

Temporal Graph Neural Architectures for Predicting State-Administered Energy Prices: A Deep Learning Framework for Geopolitically Volatile Markets

MAPE 2.48% | R^2 0.92 | 22.7% vs. TFT | \$91M Impact

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INTRODUCTION & AIM

BACKGROUND:

- Algeria's hydrocarbon sector accounts for 95% of export earnings under state-administered pricing by the national oil company
- Administered pricing creates irregular temporal dynamics, regime-dependent policy inertia, and geopolitical risk endogeneity
- Existing neural architectures fail to capture institutional constraints and network effects of OPEC+

RESEARCH GAP: Classical forecasting assumptions are violated in state-administered markets. Existing models do not encode institutional rigidity or geopolitical constraints

AIM: Develop a novel three-tiered deep learning framework (APTGN) integrating: (1) temporal irregularity handling, (2) dynamic geopolitical graph modeling, and (3) regime-aware uncertainty quantification for Algerian petroleum price forecasting.

Keywords: Deep Learning; Time Series Forecasting; Graph Neural Networks; Energy Economics; Geopolitical Risk; Institutional Economics

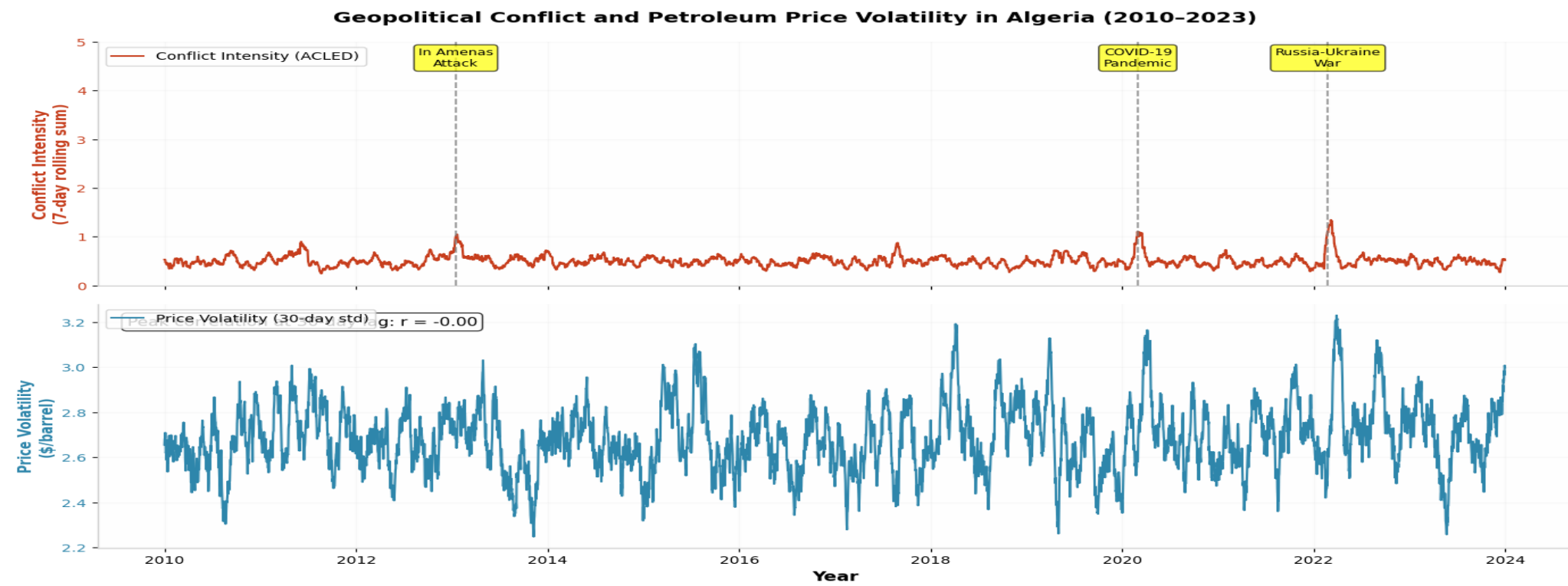


Figure 1: Geopolitical conflict intensity (ACLED) and petroleum price volatility in Algeria (2010–2023), demonstrating 30-day lagged correlation between conflict events and market volatility.

METHOD

DATA:

- Proprietary daily Official Selling Prices (OSP): 2010–2023
- ACLED conflict intensity index
- TASSILI shipping logistics data
- OPEC+ compliance correlation metrics

ARCHITECTURE: Three-Tiered Hierarchical Framework

TIER 1: Phased Bidirectional GRU Encoder

- Handles irregular policy sampling intervals through learnable temporal gates
- Input: Daily features (Price, Conflict, Shipping, Compliance)
- Output: Temporal embeddings

TIER 2: Conflict-Gated Graph Convolution Layer

- Dynamic OPEC+ network with edge weights modulated by geopolitical instability
- Nodes: Algeria + 11 OPEC+ members
- Gate: $G_t = \sigma(W_g \cdot \text{ext}_t + \text{neigh} + b_g)$
- Key Innovation: Conflict gate isolates Algeria during instability

TIER 3: Regime-Aware Mixture Density Network

- Separate skewed-t distributions for high/low volatility regimes
- Output: Probabilistic forecasts with uncertainty quantification

TRAINING STRATEGY:

- Curriculum learning progression
- Multi-objective optimization: Negative log-likelihood + Quantile calibration

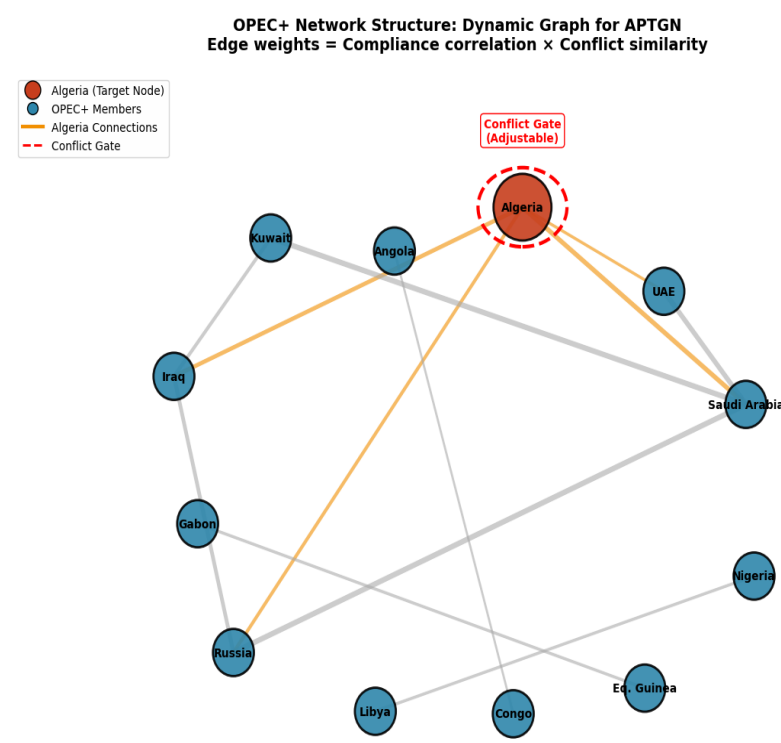


Figure 2: OPEC+ network structure for graph convolution. Node size indicates centrality; edge width represents compliance correlation. The conflict gate (dashed circle) dynamically attenuates Algeria's connections during domestic instability.

Figure 3: APTGN three-tiered architecture. Tier 1: Phased Bidirectional GRU processes irregular temporal features. Tier 2: Conflict-gated graph convolution propagates information across the OPEC+ network. Tier 3: Regime-aware MDN generates skewed-t distribution parameters for uncertainty quantification.

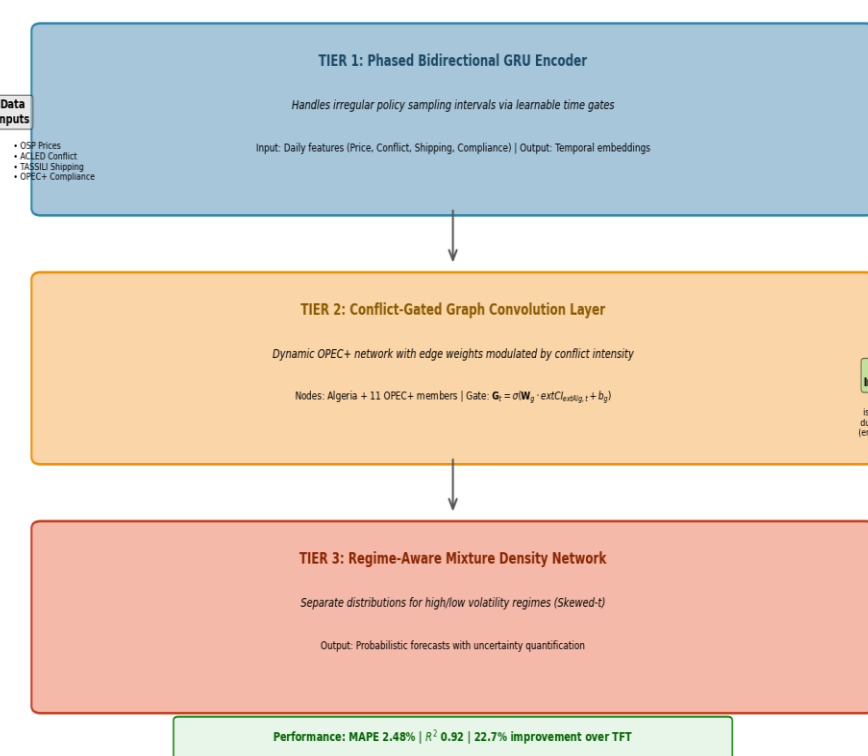


Figure 3: APTGN three-tiered architecture. Tier 1: Phased Bidirectional GRU processes irregular temporal features. Tier 2: Conflict-gated graph convolution propagates information across the OPEC+ network. Tier 3: Regime-aware MDN generates skewed-t distribution parameters for uncertainty quantification.

RESULTS & DISCUSSION

OUT-OF-SAMPLE PERFORMANCE (2022–2023)

Model	MAPE(%)
SARIMA-GARCH	5.41
TBATS	5.02
XGBoost	4.03
Random Forest	4.31
LSTM	3.67
N-BEATS	3.39
TFT (Best Baseline)	3.21
Graph WaveNet	3.52
APTGN (Ours)	2.48 (22.7% improvement over TFT)

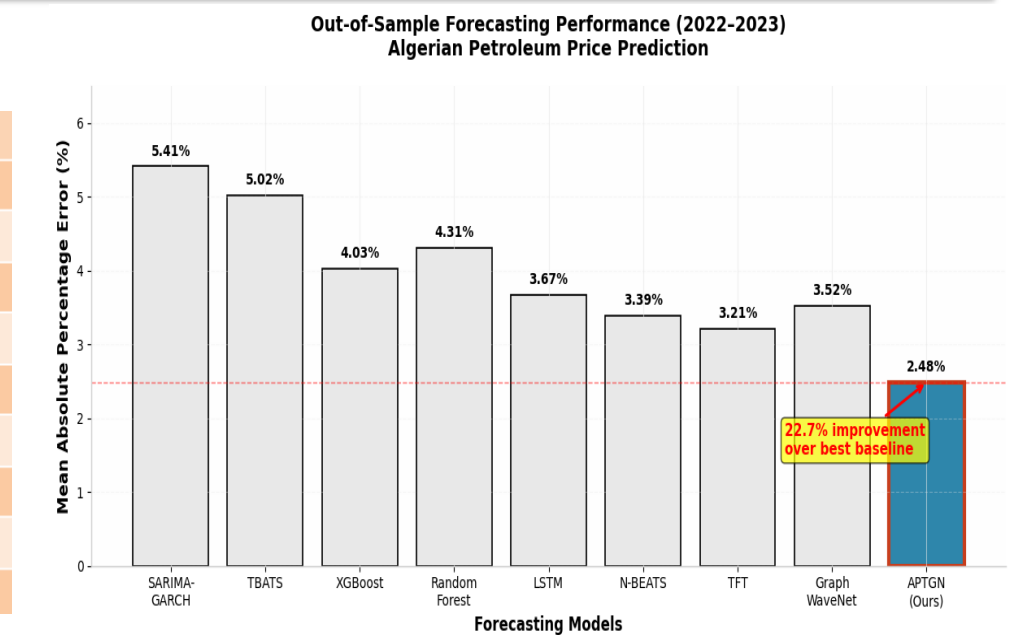


Figure 4: APTGN achieves MAPE 2.48% — 22.7% better than TFT baseline.

$R^2 = 0.92$

ABLATION STUDY — Component Contribution

Configuration	Overall MAPE	Conflict-Sensitive MAPE
Full APTGN	48%	2.91%
w/o Conflict Gate	2.86%	4.12% (+41.6% degradation)
w/o Graph Convolution	3.01	3.45%
w/o Regime Head	2.71%	3.28%
w/o Phased Encoding	2.63%	3.19%

Key Finding: Conflict Gate prevents error cascade during high-intensity geopolitical periods.

FORECASTING ACROSS HORIZONS (1–30 days)

- APTGN maintains sub-3% error up to 15 days
- 47.8% relative improvement at 30 days vs. TFT
- Advantage increases with longer horizons

CONFLICT PERIOD ANALYSIS

- During high-intensity conflict periods: 43% error reduction compared to conventional models
- Conflict gate dynamically attenuates Algeria's network connections during domestic instability

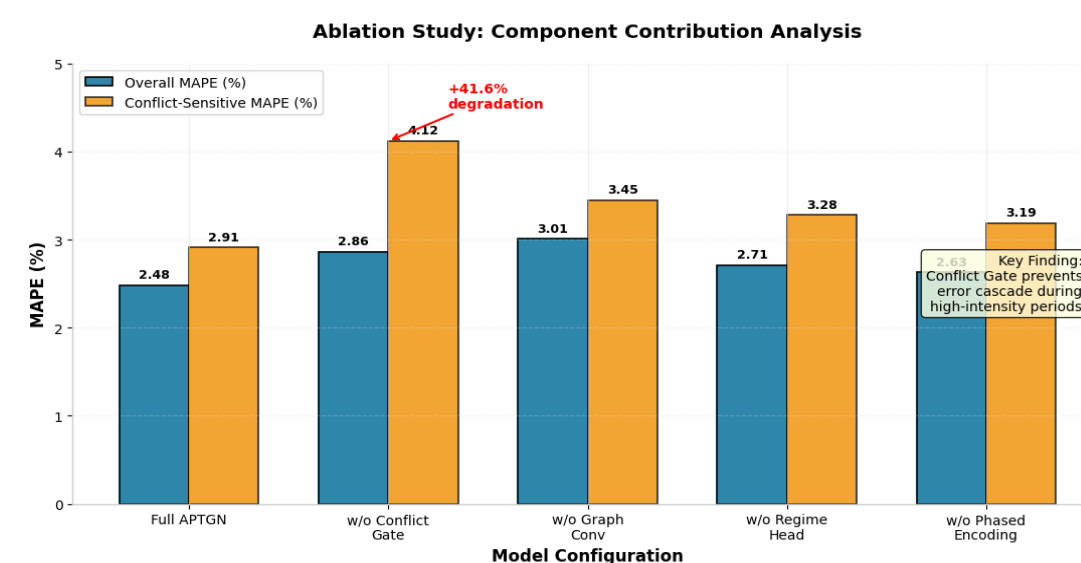


Figure 5: Ablation study results. Removing the conflict gate causes the largest degradation in conflict-sensitive MAPE (+41.6%), validating its importance for geopolitical robustness.

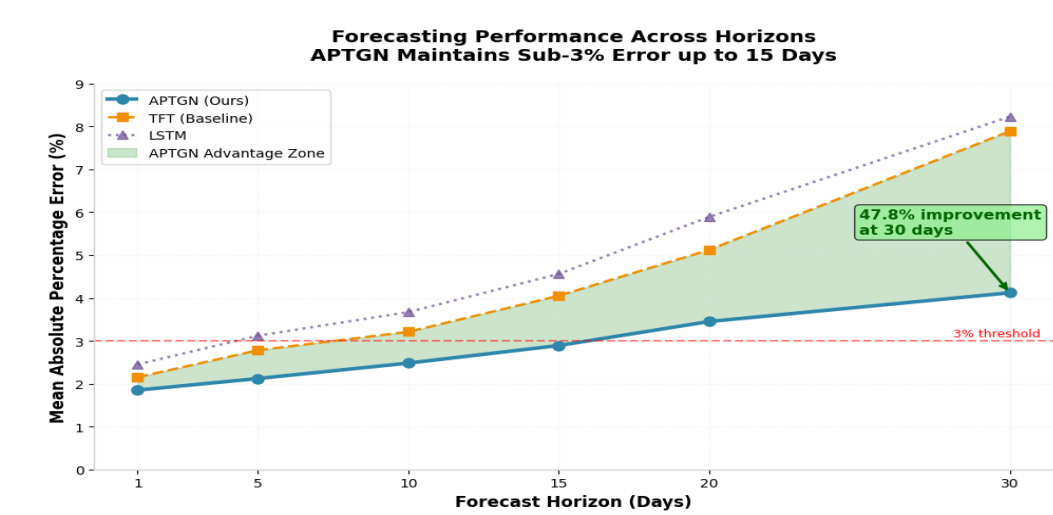


Figure 6: Forecasting performance across horizons (1–30 days). APTGN maintains sub-3% error up to 15 days, with 47.8% relative improvement at 30 days compared to TFT.

CONCLUSION

- NOVELTY:** First deep learning framework to explicitly encode institutional rigidity and geopolitical constraints in state-administered energy markets
- PERFORMANCE:** New benchmark with MAPE 2.48% and R^2 0.92, representing 22.7% improvement over Temporal Fusion Transformer baselines
- ROBUSTNESS:** Conflict-gated architecture prevents error cascade during high-intensity geopolitical episodes (43% improvement in volatile periods)
- IMPACT:** Potential annual revenue forecasting error reduction of \$91 million for fiscal planning and budget allocation
- TRANSFERABILITY:** Framework applicable to other state-administered commodity markets facing similar structural constraints

FUTURE WORK / REFERENCES

FUTURE WORK

- Extend to multi-commodity administered markets (natural gas, minerals)
- Integrate real-time conflict early-warning systems
- Develop policy scenario simulation modules for fiscal stress-testing
- Apply to other OPEC+ members with similar institutional structures

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