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From CO_x to Light Olefins:

Computer-Aided Catalyst Design

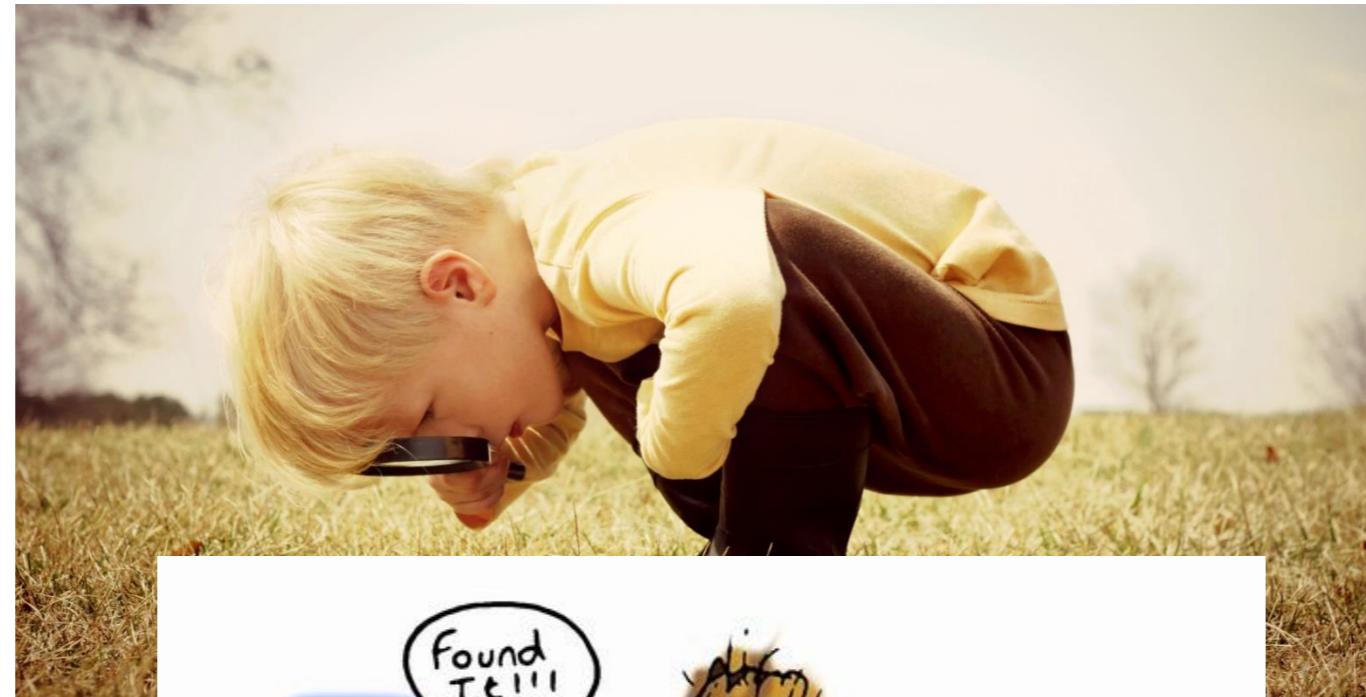
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08/12/2022

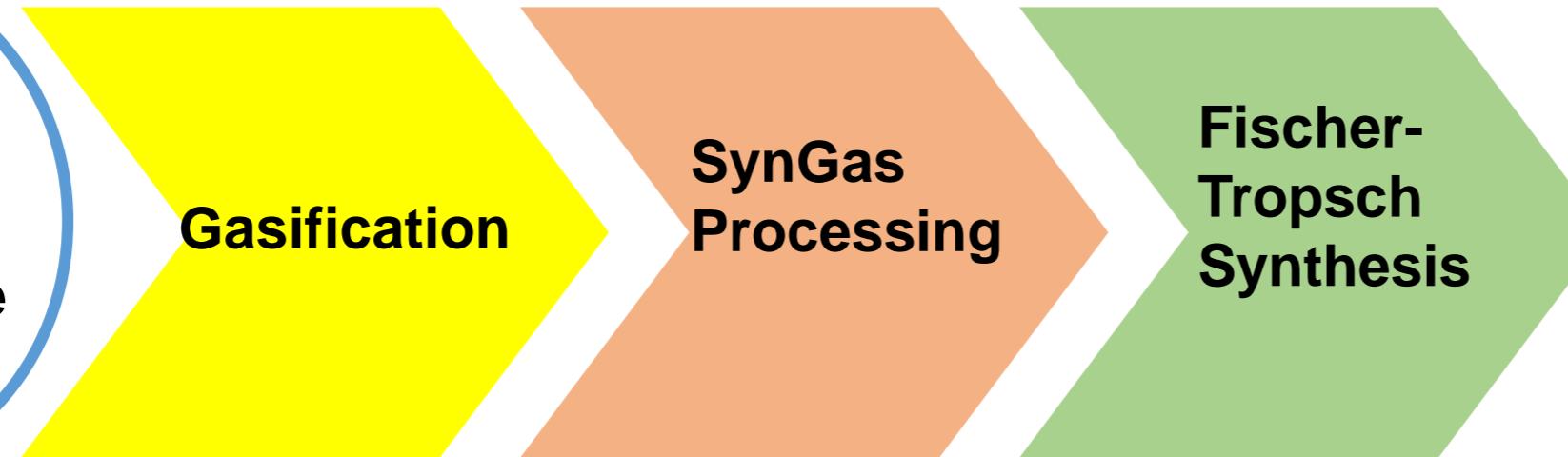
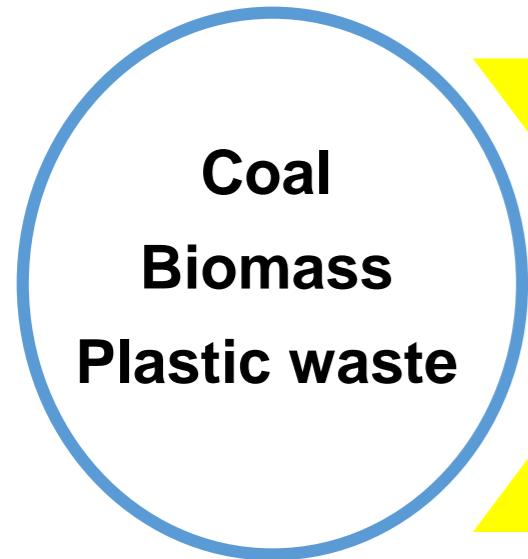
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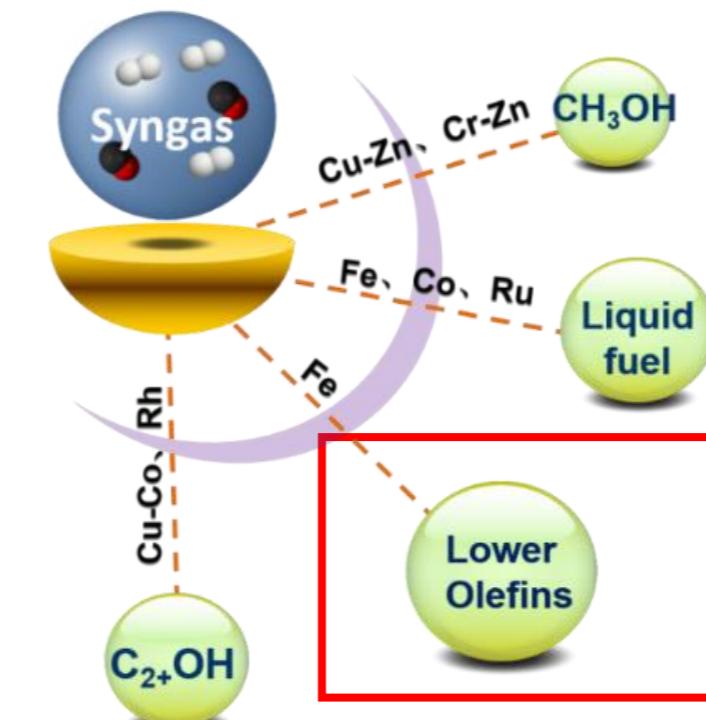
ideal catalyst: needle in a haystack



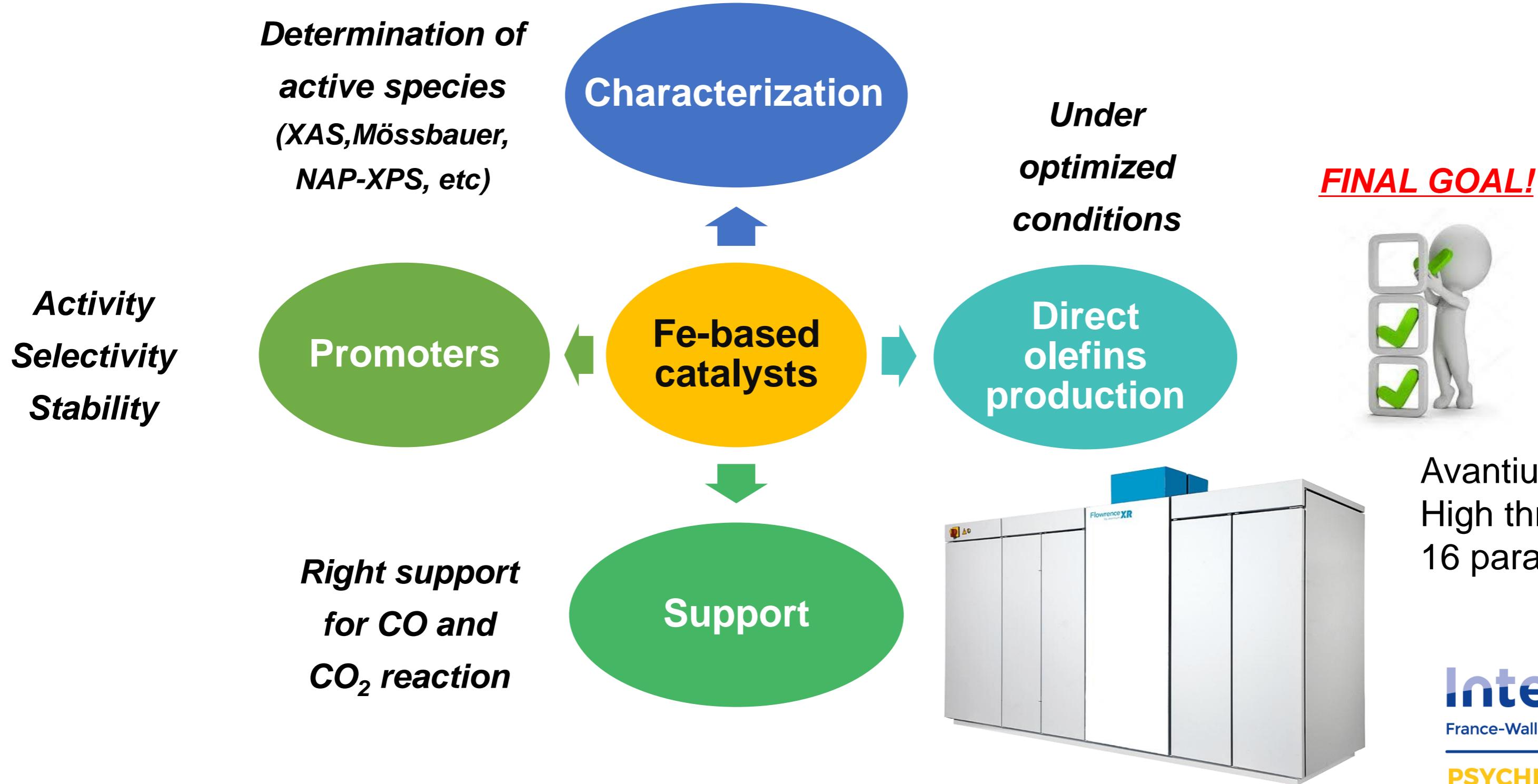
Fischer Tropsch Synthesis



- carbon monoxide (CO) (or carbon dioxide (CO₂)) and hydrogen (H₂), conversion into hydrocarbons.
$$(2n+1) H_2 + n CO \rightarrow C_n H_{(2n+2)} + n H_2O$$
$$CO + H_2O \rightarrow H_2 + CO_2$$
- insight in reaction chemistry and process via modelling:
 - ✓ elementary steps
 - ✓ machine learning



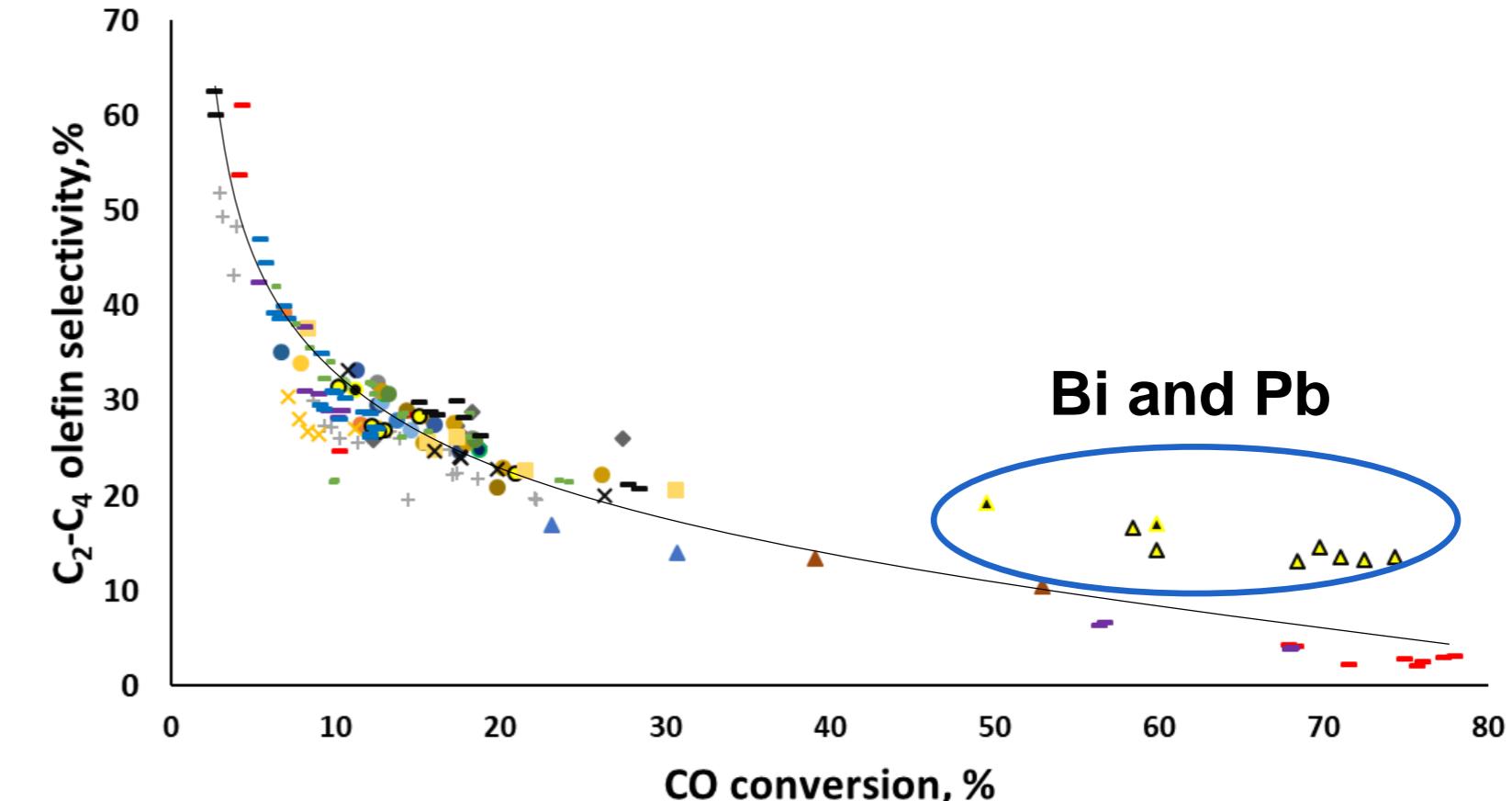
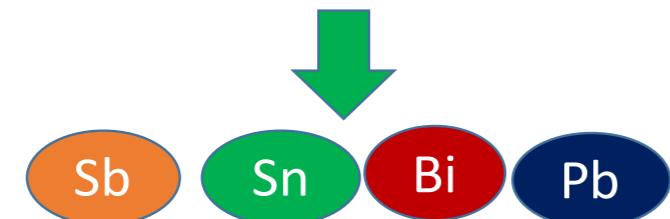
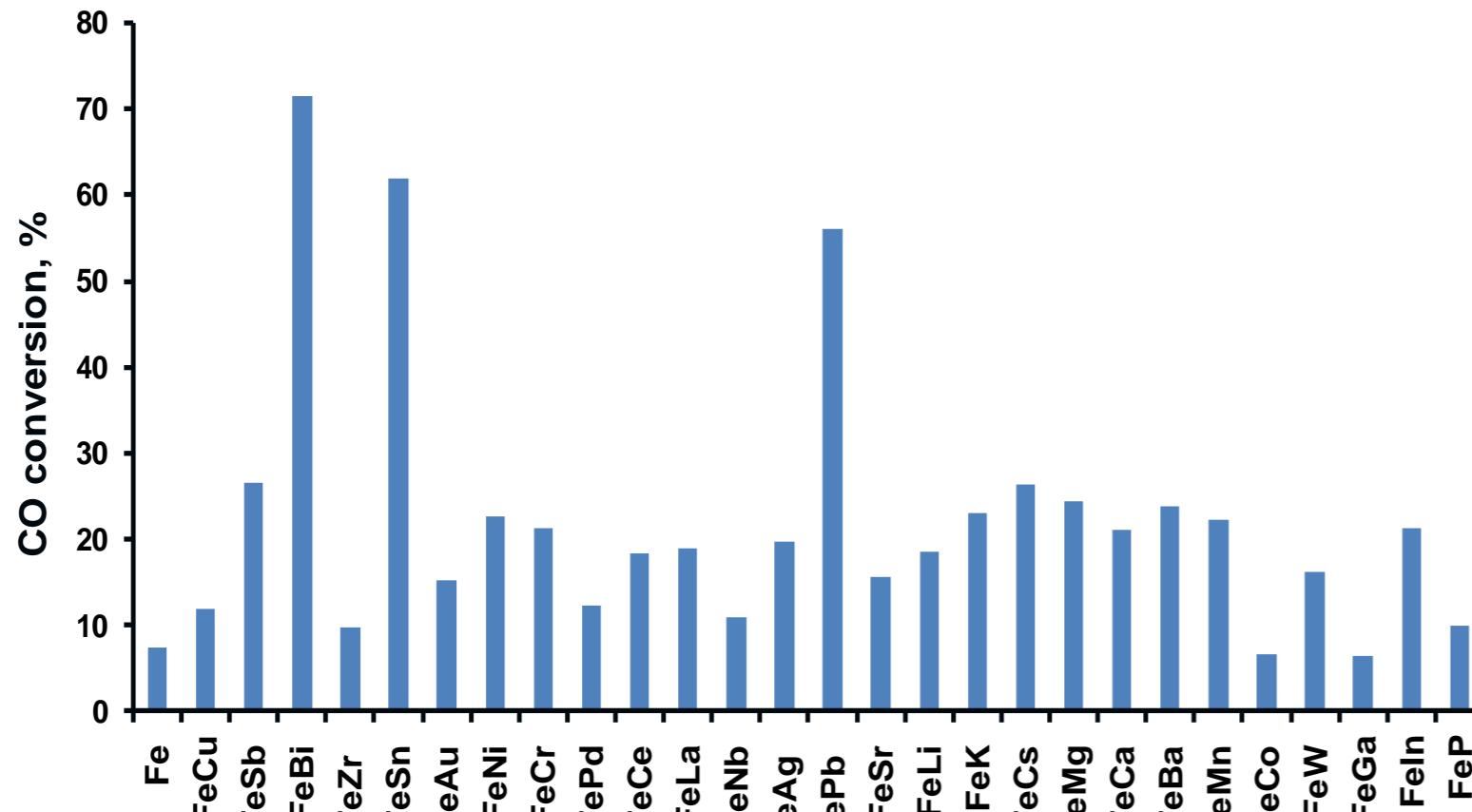
experimental search for best catalysts



light olefin synthesis from CO

- Fe/SiO₂ catalyst was used as reference
- HTE used to evaluate 27 promoters

T= 350 °C, H₂/CO= 1, P= 10 bar



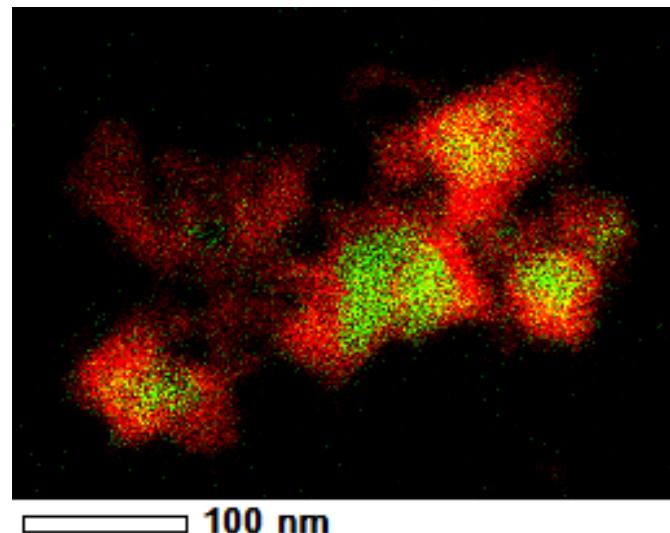
- Maximum olefins selectivity was obtained at a lower CO conversion
- Bi and Pb show higher olefin conversion at similar conversion levels compared to other promoters

summary: light olefin synthesis from CO

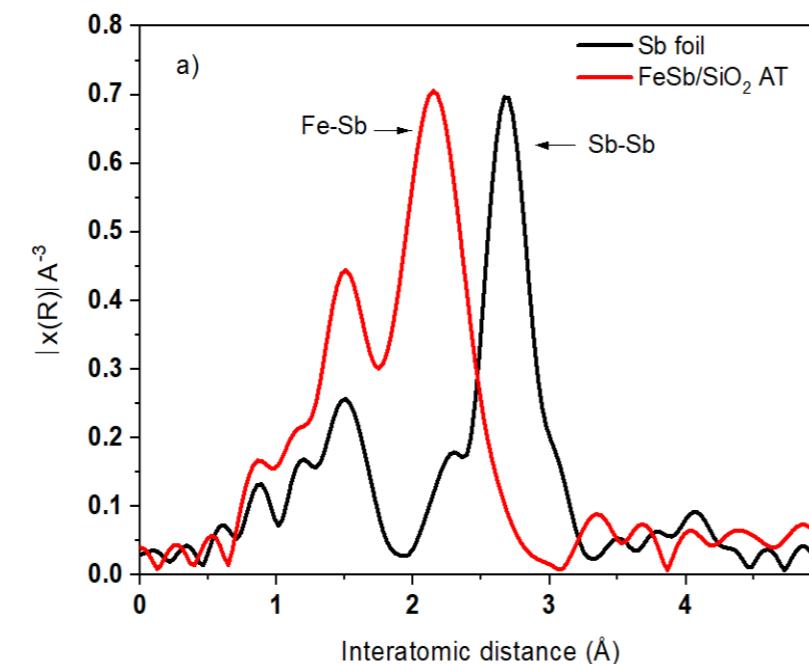
- Promotion with soldering metals (Sn, Sb and Bi)
- Diffusion on catalyst surface
- Strong Fe-promoter interaction

Iron carbides formation was systematically observed by different techniques (XRD, Mössbauer, NAP(XPS) and Magnetization

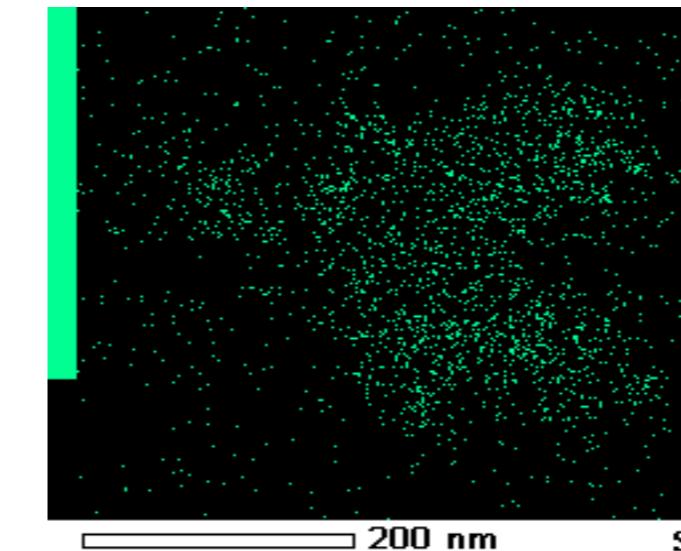
core-shell structures



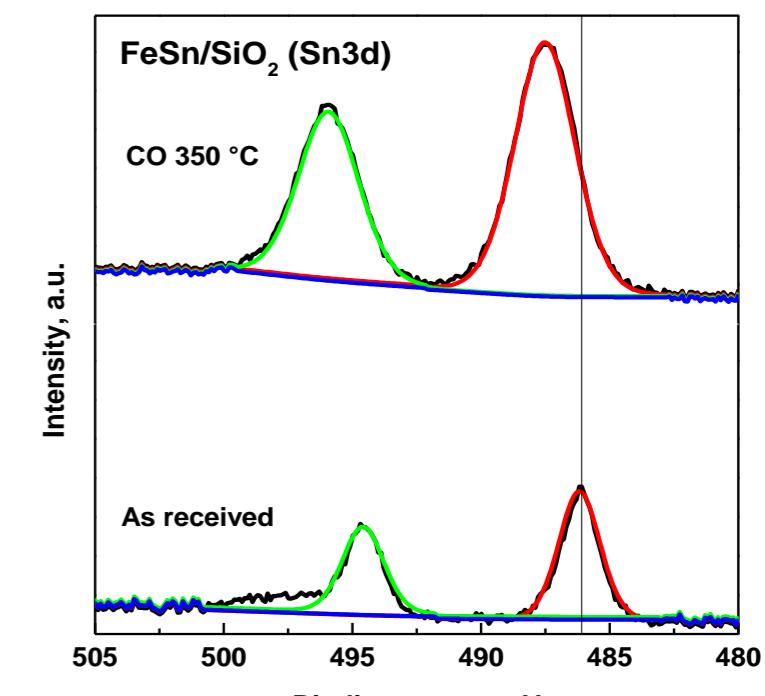
Alloy formation



Close to FeNPs

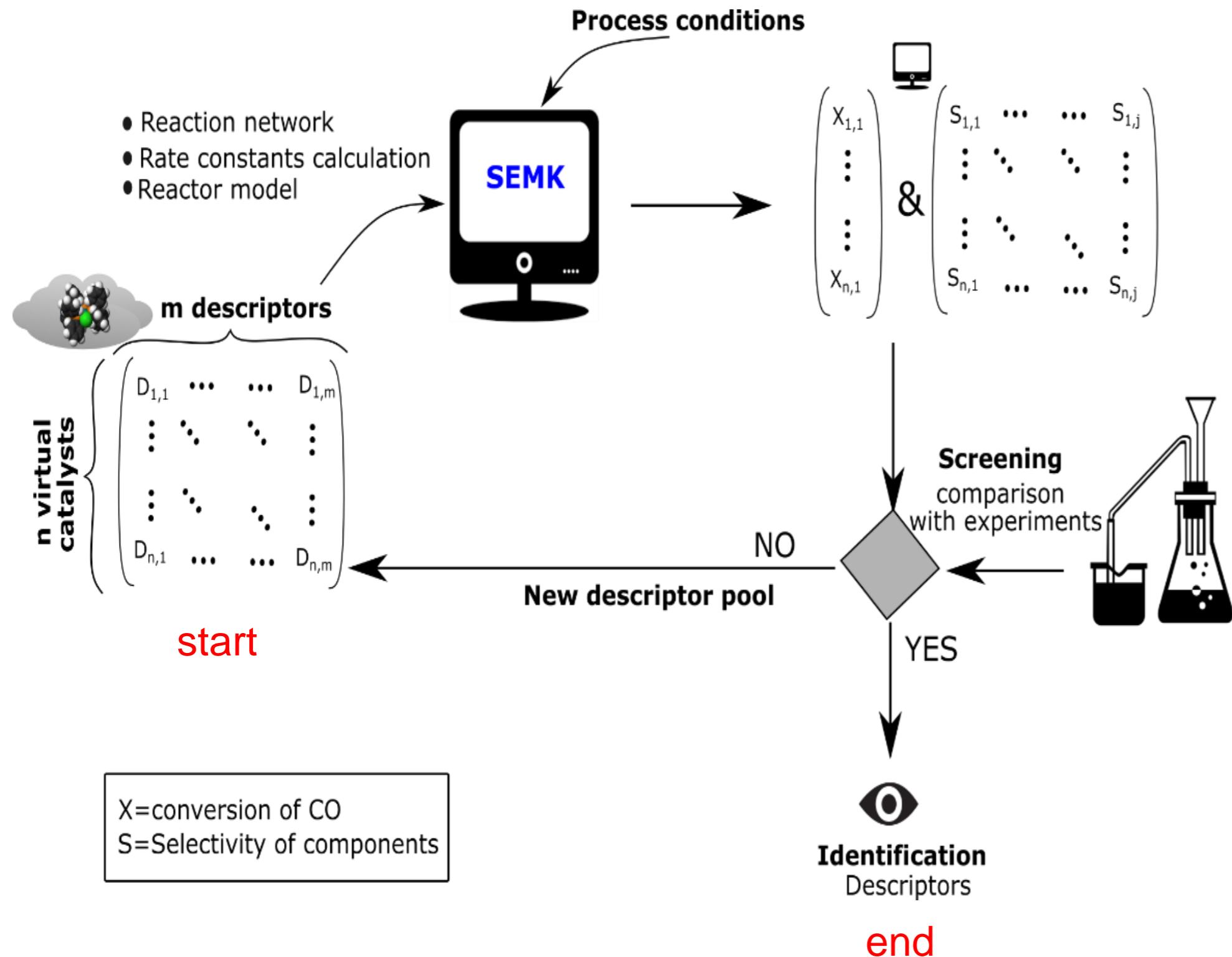


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TOF increases because of close interaction of active sites with the promoters

virtual catalyst design



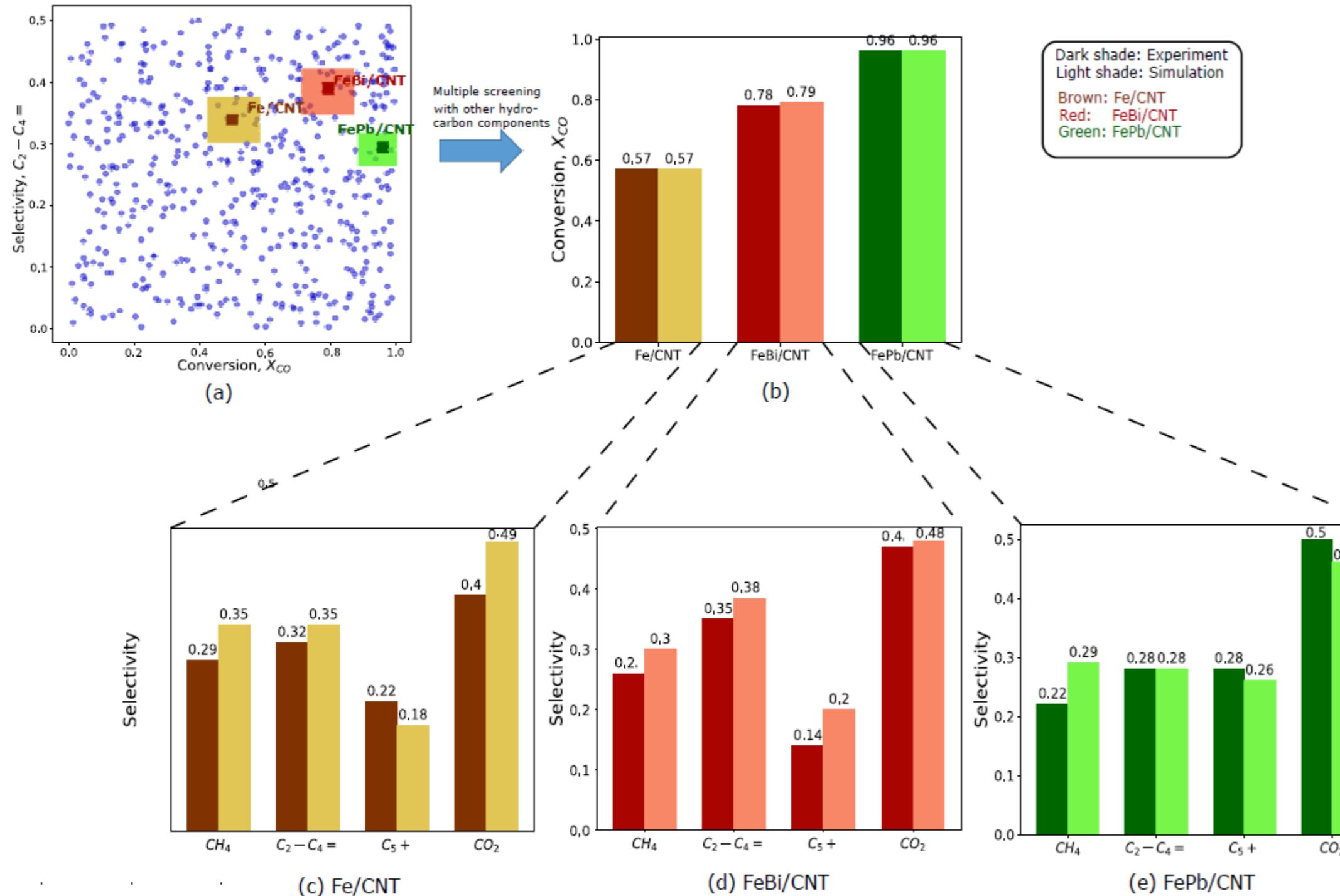
SEMK framework :

- network generation for FTS
- kinetic and catalyst descriptors.

virtual catalyst design :

- generation of virtual catalyst library.
- numerical simulation using SEMK.
- comparison and screening with experimental results (iterative process).

identification of descriptors

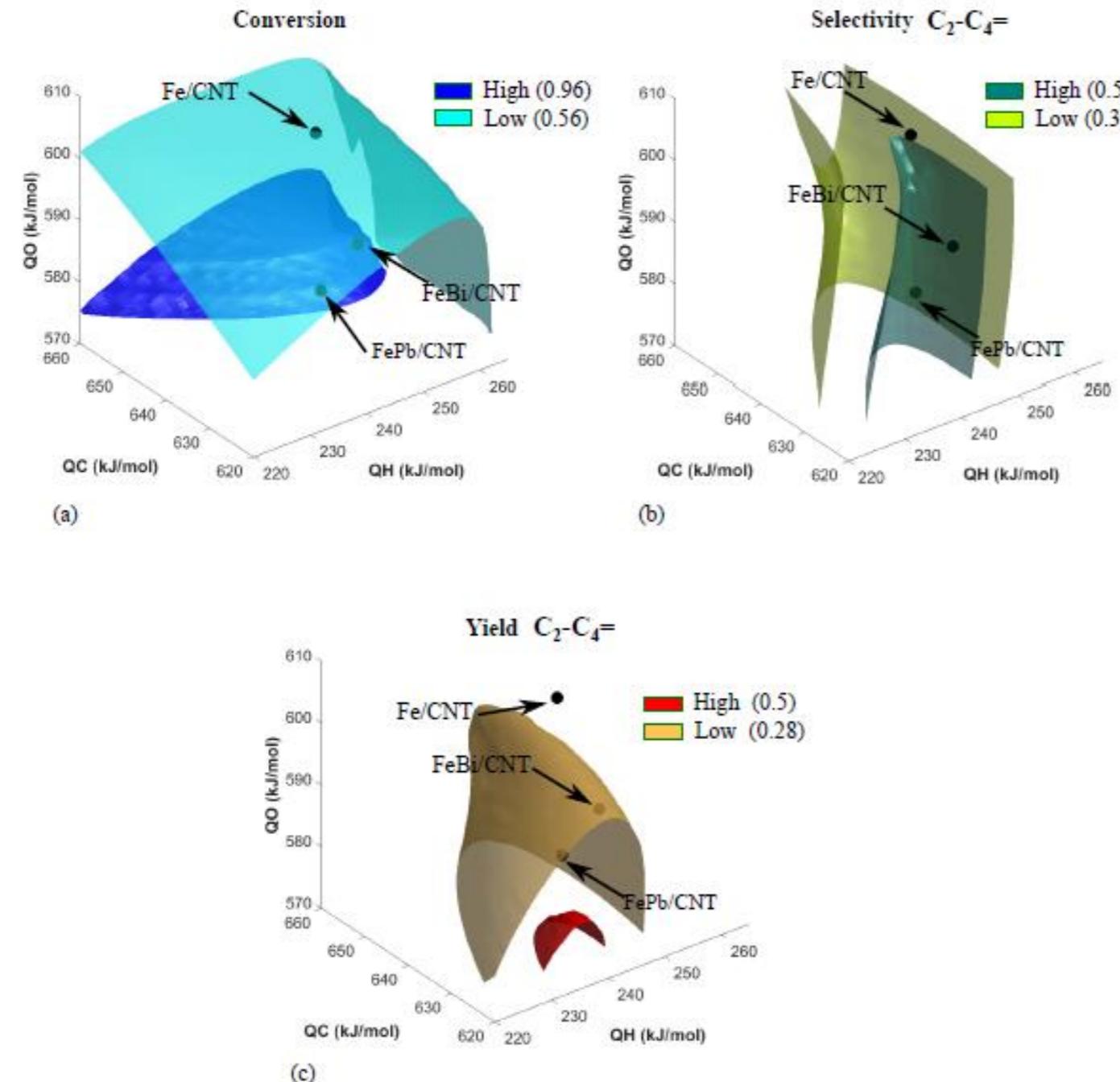


Reaction family/elementary reaction	E_a^{for} (kJ/mol)
Reactant adsorption	
1. $H_2 + 2M \rightleftharpoons 2MH$	0
2. $CO + 2M \rightleftharpoons MMCO$	0
Initiation reactions	
3. $MMCO + 3M \rightleftharpoons MMMC + MMO$	56.81 ± 0.53
4. $MMMC + MH \rightleftharpoons MMCH + M$	77.66 ± 0.70
5. $MMCH + MH \rightleftharpoons MMCH_2 + 2M$	11.94 ± 0.10
6. $MMCH_2 + MH \rightleftharpoons MCH_3 + 2M$	61.88 ± 0.50
Chain growth	
7. $MC_nH_{2n+1} + MMCH_2 \rightleftharpoons MC_{n+1}H_{2n+3} + 2M$	44.79 ± 0.43
Formation of alkanes	
8. $MC_nH_{2n+1} + MH \rightleftharpoons C_nH_{2n+2} + 2M$	117.75 ± 0.67
Formation of metal alkenes	
9. $MC_nH_{2n+1} + M \rightleftharpoons MC_nH_{2n} + MH$	96.27 ± 0.50
Alkene desorption	
10. $MC_nH_{2n} \rightleftharpoons C_nH_{2n} + M$	$62.09 (n=2)$ $59.08 (n=3-10)$
Formation of carbon dioxide	
11. $O - CHO - M + M - OH + O \rightleftharpoons O - COOH - M + O - H + M$	138.95 ± 1.15
Water formation	
12. $MMO + MH \rightleftharpoons MOH + 2M$	103.80 ± 0.96
13. $MOH + MH \rightleftharpoons H_2O + 2M$	86.22 ± 0.62
Atomic Chemisorption enthalpies	
Fe/CNT (kJ/mol)	249.5
FeBi/CNT (kJ/mol)	247.7
FePb/CNT (kJ/mol)	248.4
Q _H (Fe _x C – H)	644.1
Q _C (Fe _x C – C)	601.0
Q _O (Fe _x C – O)	632.1
	641.5
	589.1
	577.1

Gu et al. Applied Catalysis B: Environmental **234**, 153 (2018).

Chakkingal et al. Chemical Engineering Journal **419**, 129633 (2021)

identification of optimal catalyst descriptors

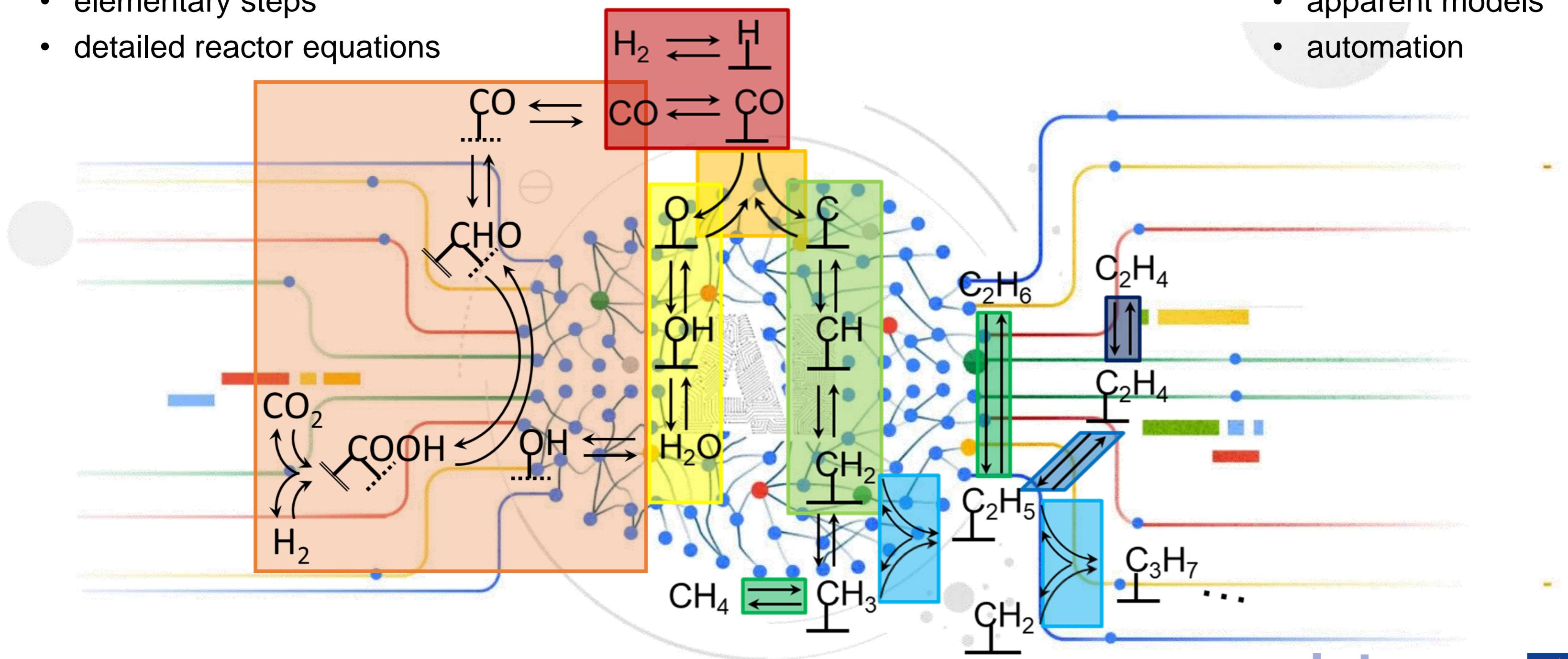


- 3D descriptor spaces representing conversion, selectivity & yield
- experimentally observed yields:
 - Fe/CNT: 20%
 - FeBi/CNT: 27%
 - FePb/CNT: 30%
- maximum achievable light olefin yield: 50%
 - $Q_H \approx 234$ kJ/mol
 - $Q_C \approx 622$ kJ/mol
 - $Q_O \approx 576$ kJ/mol

Fig: Iso-surfaces of conversion, light olefin selectivity and yield.

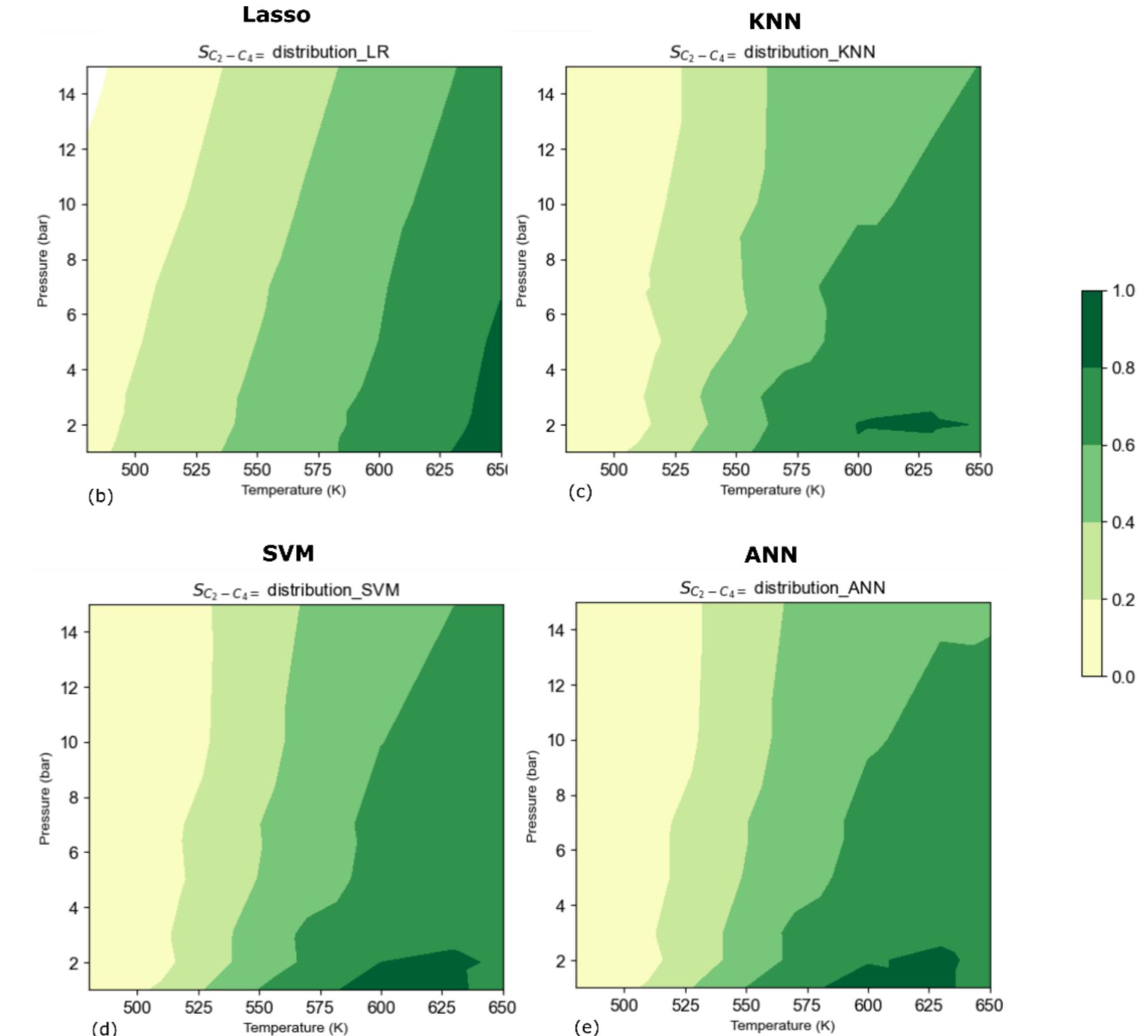
balance between effort and insight

- microkinetic model
 - elementary steps
 - detailed reactor equations
- machine learning
 - apparent models
 - automation

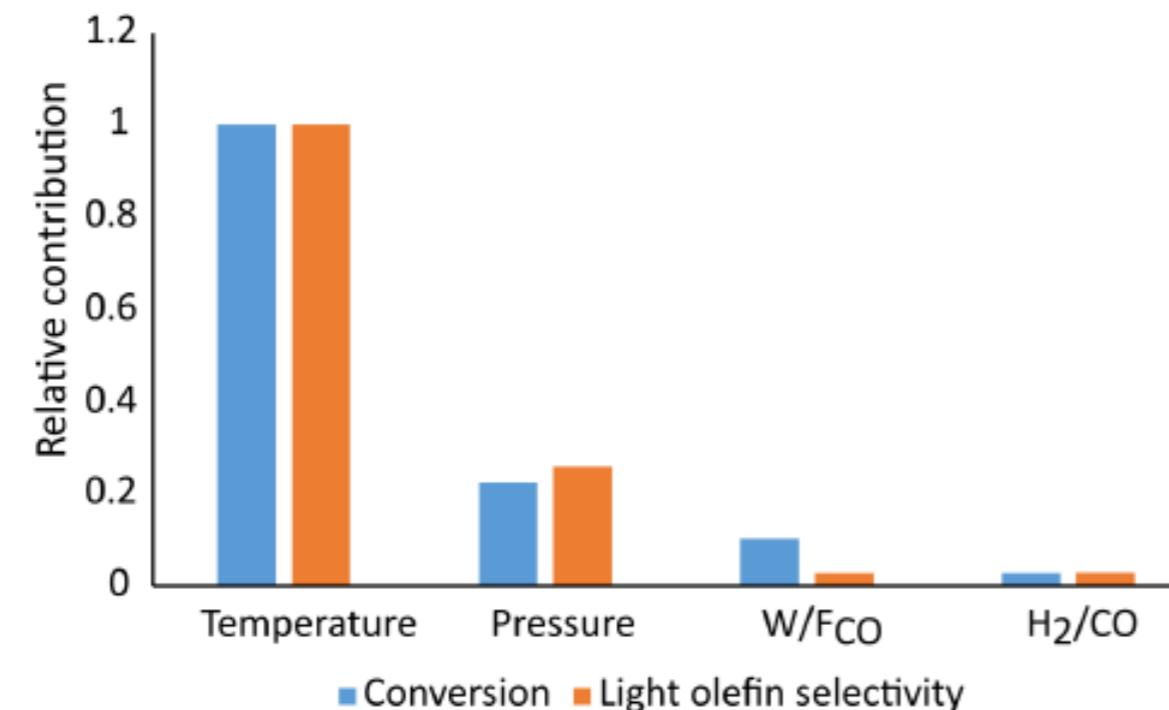


light olefin selectivity

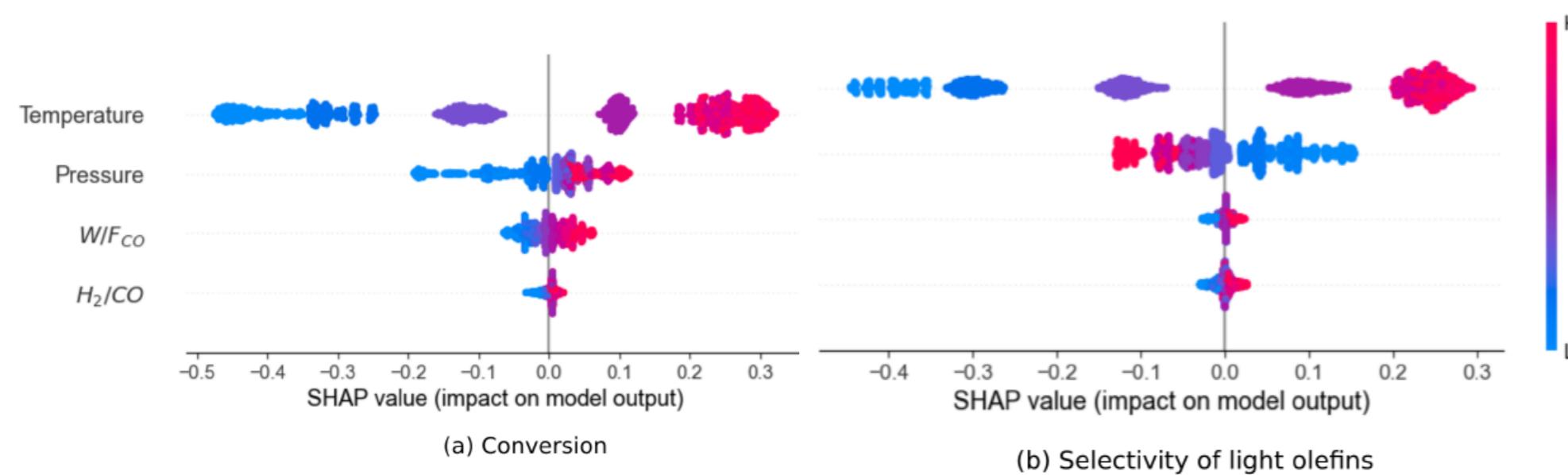
- light olefin selectivity more pronouncedly nonlinear with temperature and pressure
- lasso regression, but also kNN unable to capture these nonlinearities
- SVM and ANN predict the nonlinear relation accurately.



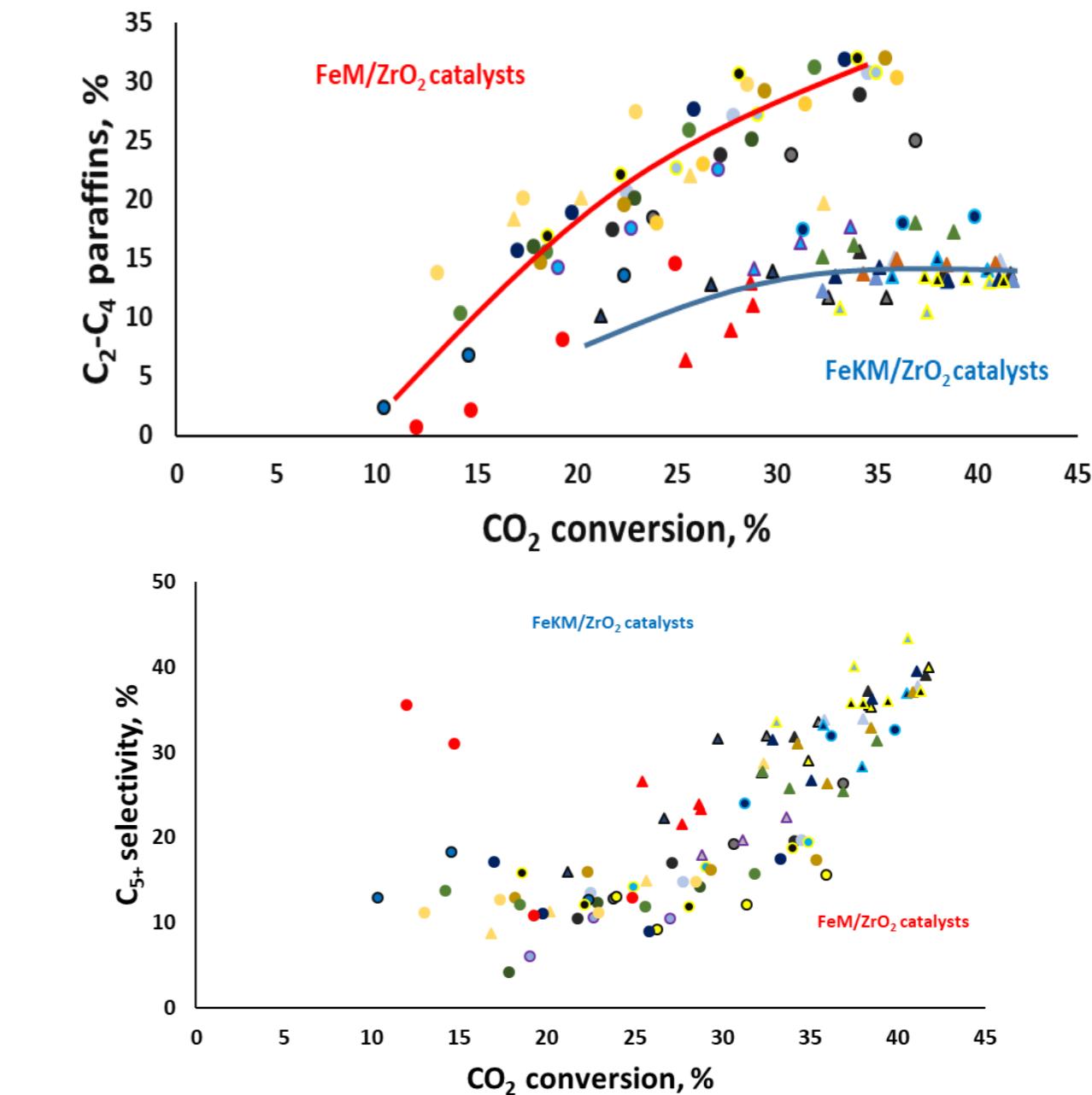
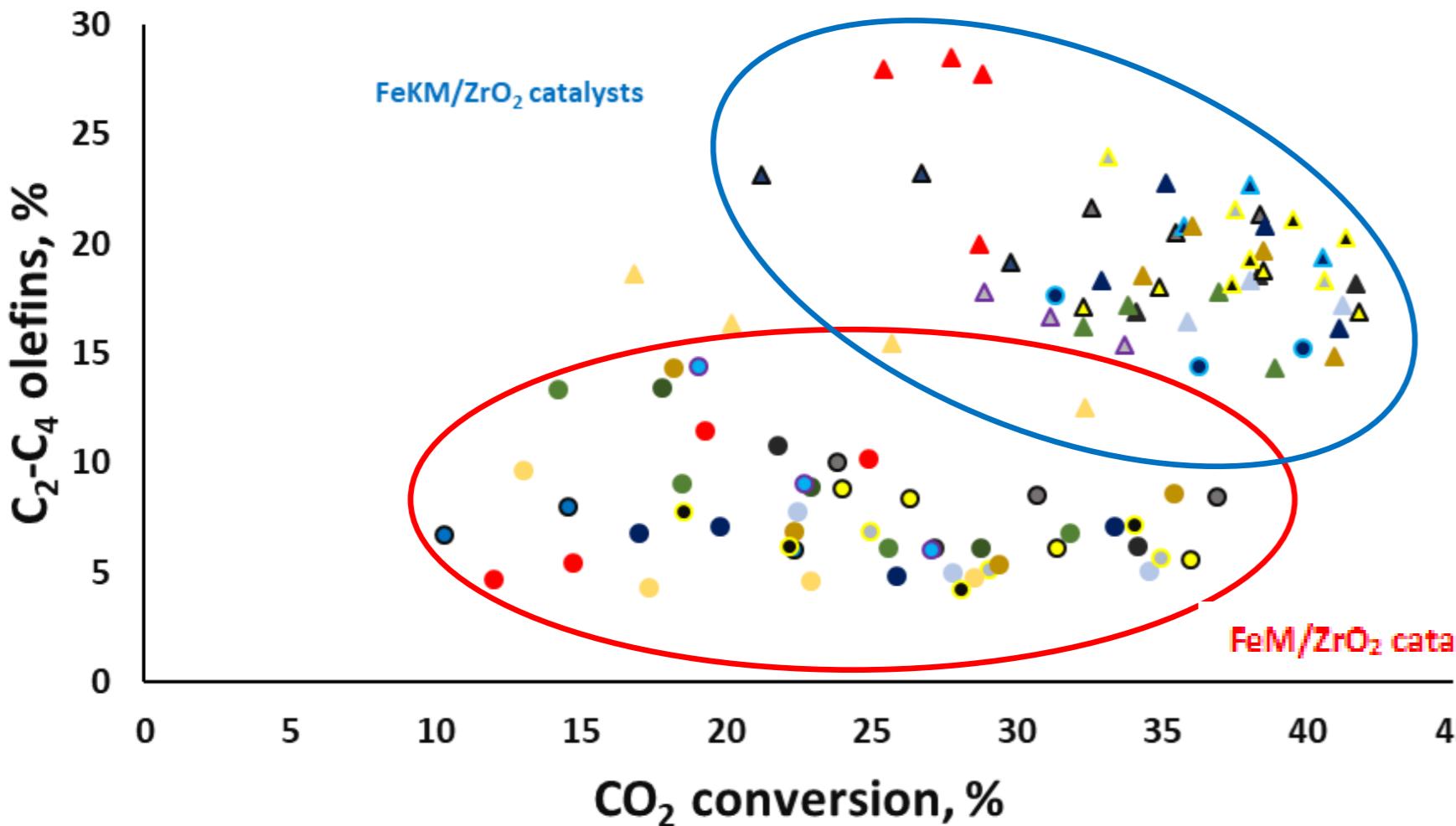
relative importance (Shap)



- temperature (1x) and pressure (0.22-0.26x) are most influential (both conversion and light olefin selectivity)
- conversion: space time (0.1x) over syngas ratio (0.03x).
- light olefin selectivity: syngas ratio (0.03x) and space-time (0.03x).



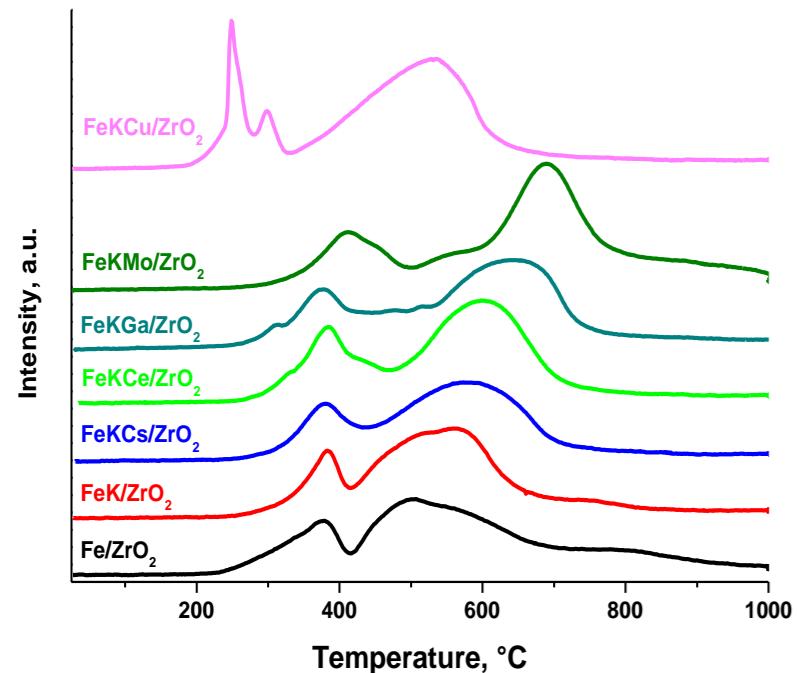
light olefin synthesis from CO_2 over promoted Fe/ ZrO_2 catalysts



- Catalysts promoted with K showed the highest olefin selectivities
- Most selective catalysts to lower olefins were selected to be further studied

summary: catalyst parameters for light olefin synthesis from CO₂

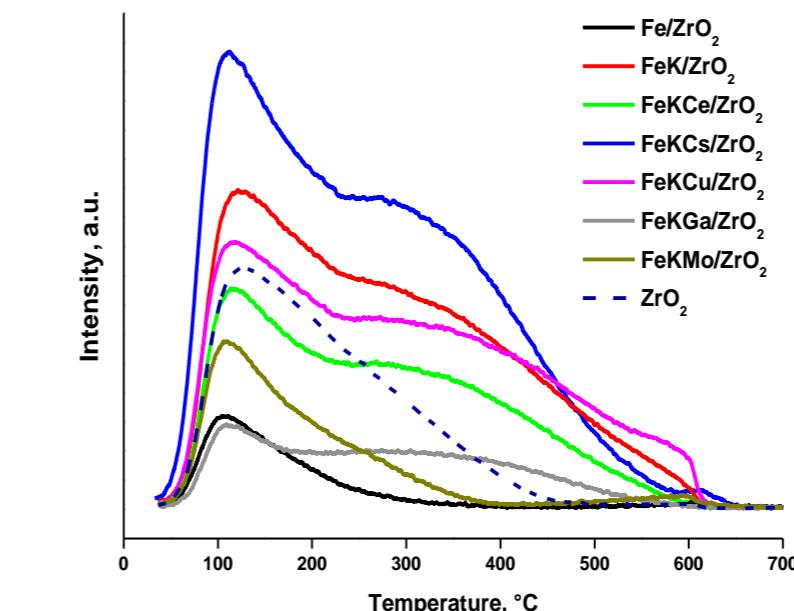
Better Fe Reducibility



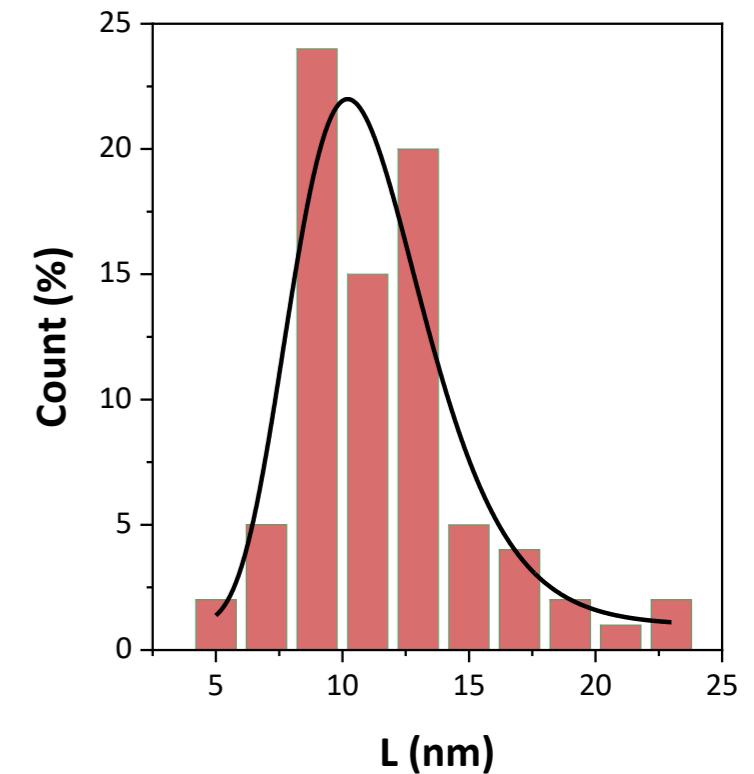
Higher extent of iron carbidization

Sample	Phase	Spectral contribution (%)
FeKMo/ZrO ₂	$\chi\text{-Fe}_5\text{C}_2$	60
	$\epsilon'\text{-Fe}_{2.2}\text{C}$	14
	Fe _x C (SPM)	10
	Fe _{1-x} O (SPM)	16

Basicity



Better Fe dispersion



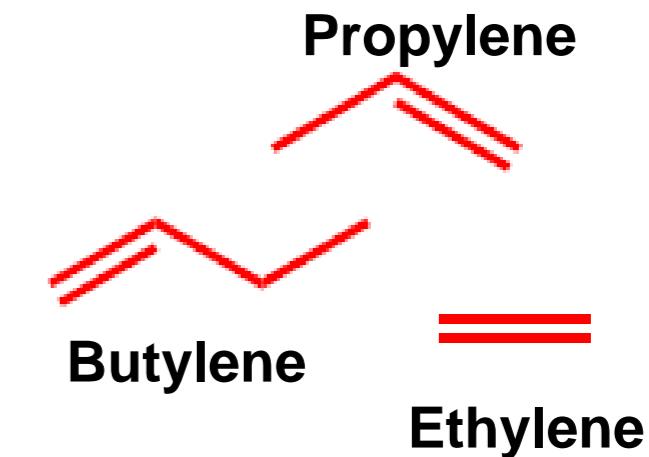
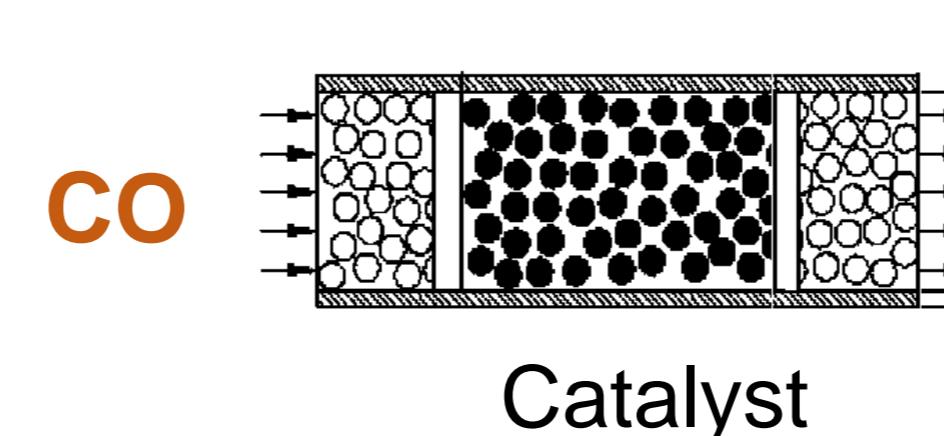
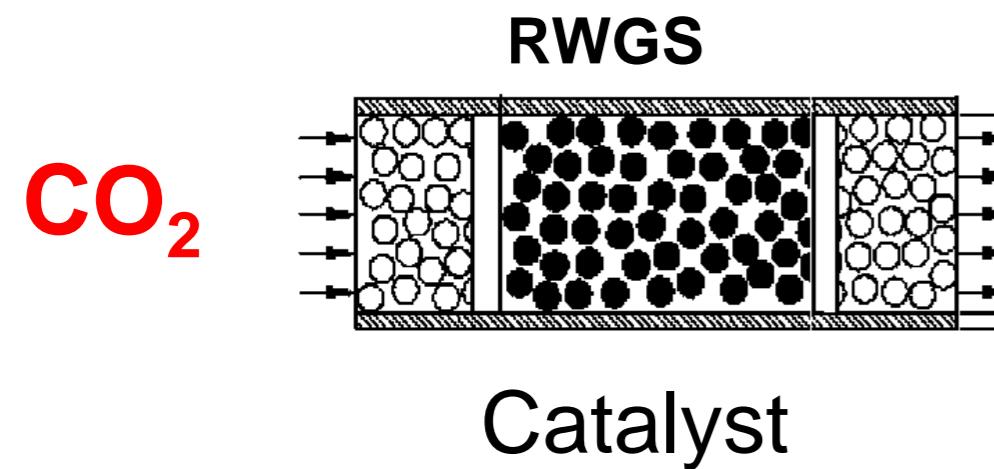
- Best promoters are alkaline metals. Work better together with Cu, Mo, Ga and Ce

light olefin synthesis from CO or CO₂ ?

The best catalysts for hydrogenation of CO to light olefins are not good for hydrogenation of CO₂ and vice versa.

CO hydrogenation shows higher light olefin selectivity compared to CO₂ hydrogenation

Importance of sustainable hydrogen !



Selectivity to CO close to 100%

Maximum selectivity to light olefins ~ 60%

conclusions

- modeling provides crucial insights in how reaction performances relate to input and operating conditions
- balance between effort and insight is pursued
 - elementary step based modeling
 - machine learning
- Fischer Tropsch synthesis case study
 - SEMK virtual catalyst design identified descriptors for enhanced light olefin selectivity.
 - Machine Learning models for optimizing operating conditions (trained on SEMK data)
 - nonlinearities in chemical kinetics require ANN and SVR ML models over Lasso or kNN
 - interpretation techniques allow opening the black box ML models

Q&A



Acknowledgements



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