Neural Network-Based Prediction of RPC Efficiency with Alternative Gas Mixtures

RPC 2026 Conference — Rio de Janeiro, Brazil

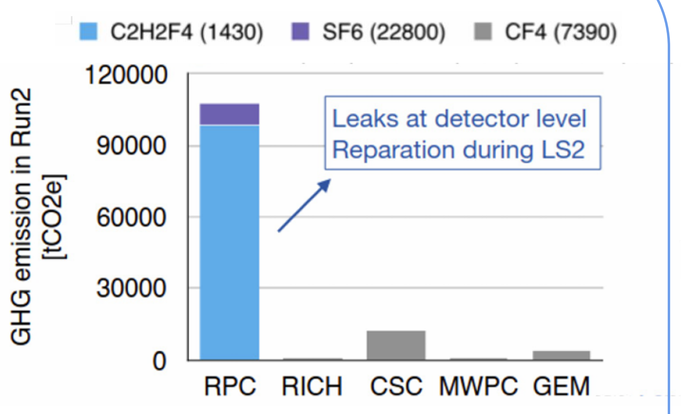
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1. INTRODUCTION

Resistive Plate Chambers (RPCs) are one of the LHC's detectors of choice for muon systems, relying on high-Global Warming Potential (GWP) fluorinated gases, now restricted under EU Regulation → shift toward alternative mixtures.



This work uses a neural network to predict RPC efficiency-curve parameters from gas composition, comparing two feature-encoding strategies across 16 mixtures measured by the EP-DT Gas Group at GIF++ (CERN).

2. FEATURE ENCODING: SCALAR VS. FERMI-LIKE MODEL

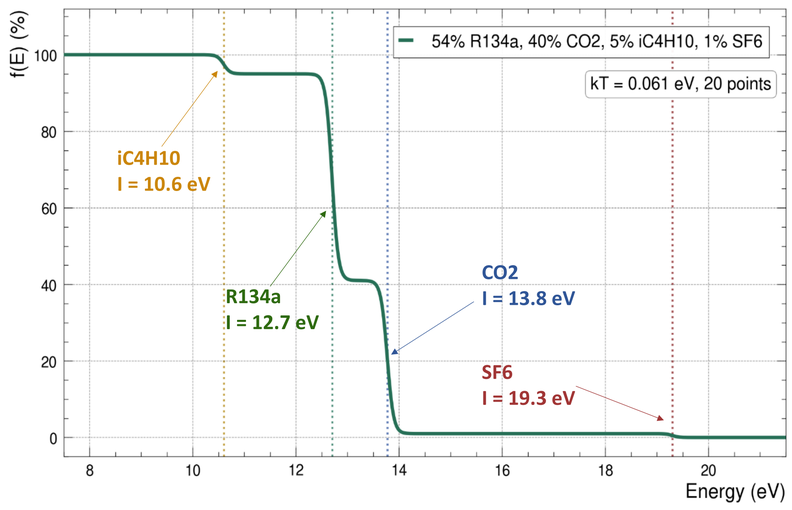
SCALAR MODEL

- **Input features:** gas % + ionization energy per component
- Absent gas → energy set to 0 (placeholder)

FERMI-LIKE MODEL

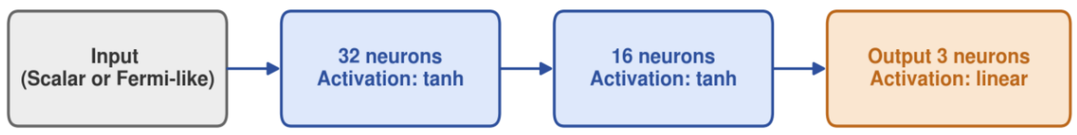
- **Input features**: single curve f(E), a sum of Fermi-like steps weighted by gas %
- Absent gas → contributes nothing (no placeholder)

$$f(E) = \sum_i \frac{m_i}{1 + e^{\left(\frac{E - ie_i}{kT}\right)}}$$



f(E) curves for one of the mixtures. Each step sits at a component's ionization energy; step height reflects its share

3. MODEL ARCHITECTURE & VALIDATION



TRAINING

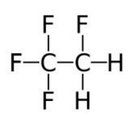
- Outputs: HV_{50}, γ, eff_max
- Loss function weights: 4 / 1 / 1
- AdamW (lr = 5×10^{-4})
- Early stopping (patience 40, max 800 epochs)

LEAVE-ONE-OUT VALIDATION

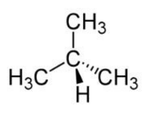
- 1 of 16 mixtures held out for testing per fold
- 80/20 training/validation split
- Per-fold metrics: reduced χ^2, R^2

3.1 GAS COMPONENTS IN THIS STUDY

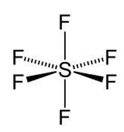
STANDARD GAS MIXTURE



R134a



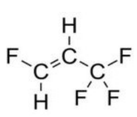
Isobutane



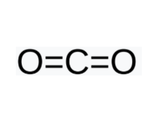
SF6

- ✅ High efficiency and stability
- ❌ Extremely large GWP

ALTERNATIVES



HFO



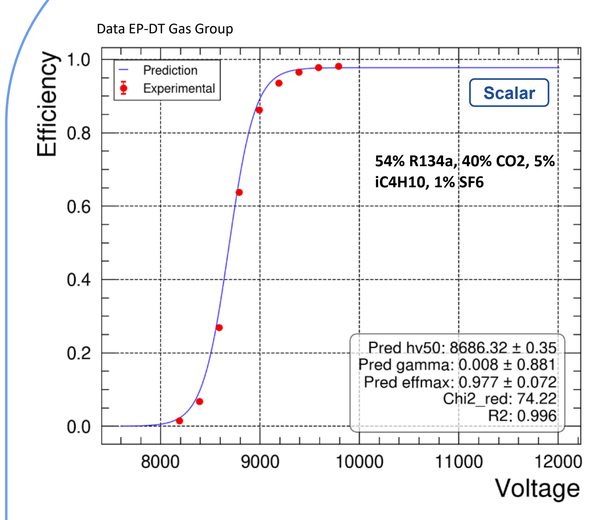
CO2

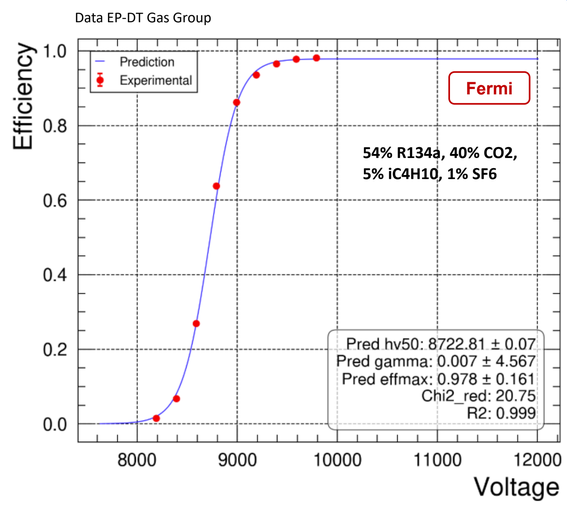


NOVEC 4710

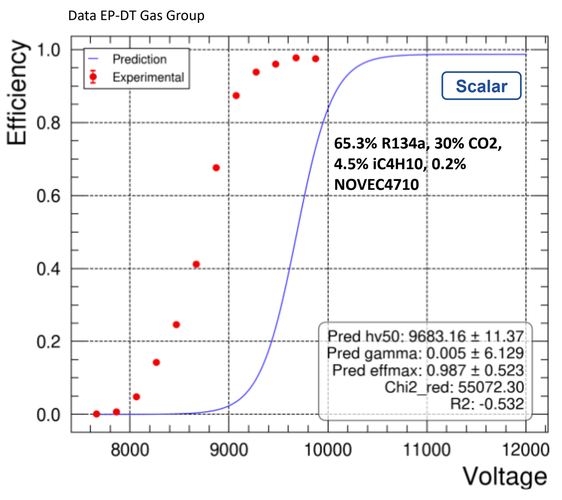
- ✅ Lower gas mixture GWP
- ❌ Impact on Working Point and Streamer Probability

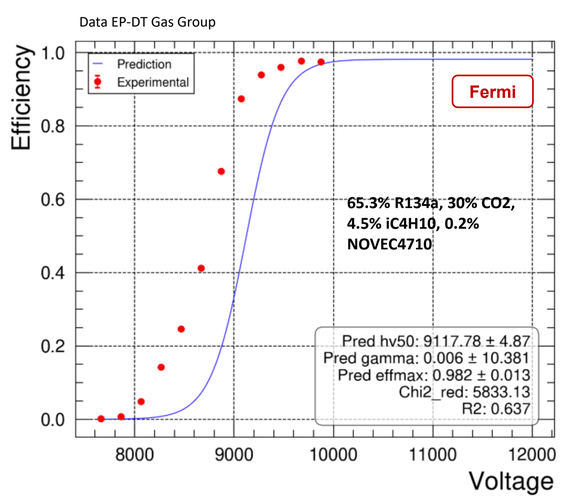
4. RESULTS: PREDICTED VS. EXPERIMENTAL EFFICIENCY CURVES





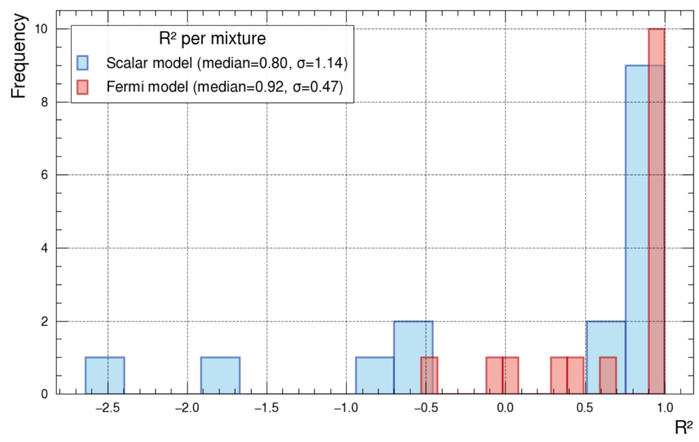
Scalar R^2 = 0.996 | Fermi R^2 = 0.999 → both models reproduce the curve almost perfectly; Fermi gives a further reduction in χ^2 and a tighter HV_{50} uncertainty.





Scalar R^2 = −0.532 | Fermi R^2 = 0.637 → Scalar fails, Fermi's reduced χ^2 improves nearly 10×. NOVEC4710 appears only once in training, a hard extrapolation for both.

4.1 R^2 DISTRIBUTION



Distribution of R^2 across the 16 mixtures under Leave-One-Out cross-validation:

- Scalar: median R^2 = 0.802 (σ = 1.138)
- Fermi: median R^2 = 0.916 (σ = 0.474)

5. CONCLUSIONS

▶ Fermi-like encoding improves both the accuracy and robustness of efficiency-curve prediction, with no artificial placeholder values for absent gases.

▶ The improvement is systematic across the dataset, confirmed by the aggregate R^2 distribution, not just by individual curves.

▶ Next steps: more measurements for alternative gas compositions and systematic studies of the Fermi model across a wider range of kT.

REFERENCES

[1] M. A. Shah, et al. "The CMS RPC detector performance and stability during LHC RUN2". JINST 14 C11012 (2019).

[2] L. quaglia et al., Exploring Eco-Friendly Gas Mixtures for Resistive Plate Chambers: A Comprehensive Study on Performance and Aging", arXiv:2402.19395 [physics.ins-det]

[3] "REGULATION (EU) 2024/573 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL". In: (2024). URL: Regulation - EU - 2024/573 - EN - EUR-Lex.

[4] I. Goodfellow, Y. Bengio, A. Courville. "Deep Learning". MIT Press (2016).