

Surrogate-Assisted Robust Multi-Objective Optimization of a Fluidized-Bed Methane Pyrolysis Reactor Under Technical and Market Uncertainty

Orlu Ndamati Moses¹; Akuma Oji²; Muwarure Peter³

^{1,3}Centre for Gas, Refining and Petrochemicals Engineering, University of Port Harcourt, Rivers State, Nigeria.

²The Department of Chemical Engineering, University of Port Harcourt, Rivers State, Nigeria.

Publication Date: 2026/10/27

Abstract: Conventional multi-objective optimisation (MOO) of methane pyrolysis reactors assumes model parameters as precisely known, while many crucial factors are highly unknown. This research uses NSGA-II and Monte Carlo sampling to produce and analyse robust Pareto fronts under uncertainty using a surrogate-assisted robust multi-objective optimisation framework. Kriging surrogates trained on 300 Latin hypercube designs with 500 Monte Carlo samples compare mean-variance, worst-case, and chance-constrained formulations. Deterministic optimisation overestimated performance and violated reliability controls in 7% of Pareto designs. The robust framework lowered the chances of failing the 60% conversion standard from 37.8% at the basic case to 6% across the robust front and zero at the selected design. MOEA/D performed poorly (hypervolume 1.20 vs. 0.54). TOPSIS configuration (1,098 °C, 4.85 bar, $U_0/U_{mf} = 2.0$, 5.0 kg catalyst, pure methane) yields 94.7% conversion, 1.4% standard deviation, 2.72 USD/kg LCOH (P95 3.91 USD/kg), and 3.4 kg/kg H₂ CO₂ intensity.

Keywords: Robust Optimization; Multi-Objective Optimization; NSGA-II; Surrogate-Assisted Optimization; Methane Pyrolysis; Fluidized Bed; Chance Constraints.

How to Cite: Orlu Ndamati Moses; Akuma Oji; Muwarure Peter (2026) Surrogate-Assisted Robust Multi-Objective Optimization of a Fluidized-Bed Methane Pyrolysis Reactor Under Technical and Market Uncertainty. *International Journal of Innovative Science and Research Technology*, 11(10), 1837-1842. <https://doi.org/10.38124/ijisrt/26oct1063>

I. INTRODUCTION

The low-carbon energy transition is predicted to rely heavily on hydrogen [1, 2]. Methane pyrolysis, in which methane is converted into hydrogen and solid carbon, produces a marketable carbon co-product and reduces CO₂ emissions ($\text{CH}_4 \rightarrow \text{C(s)} + 2\text{H}_2$, $\Delta H_{298}^\circ = +74.85 \text{ kJ/mol}$) [3, 4, 5]. FBRs are promising because they allow continuous catalyst addition and carbon withdrawal, have great temperature homogeneity, and are industrial-scale [6, 7, 8].

Multiple goals compete in methane pyrolysis FBR design. Designers want high methane conversion, high hydrogen content, and cheap hydrogen levelized cost. Objectives clash. Higher temperatures boost reaction rate and equilibrium conversion but hasten catalyst degradation and cost more. High catalyst inventories increase reactor size and catalyst cost but boost conversion. Higher pressures lower equilibrium conversion but reactor volume and compression costs lower. Multi-objective optimisation (MOO) solves these

problems by producing a collection of Pareto-optimal trade-off solutions [9, 10].

Conventional MOO assumes model parameters are known. Key methane pyrolysis parameters are unclear. From catalyst batch to batch and between laboratories, kinetic constants like activation energy and pre-exponential factor vary. Carbon morphology and operation affect deactivation. An empirical correlation with large scatter yields heat transfer coefficients and interphase mass transfer rates. Volatile market prices, especially natural gas and carbon co-product sales, affect economics [8, 11]. Once these uncertainties are acknowledged, an ideal design at nominal parameter values may perform badly or fail to meet product specifications. Robust optimisation targets designs that meet requirements with high probability or are insensitive to uncertainty [12, 13].

Computational cost is the fundamental barrier to robust mechanistic reactor model optimisation. For each candidate design, 500 Monte Carlo samples are needed to assess its

mean and variance. A robust optimisation requires millions of reactor simulations because an evolutionary algorithm like NSGA-II analyses 15,000 potential designs. Kriging (Gaussian process regression) and radial basis functions (RBFs) can describe the expensive model's input–output behaviour for a fraction of its cost, making robust optimisation possible [14, 15].

II. METHOD

➤ Reactor and Techno-Economic Model Summary

This model is a one-dimensional, steady-state, two-phase (Kunii–Levenspiel) model of a bubbling fluidised bed with a Geldart group B catalyst ($d_p = 200 \mu\text{m}$, $\rho_p = 2,500 \text{ kg/m}^3$) and a 0.10 m internal diameter. An axial energy balance, gas–solid hydrodynamics, power-law kinetics, first-order catalyst deactivation, hydrogen inhibition, and interphase mass transfer are included in the model. Five factors determine a design: reactor temperature (800–1,100 °C), pressure (1–5 bar), fluidisation ratio (2–5), catalyst mass (0.5–5 kg), and feed methane mole fraction (0.5–1.0). The model calculates methane conversion (X_{CH_4}), hydrogen mole fraction (Y_{H_2}), carbon generation rate, outlet temperature, heat duty, and hydrodynamic properties. This techno-economic model assesses LCOH and CO₂ intensity for a 2,000 kg/h methane processing facility operating 8,000 h/year. Capital expenditures are assessed using the module-factor (Guthrie) technique at a CEPCI of 800 (2024 base). Additional information is in the reactor-model publication.

➤ Uncertainty Characterisation

We identified eight uncertain parameters: six technical (activation energy, pre-exponential factor, deactivation constant, bed-to-wall heat transfer coefficient, wall heat-loss coefficient, and interphase mass-transfer correction factor) and two market (carbon selling price and natural gas Distributions reflected literary values and engineering opinion. Activation energy, pre-exponential factor, deactivation constant, pricing, and transport coefficients were distributed using normal, log-normal, triangular, and uniform distributions, respectively. Supplemental uncertainty-quantification article provides specifics.

➤ Surrogate Construction

Surrogates were trained for six primary statistics (μ_X , σ_X , μ_Y , σ_Y , μ_{LCOH} , and σ_{LCOH}) based on five decision factors (scaled to [0, 1]) after Architecture B. $N_{\text{train}} = 300$ training points and $N_{\text{test}} = 50$ test points were used to sample the five-dimensional design space using Latin hypercube sampling. We used a Monte Carlo technique ($N = 500$) at each design point, resulting in 150,000 entire model runs for training and 25,000 for testing. Pedregosa et al. [16] used Kriging, a Gaussian process regression with a constant $\times$ Matérn 5/2 kernel and automatic relevance determination, implemented with scikit-learn's GaussianProcessRegressor. A thin-plate spline radial basis function interpolation with a linear polynomial tail was the benchmark (SciPy RBFInterpolator) [17]. Additional information is in the surrogate-modelling study.

➤ Formulation of the Optimization Problems

Deterministic problem. At nominal parameter values θ_0 :

$$\min_{\mathbf{x}} [-X_{CH_4}(\mathbf{x}, \theta_0), -Y_{H_2}(\mathbf{x}, \theta_0), LCOH(\mathbf{x}, \theta_0)]$$

Subject to:

$$X_{CH_4} \geq 0.60, Y_{H_2} \geq 0.75, \mathbf{x}_L \leq \mathbf{x} \leq \mathbf{x}_U$$

Robust framework problem (main formulation, mean–variance with chance constraints):

Subject to:

$$\min_{\mathbf{x}} [-\mu_X(\mathbf{x}), \sigma_X(\mathbf{x}), \mu_{LCOH}(\mathbf{x})]$$

$$P[X_{CH_4}(\mathbf{x}, \theta) < 0.60] \leq 0.05, \quad P[Y_{H_2}(\mathbf{x}, \theta) < 0.75] \leq 0.05, \quad T \leq 1100^\circ\text{C}$$

The chance constraints were implemented using an empirical P5 surrogate (or equivalently, a safety factor of 1.75 instead of 1.645) to guarantee the 5% target in the lower tail of the left-skewed conversion distribution. Three alternative robust formulations were compared:

- Formulation A (mean–variance): $\min [-\mu_X, \sigma_X, \mu_{LCOH}]$ subject only to the Y_{H_2} chance constraint.
- Formulation B (worst-case): $\min [-\min_{\theta} X(\mathbf{x}, \theta), \mu_{LCOH}]$ subject to the Y_{H_2} chance constraint, where the minimum is taken over the 500 Monte Carlo samples.
- Formulation C (chance-constrained): $\min [-\mu_X, \mu_{LCOH}]$ subject to both chance constraints.

➤ Algorithm: NSGA-II on the Surrogates

NSGA-II [10] as implemented in pymoo 0.6 [11] was used with a population of 100, 150 generations (15,000 evaluations), simulated binary crossover (probability 0.9, $\eta_c = 15$), polynomial mutation ($\eta_m = 20$, probability $1/n_{\text{var}}$) and constraint-domination handling. All robust objectives and constraints were evaluated with the Kriging surrogates. The deterministic problem, which needs only one model run per design, was optimised directly on the full model. For benchmarking, MOEA/D [19] with 105 Das–Dennis reference directions, 15 neighbours and the same variation operators was run with the same budget, with constraints handled by a static penalty. Each algorithm was run with five random seeds.

➤ Pareto Analysis and Design Selection

Front quality was measured by the hypervolume (reference point 1.1 in each normalised objective), the inverted generational distance with respect to the combined non-dominated set of all runs, and the generalised spread [20].

Before applying TOPSIS, the knee-point of the robust Pareto front was identified explicitly. The objectives were first normalised to [0, 1]. The two extreme designs of the front were identified, and the perpendicular distance of each Pareto

design from the line joining these extremes was computed in the normalised objective space. The design with the maximum perpendicular distance was taken as the knee-point, representing the best compromise between expected conversion, conversion variability and expected LCOH.

TOPSIS [21] was then applied to the knee region of the robust pareto front, using vector normalisation and equal weights on μX (benefit), σX (cost) and $\mu LCOH$ (cost). The relative closeness of design k to the ideal point is:

$$C_k = (d_k^-) / (d_k^- + d_k^+)$$

Where d_k^+ and d_k^- are the Euclidean distances to the ideal and anti-ideal points in weighted normalised space. The sensitivity of the selected design to the weights was also examined.

➤ Validation of the Robust Pareto Front

Twenty designs spread along the robust front (including the TOPSIS design) were re-evaluated with the full reactor model and the full Monte Carlo ($N = 500$). If the relative error of the surrogate in μX , σX , μY , $\mu LCOH$ or $\sigma LCOH$ exceeded 8 % for any point, those 20 points were added to the DOE, the surrogates were retrained, the optimization was repeated, and the validation was performed again. The final robust front was also evaluated entirely with the full Monte Carlo to obtain empirical failure probabilities.

➤ Software and Hardware

The reactor model (ode45) reference implementation was MATLAB R2024a. Vectorised model, Kriging (scikit-learn), LHS support (SALib), NSGA-II, MOEA/D, hypervolume and IGD (pymoo 0.6), and figures (Matplotlib) utilised Python 3. The complete study ran on an 8-GB RAM two-core cloud workstation. Each surrogate-based NSGA-II run took 4 s.

III. RESULTS

Before you begin to format your paper, first write and save the content as a separate text file. Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any

kind of pagination anywhere in the paper. Do not number text heads-the template will do that for you.

Finally, complete content and organizational editing before formatting. Please take note of the following items when proofreading spelling and grammar:

➤ Deterministic Versus Robust Pareto Fronts

In deterministic designs, conversion was 0.798 to 0.992 and LCOH was 1.41 to 17.5 USD/kg. The robust designs predicted conversion from 0.769 to 0.991 and LCOH from 1.49 to 2.08 USD/kg. The deterministic front had 7 of 100 designs breaking the 5% chance constraint; the robust front had 4 (max 6.0%). Robust front failure probability averaged 0.8%.

Assuming uncertainty, deterministic designs have 1.5–6% greater LCOH and 0.014 lower conversion. It's most skewed at the front's low cost, low conversion. Deterministic optimisation overprices performance and underprices cost. Among 100 deterministic Pareto designs, 37.8% produced effluent with less than 75% H_2 , demonstrating that deterministic optimisation does not regulate reliability. In the robust framework, conversion specification failure dropped from 37.8% in the basic case to 6% throughout the robust front and 0% at the selected design. Due to the normal approximation $\mu - 1.645\sigma$ underestimating the left-skewed conversion distribution's bottom tail, the four resilient designs exceeded the 5% objective (maximum 6.0%) To meet the 5% target, use a safety factor of 1.75 or an empirical P5 surrogate for chance restriction. Charnes & Cooper [22] and Sahinidis [23] recommend chance-constrained programming. Lowering σ_X from 0.09 to 0.014 improves estimated LCOH from 1.5 to 2.7 USD/kg, reflecting robustness costs. When conversion saturates and kinetic parameters become insensitive, functioning close to equilibrium at high temperature, pressure, and catalyst loading minimises variability. Strong, reliable designs are expensive.

➤ Comparison of Robust Formulations

All three robust formulations (mean–variance, worst-case, chance-constrained) yielded reliable designs with <1% failure probability and similar minimal anticipated LCOH (1.51–1.52 USD/kg).

Table 1 Deterministic versus Robust pareto Fronts

Metric	Deterministic	Robust
Number of designs	100	100
Conversion range	0.798 – 0.992	0.769 – 0.991
LCOH range (USD/kg)	1.41 – 17.5	1.49 upward (median 2.08)
Mean failure probability	-	0.8%
Designs violating 5% chance constraint	7 of 100	4 of 100 (max 6.0%)

Table 2 Comparison of Robust Formulations (Full Monte Carlo Evaluation of Each Front)

Formulation	Objectives	Mean μ_X	Min μ_{LCOH} (USD/kg)	Median μ_{LCOH} (USD/kg)	Mean P ($X < 0.6$) (%)	Mean T ($^{\circ}\text{C}$)
A: mean–variance	$-\mu_X, \sigma_X, \mu_{LCOH}$	0.913	1.52	2.14	0.77	1,074
B: worst-case	$-\min_0 X, \mu_{LCOH}$	0.933	1.51	3.15	0.40	1,088
C: chance-constrained	$-\mu_X, \mu_{LCOH}$	0.932	1.52	4.54	0.58	1,091
Framework (A + chance constraints)	$-\mu_X, \sigma_X, \mu_{LCOH}$	0.911	1.52	2.08	0.77	1,072

Most temperatures were studied using mean–variance, whereas worst-case and chance-constrained calculations pushed designs toward higher temperatures and conversion at higher median cost. Design selection employed the mean–variance with chance constraints paradigm, which combines the explicit variance trade-off with reliability guarantee. In practice, worst-case is most conservative and chance-constrained is most interpretable, depending on risk tolerance. Similar to Ben-Tal and Nemirovski [24] and Beyer and Sendhoff [12], who compared robust optimisation approaches. Since all formulations had the same minimal LCOH, the economic optimum is formulation-resistant, but front shape and design vary.

➤ Algorithm Benchmark: NSGA-II Versus MOEA/D

NSGA-II had a hypervolume of 1.202 ± 0.002 , while MOEA/D had 0.541 ± 0.009 . IGD of 0.039 and generalised spread of 0.44 for NSGA-II, compared to 0.168 and 0.99 for MOEA/D.

MOEA/D stagnated early at a lower hypervolume and covered the front less consistently due to its fixed weight vectors' poor mapping onto the front's non-uniform shape. NSGA-II with constraint domination is preferred, as planned. Deb et al. [10] and Zhang and Li [19] discovered that MOEA/D performs better for uniform Pareto fronts and NSGA-II for non-uniform ones. The constraint-domination principle of NSGA-II handles chance constraints without penalty functions, making it better. MOEA/D stalled early because a penalty function for constraints twisted the objective space. Blank and Deb [18] found constraint handling essential for MOEA/D. Restricted robust optimisation works best with NSGA-II.

➤ Validation of the Robust Pareto Front

In the initial round, errors in σ_X , μ_{LCOH} , and σ_{LCOH} were 16.1%, 19.0%, and 17.9%. Retraining with 320 designs reduced mistakes to 0.30%, 4.47%, 0.13%, 2.93%, and 4.50%.

Retraining and adding 20 points to the DOE decreased extreme corner surrogate-based front errors of up to 19%. We must always compare surrogate-based optimisation findings to the original model. Validation-and-retraining is needed for robust optimisation. During the first round, the optimiser made mistakes at the high-conversion end of the design space (T 1,100 $^{\circ}\text{C}$, P 5 bar, W_cat 5 kg) in the 300-point DOE. Optimisers use surrogate error, according to Forrester et al. [14] and Jones [25]. In surrogate-inaccurate places, add points with adaptive sampling like predicted improvement. The surrogate learnt corner behaviour with extra data because mistakes dropped below 8% after one retraining round.

➤ Selection of the Preferred Design by TOPSIS

The equal-weight TOPSIS design (1,098 $^{\circ}\text{C}$, 4.85bar, $U_0/U_{mf} = 2.02$, 4.99kg catalyst, pure methane) produces 0.947 conversion, $\sigma_X = 0.014$, 2.72 USD/kg LCOH (P95 3.91 USD/kg), and 3.37 kg/kg H_2 CO_2 intensity. Compared to the base scenario, it enhances projected conversion by 31%, reduces conversion standard deviation by 89%, and lowers anticipated and P95 LCOH by 28% and 40%.

LCOH weight matters: 0.5 selects 1,069 $^{\circ}\text{C}$, 0.6 1,022, and 0.8 1,020. Increased conversion weight retains equal-weight selection. Cost-conscious designers would choose a 1,020–1,070 $^{\circ}\text{C}$ design, which is more reliable than the base scenario. While the minimum-LCOH design (1,023 $^{\circ}\text{C}$) has the lowest estimated cost (1.52 USD/kg), it faces a 6% probability of falling below 60% conversion and a CO_2 intensity more than double that of TOPSIS. Hwang and Yoon [21] say TOPSIS is weight-sensitive and the decision-maker's preferences dictate the design. As TOPSIS approaches equilibrium, kinetic uncertainty does not affect conversion. Kinetic parameter adjustments have limited effect on performance because the design converts close to the thermodynamic limit due to high temperature, pressure, catalyst loading, and pure methane. Working in a region where performance is insensitive to uncertainty, not adding conservative margins, creates robust design. Flat performance zones in the design space enable resilient design, according to Beyer and Sendhoff [12] and Deb and Gupta [13].

Table 3 NSGA-II and MOEA/D Performance on the Robust Framework Problem (Five Seeds)

Algorithm	Evaluations	Hypervolume	IGD	Generalised spread
NSGA-II	15,000	1.202 ± 0.002	0.039	0.44
MOEA/D	15,750	0.541 ± 0.009	0.168	0.99

Table 4 Validation of the Robust Pareto Front against the Full Model with Monte Carlo (20 Designs Per Round)

Round	Training designs	Max error μ_X (%)	Max error σ_X (%)	Max error μ_Y (%)	Max error μ_{LCOH} (%)	Max error σ_{LCOH} (%)	Outcome
1	300	1.20	16.12	1.04	19.03	17.93	Retrain
2	320	0.30	4.47	0.13	2.93	4.50	Accepted

Table 5 Performance of the Base Case, the Robust Minimum-LCOH Design and the TOPSIS Design (Full Monte Carlo, N = 500)

Quantity	Base case	Robust min-LCOH	Robust TOPSIS
T (°C), P (bar)	900, 1.0	1,023, 5.0	1,098, 4.85
U_0/U_{mf} , W_{cat} (kg), y_{CH_4}	3.0, 2.0, 0.80	3.21, 2.73, 1.00	2.02, 4.99, 1.00
Mean conversion μ_X	0.636	0.767	0.947
Std. dev. σ_X	0.133	0.092	0.014
P($X < 0.60$)	0.378	0.060	0.000
Mean LCOH (USD/kg)	3.78	1.52	2.72
P95 LCOH (USD/kg)	6.53	2.83	3.91
Mean CO ₂ (kg/kg H ₂)	13.0	7.4	3.4

IV. CONCLUSION

The surrogate-assisted NSGA-II framework validated robust Pareto fronts that indicate the trade-off between expected conversion, conversion variability, and expected LCOH. Deterministic optimisation overestimated performance and violated reliability targets in 7% of Pareto designs. The robust framework reduced the likelihood of failing the 60% conversion criterion from 37.8% at the base case to 6% across the robust front and zero at the selected design. MOEA/D scored 0.54 compared to 1.20 for NSGA-II. The TOPSIS design (1,098 °C, 4.85 bar, U_0/U_{mf} = 2.0, 5.0 kg catalyst, pure methane) yields 94.7% conversion, 1.4% standard deviation, 2.72 USD/kg LCOH (P95 3.91 USD/kg), and 3.4 kg/kg H₂ CO₂ intensity. A cost-oriented robust design (1,023 °C, 5 bar) achieves 1.52 USD/kg LCOH with inferior dependability and greater emissions.

Future work should replace the normal approximation in the chance constraints with an empirical quantile surrogate (such as P5 of conversion) or a safety factor of about 1.75 to guarantee the 5% reliability target in the lower tail, extend the decision variables to include catalyst cycle (regeneration) time and catalyst price/type, and apply the framework to other uncertain gas–solid reactors relevant to the Nigerian gas industry.

An integrated, validated surrogate-assisted robust multi-objective optimisation framework (Architecture B) for fluidized-bed methane pyrolysis is presented in the study, coupling a mechanistic two-phase reactor model, Latin hypercube Monte Carlo, Kriging surrogates, NSGA-II with chance constraints, TOPSIS selection, and full-model validation with adaptive retraining.

ACKNOWLEDGMENT

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g.” Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

REFERENCES

- [1]. International Energy Agency, The Future of Hydrogen: Seizing Today's Opportunities. Paris, France: IEA, 2019.
- [2]. International Energy Agency, Global Hydrogen Review 2023. Paris, France: IEA, 2023.

- [3]. N. Z. Muradov and T. N. Veziroğlu, “From hydrocarbon to hydrogen–carbon to hydrogen economy,” *Int. J. Hydrogen Energy*, vol. 30, no. 3, pp. 225–237, 2005.
- [4]. H. F. Abbas and W. M. A. Wan Daud, “Hydrogen production by methane decomposition: A review,” *Int. J. Hydrogen Energy*, vol. 35, no. 3, pp. 1160–1190, 2010.
- [5]. N. Sánchez-Bastardo, R. Schlögl, and H. Ruland, “Methane pyrolysis for zero-emission hydrogen production: A potential bridge technology from fossil fuels to a renewable and sustainable hydrogen economy,” *Ind. Eng. Chem. Res.*, vol. 60, no. 32, pp. 11855–11881, 2021.
- [6]. D. Kunii and O. Levenspiel, *Fluidization Engineering*, 2nd ed. Boston, MA: Butterworth-Heinemann, 1991.
- [7]. P. Ammendola, R. Chirone, G. Ruoppolo, G. Russo, and R. Solimene, “Some issues in modelling methane catalytic decomposition in fluidized bed reactors,” *Int. J. Hydrogen Energy*, vol. 33, no. 11, pp. 2679–2694, 2008.
- [8]. R. A. Dagle, V. Dagle, M. D. Bearden, J. D. Holladay, T. R. Krause, and S. Ahmed, “An overview of natural gas conversion technologies for co-production of hydrogen and value-added solid carbon products,” Argonne National Laboratory and Pacific Northwest National Laboratory, Rep. ANL-17/11; PNNL-26726, 2017.
- [9]. K. Deb, *Multi-Objective Optimization Using Evolutionary Algorithms*. Chichester, U.K.: Wiley, 2001.
- [10]. K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: NSGA-II,” *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, 2002.
- [11]. T. Keipi, H. Tolvanen, and J. Kontinen, “Economic analysis of hydrogen production by methane thermal decomposition: Comparison to competing technologies,” *Energy Convers. Manage.*, vol. 159, pp. 264–273, 2018.
- [12]. H.-G. Beyer and B. Sendhoff, “Robust optimization – A comprehensive survey,” *Comput. Methods Appl. Mech. Eng.*, vol. 196, no. 33–34, pp. 3190–3218, 2007.
- [13]. K. Deb and H. Gupta, “Introducing robustness in multi-objective optimization,” *Evol. Comput.*, vol. 14, no. 4, pp. 463–494, 2006.
- [14]. A. I. J. Forrester, A. Söbester, and A. J. Keane, *Engineering Design via Surrogate Modelling: A Practical Guide*. Chichester, U.K.: Wiley, 2008.

- [15]. A. Bhosekar and M. Ierapetritou, “Advances in surrogate based modeling, feasibility analysis, and optimization: A review,” *Comput. Chem. Eng.*, vol. 108, pp. 250–267, 2018.
- [16]. F. Pedregosa et al., “Scikit-learn: Machine learning in Python,” *J. Mach. Learn. Res.*, vol. 12, pp. 2825–2830, 2011.
- [17]. P. Virtanen et al., “SciPy 1.0: Fundamental algorithms for scientific computing in Python,” *Nat. Methods*, vol. 17, pp. 261–272, 2020.
- [18]. J. Blank and K. Deb, “pymoo: Multi-objective optimization in Python,” *IEEE Access*, vol. 8, pp. 89497–89509, 2020.
- [19]. Q. Zhang and H. Li, “MOEA/D: A multiobjective evolutionary algorithm based on decomposition,” *IEEE Trans. Evol. Comput.*, vol. 11, no. 6, pp. 712–731, 2007.
- [20]. A. Zhou, Y. Jin, Q. Zhang, B. Sendhoff, and E. Tsang, “Combining model-based and genetics-based offspring generation for multi-objective optimization using a convergence criterion,” in *Proc. 2006 IEEE Congr. Evol. Comput.*, 2006, pp. 892–899.
- [21]. C.-L. Hwang and K. Yoon, *Multiple Attribute Decision Making: Methods and Applications*. Berlin, Germany: Springer, 1981.
- [22]. A. Charnes and W. W. Cooper, “Chance-constrained programming,” *Manage. Sci.*, vol. 6, no. 1, pp. 73–79, 1959.
- [23]. N. V. Sahinidis, “Optimization under uncertainty: State-of-the-art and opportunities,” *Comput. Chem. Eng.*, vol. 28, no. 6–7, pp. 971–983, 2004.
- [24]. A. Ben-Tal and A. Nemirovski, “Robust convex optimization,” *Math. Oper. Res.*, vol. 23, no. 4, pp. 769–805, 1998.
- [25]. D. R. Jones, M. Schonlau, and W. J. Welch, “Efficient global optimization of expensive black-box functions,” *J. Global Optim.*, vol. 13, no. 4, pp. 455–492, 1998..