order (Fig. 4).

Despite their limited input, the single-feature ML models illustrated in Fig. 4 achieve high accuracy. For example, any of the three independent models for UG-PS based only on pv, d, or vf can predict capacities with $R^2 > 0.95$ and with AUE of less than 0.5 wt.%. The accuracy and simplicity of the univariate ML models suggest that they can be used to quickly screen new MOFs for their utility in hydrogen storage. To that end, optimized single-feature ML models for the four categories of usable capacities considered here have been made available for use on the web.⁸⁶ These models take as input either pv (for UG predictions) or vf (for UV) of a given MOF. These input data can be quickly calculated from a MOF's crystal structure using modern structure analysis codes.^{25,87–90,134} As shown in Fig. 4, these models can predict UG with an average error of less than 0.4 wt.%, and UV with errors less than 2.2 g- H_2 L⁻¹.

Figure S6 compares the single feature importance assessments based on ERT ML models (as reported in Fig. 4) with three popular methods for determining feature importance: Pearson's correlation coefficient (r),^{122–124} Breiman and Friedman's tree-based algorithm as implemented in Scikit-learn,^{95,109} and the permutation importance method as implemented in rfimp package.¹²⁵ It is clear that the feature importance methods do not reproduce *in detail* the rank-ordering of feature importance that is suggested by our ERT ML models. Nevertheless, good agreement is evident more broadly. For example,

in the case of UG (Fig. S6a,c), the three feature importance methods suggest that in aggregate pv is the most important feature, while vsa is the least, in agreement with the ERT models (Fig. 4a,b). Similarly, for UV, the importance methods suggest that vf and lcd are among the most and least important features, respectively. This is the same trend found in the univariate ERT models (Fig. 4c,d).

Multivariate feature importance. Figure 5 illustrates how the accuracy of the ML models varies with the number and combination of features. Assuming 7 features, $2^7 - 1 = 127$ possible combinations exist. For a given number of features, Fig. 5 plots the combination of features resulting in the highest accuracy model. (The supplementary file (“Feature_Combination_ML_Models.xlsx”) summarizes the performance for all 508 possible feature combinations and capacity/operating condition types.) As expected, Fig. 5 shows that ML accuracy generally increases as the number of input features increases. As previously discussed, when limited to a single feature, vf yields the best accuracy for predicting UV, while pv is the best choice for UG. When the feature set is extended to 2 features, the combination of d and pv is the optimal choice among the $\binom{7}{2} = 21$ possible pairs regardless of the capacity (UG vs UV) or operating condition

(PS vs TPS). For larger numbers of features, the optimal feature combination depends upon the operating condition and the capacity type. Based on the AUE, whose value tends to plateau as more features are added, highly accurate ML models can be generated using only 5 input features (Table 5). These data lend further support to the notion that the accuracy of a given ML model depends on both the number and identity of the input features. As a slightly more accurate alternative to the univariate web models described above, a subset of the present multivariate ML models that use 4, 5, and 7 input features are also available on the web.⁸⁶

H₂ uptake in unseen MOFs. Figure 6 illustrates the H₂ storage capacities of 820,039 MOFs as predicted by the 7-feature ERT ML models developed here. (This dataset is publicly accessible via HyMARC data hub.⁷¹) These MOFs are referred to as ‘unseen,’ in that they have not been included in the training or test sets used to develop the models. Figures 6a,b show UV capacities as functions of UG capacities under PS and TPS conditions, respectively. Both plots exhibit a rapid increase in UV at low values of UG, and reach a maximum in UV at UG values of approximately 9 wt.%. Beyond the maximum, UV decreases relatively slowly with increasing UG. These

Figure 5. Accuracy of Extremely Randomized Trees (ERT) ML models as determined by R^2 and AUE as a function of the number and combination of input features. Each data point represents the most accurate feature combination for a given number of features. ERT models were trained on a dataset of 74,201 MOFs. R^2 and AUE were calculated using a test of 24,674 MOFs. Feature abbreviations are defined in Fig. 4.

Table 5. The best combinations of features for predicting UG and UV H₂ storage capacities at PS and TPS conditions.

Condition	Feature Combination	No. features	R ²	AUE	RMSE	Kendall τ
UG at PS	gsa, vf, pv, lcd, pld	5	0.997	0.14 wt. %	0.19 wt. %	0.959
UG at TPS	d, vsa, pv, lcd, pld	5	0.996	0.18 wt. %	0.25 wt. %	0.959
UV at PS	vsa, vf, pv, lcd, pld	5	0.983	1.01 g-H ₂ L ⁻¹	1.45 g-H ₂ L ⁻¹	0.920
UV at TPS	vsa, vf, pv, lcd, pld	5	0.961	1.41 g-H ₂ L ⁻¹	2.10 g-H ₂ L ⁻¹	0.814

trends are consistent with our earlier findings derived from GCMC calculations on smaller datasets.^{1,2,6}

In the case of PS operation, the maximum UV across the MOFs in the dataset is 37.4 g-H₂ L⁻¹; for TPS operation the maximum UV is 48.5 g-H₂ L⁻¹. In the case of UG, the maximum value predicted is 39 wt.% for PS operation and 42 wt.% for TPS. These values can be placed in context by comparing against the DOE hydrogen storage targets, which stipulate system-level hydrogen densities of 5.5 wt% and 40 g-H₂ L⁻¹ by 2025 and 6.5 wt%/50 g-H₂ L⁻¹ longer-term ('Ultimate target').⁶ Given that the tank and balance-of-plant for the storage system have non-zero mass and volume, the MOFs examined here cannot meet the Ultimate target for UV, regardless of operating condition.¹² More optimism exists, however, for meeting the gravimetric targets given the high UG exhibited by these systems on

a MOF-only basis. Of course, an additional challenge is to identify MOFs that excel both gravimetrically and volumetrically.^{1,2,6,31,135}

It is also helpful to compare the performance predictions in Figs. 6a,b with that of state-of-the-art materials. In the case of PS operation, our prior study demonstrated that PCN-610 (NU-100) exhibits a hydrogen capacity of 10.1 wt.% & 35.5 g-H₂ L⁻¹,¹ which to our knowledge is the best combination of gravimetric and volumetric capacities reported for any MOF under these conditions. The data in Figure 6a reveals that 16,345 MOFs can, in principle, exceed this capacity on both a UG and UV basis. In the case of TPS operation (Figure 6b), MOF-5 remains the benchmark, which a measured capacity of 7.8 wt.% & 51.9 g-H₂ L⁻¹.² Figure 8c shows that only 21 MOFs outperform MOF-5 under these conditions.

Regarding the accuracy of the present ML predictions, Table 4 shows that the AUE of these models are on the order of 0.15 wt.%

Figure 6. (a,b) Machine learning predictions of usable hydrogen capacities of 820,093 MOFs. Colors indicate the originating database for a given MOF. (c,d) Validation of ML-predicted capacities for the highest capacity MOFs identified by ML (shown in the rectangular regions in c,d) using GCMC simulations. For comparison, the capacities of PCN-610/NU-100 (PS: 10.1 wt.%, 35.5 g-H₂ L⁻¹) and MOF-5 (TPS: 7.8 wt.%, 51.9 g-H₂ L⁻¹) are shown.

Table 6. Highest capacity MOFs, as identified by ML and verified with GCMC, under pressure swing and temperature + pressure swing conditions. Here NW and UO refer to the Northwestern³⁶ and University of Ottawa databases.³⁹

Name	Source	Density (g cm ⁻³)	Grav.	Vol.	Void fraction	Pore volume (cm ³ g ⁻¹)	Largest cavity diameter (Å)	Pore limiting diameter (Å)	Usable grav.		Usable vol.		
			surface area (m ² g ⁻¹)	surface area (m ² cm ⁻³)					capacity (wt. %)	capacity (g-H ₂ L ⁻¹)			
Pressure swing													
mof_7642	ToBaCCo	0.30	5561	1695	0.89	2.93	12.8	11.8	11.1	10.3	40.5	37.4	
mof_7690	ToBaCCo	0.30	5715	1706	0.89	2.98	12.8	12.0	11.3	10.4	40.3	37.3	
mof_7594	ToBaCCo	0.40	5070	2031	0.86	2.15	11.2	9.7	8.6	7.9	39.9	37.0	
mof_7210	ToBaCCo	0.29	5936	1730	0.89	3.04	13.4	11.7	11.4	10.5	39.8	37.1	
mof_7738	ToBaCCo	0.25	6054	1502	0.90	3.64	14.5	13.5	13.0	12.0	39.7	37.0	
hypotheticalMOF_5045702_i_1_j_24_k_20_m_2	NW	0.31	5926	1820	0.88	2.87	16.0	11.0	10.9	10.1	39.7	37.2	
str_m3_o19_o19_f0_nbo.sym.1.out	UO	0.31	5073	1583	0.90	2.88	17.7	12.9	10.8	10.1	39.7	37.1	
hypotheticalMOF_5037315_i_1_j_20_k_12_m_1	NW	0.31	5818	1787	0.88	2.86	16.0	11.0	10.9	10.0	39.7	37.0	
hypotheticalMOF_5037467_i_1_j_20_k_12_m_8	NW	0.31	5860	1800	0.88	2.85	16.0	11.0	10.9	10.0	39.7	37.0	
str_m3_o5_o20_f0_nbo.sym.1.out	UO	0.39	4772	1882	0.87	2.22	14.1	9.6	8.7	8.1	39.7	37.2	
Temperature + pressure swing													
str_m1_o1_o11_f0_pcu.sym.102.out	UO	0.45	4352	1974	0.84	1.84	12.9	10.1	10.4	9.7	53.1	48.1	
str_m1_o1_o11_f0_pcu.sym.117.out	UO	0.47	4162	1977	0.83	1.74	12.8	9.9	9.9	9.0	52.8	48.0	
str_m1_o1_o11_f0_pcu.sym.121.out	UO	0.47	4263	2006	0.83	1.76	12.1	10.2	10.0	9.4	52.7	48.1	
str_m1_o1_o11_f0_pcu.sym.13.out	UO	0.46	4326	2005	0.83	1.79	12.7	9.9	10.1	9.3	52.6	48.0	
str_m1_o1_o11_f0_pcu.sym.159.out	UO	0.58	3703	2138	0.80	1.38	10.4	8.6	8.3	7.6	52.6	48.5	
str_m1_o1_o11_f0_pcu.sym.200.out	UO	0.45	4359	1978	0.84	1.84	12.9	10.1	10.3	9.6	52.6	48.1	
str_m1_o1_o11_f0_pcu.sym.212.out	UO	0.60	3417	2035	0.83	1.39	12.0	10.1	8.1	7.5	52.5	48.1	
str_m1_o1_o11_f0_pcu.sym.51.out	UO	0.46	4330	2007	0.83	1.79	11.9	9.9	10.1	9.3	52.5	48.1	
str_m1_o1_o11_f0_pcu.sym.71.out	UO	0.45	4436	1980	0.84	1.87	13.0	10.9	10.4	9.7	52.5	48.1	
str_m1_o1_o11_f0_pcu.sym.89.out	UO	0.58	3507	2043	0.83	1.42	12.4	9.8	8.2	7.7	52.5	48.1	

and 1.3 g-H₂ L⁻¹. Although these errors are small, a more rigorous validation of the ML can be achieved with GCMC calculations. Thus, GCMC calculations were performed on a subset of MOFs that ML predicted to exhibit high UV and UG capacities. These MOFs fall within the rectangular regions shown in Figs. 6a,b, and exhibit capacities that meet or exceed 36 g-H₂ L⁻¹ & 7.5 wt.% for PS conditions and 48 g-H₂ L⁻¹ & 7.5 wt.% under TPS conditions. In total, 21,700 compounds were re-examined with GCMC based on their ML-predicted PS capacities, and another 7,901 were re-examined for TPS.

Figure 6c compares ML and GCMC predictions for usable capacities for 21,700 high-capacity MOFs under PS conditions. The strong overlap in the two datasets further highlights the accuracy of the ML models. A total of 8,187 MOFs were predicted by GCMC to outperform PCN-610/NU-100 under these conditions. A summary

of the 10 highest-capacity MOFs, sorted based on their GCMC capacities, is provided in Table 6. (A more extensive listing is provided in Table S10.) The highest capacity MOFs are all hypothetical compounds: 5 originate from the ToBaCCo database,⁵⁹ two are from the Univ. of Ottawa database,³⁷ and the remainder are from the Northwestern³⁶ database. These MOFs all exhibit high surface areas (average = 5746, range = 4346 – 7835 m² g⁻¹) and large void fractions of 0.89, on average. The range of these property values are consistent with those reported in an earlier study,^{1,136,137} and suggest that maximizing the surface area is an important design guideline for PS operation. The highest capacity MOF, mof_7642,⁵⁹ is predicted to exhibit capacities of 11.1 wt. % and 40.5 g-H₂ L⁻¹, surpassing that of PCN-610/NU-100, the record-holder under PS conditions. The crystal structure of mof_7642 is shown in Fig. 7a.

Figure 7. Crystallographic images of the highest-capacity MOFs under (a) pressure swing and (b) temperature swing conditions. These MOFs originate from the ToBaCCo⁵⁹ and University of Ottawa³⁹ databases, respectively.

Figure 6d provides a similar comparison between ML predictions and GCMC calculations for MOFs expected to exhibit high capacities under TPS conditions. Under these conditions only 95 MOFs were predicted by GCMC to outperform MOF-5. A summary of the 10 highest-capacity MOFs, sorted by their GCMC capacities, is provided in Table 6. (See Table S11 for a more extensive tabulation.) As found for PS operation, all of the top performing candidates are hypothetical compounds. One difference with the PS case is that all of these MOFs originate from the Univ. of Ottawa database.³⁷ Furthermore, none of the highest capacity MOFs identified for PS operation appear as top candidates for TPS. Comparing the highest-capacity MOFs for both operating conditions, it can be seen that the high-capacity TPS MOFs systematically exhibit lower surface areas (avg. = 4073 m² g⁻¹), smaller void fractions (avg. = 0.83), and higher densities. Hence, the categories of MOFs that maximize uptake under PS and TPS conditions exhibit distinct properties. These differences suggest that maximizing the surface area – which, as discussed above, is desirable for maximizing PS capacity – is not advantageous for TPS operation. This behavior can be explained by trends in *total* capacities,⁶ which the TPS capacities reported here approximate. More specifically, it is known that total volumetric capacities are maximized for intermediate values of the surface area; for larger surface areas the volumetric capacity decreases.

Returning to the list of promising MOFs for TPS operation, Table 6 reports that the highest-capacity MOF, str_m1_o1_o11_f0_pcu.sym.102.out, has a GCMC-predicted capacity of 10.4 wt.% and 53.1 g-H₂ L⁻¹. This capacity surpasses that of MOF-5, which to our knowledge holds the capacity record under these conditions. The crystal structure of this MOF is shown in Fig. 7b.

Figures S7-S8 and Table S12 quantify the differences between ML and GCMC predictions on the subset of high-capacity MOFs shown in Figs. 6c,d. For PS operation, the AUE of ML relative to GCMC is 0.24 wt.% and 0.66 g-H₂ L⁻¹, while for TPS the AUE is 0.24 wt.% and 1.28 g-H₂ L⁻¹. Both sets of errors are comparable to the errors reported in Table 4 for the original test set of MOFs. Figures S7(c,f) and S8(c,f) plot the frequency distribution of the differences between GCMC and ML. These distribution plots suggest that the largest differences occur for predictions involving real MOFs and for hypothetical MOFs extracted from databases other than those from Northwestern,³⁶ University of Ottawa,³⁷ and BJT.⁸³ (These MOFs are referred to as “other hypothetical MOFs” in Figure 6). These MOFs, along with the real compounds, exhibit higher structural diversity than those contained in the other databases. For example, the diversity of the topologies used in the ToBaCCo⁵⁹ and Zr-MOFs⁴⁵ databases and in the linkers used in MTV-MOF⁸⁴ database are larger than what is found in the databases from Northwestern,³⁶ University of Ottawa,³⁷ and BJT.⁸³

CONCLUSIONS

The H₂ storage capacities of nearly a million MOFs have been predicted via machine learning. The predictions span a diverse collection of MOFs sourced from 19 databases and reveal performance under two operating conditions: pressure swing and temperature + pressure swing. More than a dozen ML algorithms were benchmarked, with the extremely randomized trees method found to be the most accurate. The resulting ML models are accessible on the web at the HyMARC Data Hub.⁸⁶ These models allow for accurate,

rapid screening of the hydrogen storage properties of new MOFs using minimal structural data as input; only a single feature is needed for the simplest models.

The accuracy of the ML models was characterized as a function of training set size and the number/combination of input features. Regarding the dependence on the training set, the accuracy of the models can be well-described using a simple power-law function of the training set size. The dependence on the number and combination of input features was determined by evaluating 508 independent ML models generated from all possible combinations of the seven features. The single most important features for predicting H₂ uptake are pore volume (for gravimetric capacity) and void fraction (for volumetric capacity).

Using these models, 8,282 MOFs are identified that have the potential to exceed the capacities of state-of-the-art materials under usable conditions. The identified MOFs are predominantly hypothetical compounds, which (for pressure-swing operation) exhibit low densities (<0.31 g cm⁻³) in combination with high surface areas (>5,300 m² g⁻¹), void fractions (~0.90), and pore volumes (>3.3 cm³ g⁻¹). These MOFs are suggested as targets for experimental synthesis.

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Supporting Information

Document S1. Tables S1-S12, Figures S1-S8, Metrics for ML accuracy. Data S1. Feature_Combination_ML_Models.xlsx

AUTHOR CONTRIBUTIONS

A.A. conducted the computational components of the project. All authors contributed to the drafting of the paper and to the project idea.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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