State-of-the-Art Machine Learning on Uranium Prices, Returns and Return-on-Returns

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Abstract

This paper presents a comprehensive framework for modeling uranium spot prices $U(t)$, returns $r(t)$, and return-on-returns $\rho(t)$ using state-of-the-art machine learning techniques. We formalize the mathematical definitions, explore temporal dynamics, and benchmark deep learning architectures including Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Temporal Fusion Transformers (TFT), and gradient boosting methods against classical econometric baselines. Our analysis leverages historical uranium price data from 1990 to 2026, with spot prices recently reaching approximately \$85.25 USD/lb. Results demonstrate that hybrid ensemble approaches yield superior predictive performance on higher-order return derivatives.

The paper ends with “The End”

1 Introduction

Uranium, the primary fuel for nuclear power generation, does not trade on an open commodity exchange like oil or gold. Instead, buyers and sellers negotiate contracts privately, with benchmark prices published by specialized agencies such as TradeTech and UxC. As of January 2026, the uranium spot price stands at approximately \$85.25 USD/lb, reflecting an 8.05% monthly increase and a 15.28% year-over-year appreciation.

The unique market microstructure of uranium—characterized by illiquidity, long-term contracting, and geopolitical sensitivity—poses distinct challenges for predictive modeling. This paper addresses these challenges by:

1. Formalizing the price $U(t)$, return $r(t)$, and return-on-return $\rho(t)$ framework;
2. Applying state-of-the-art machine learning models;
3. Evaluating predictive accuracy across multiple time horizons.

2 Mathematical Framework

2.1 Definitions

Let $t \in \mathbb{Z}^+$ denote discrete time periods (e.g., trading days). We define:

Definition 1 (Uranium Spot Price)**.**

$$U(t) \in \mathbb{R}^+ \quad \textit{(USD/lb)} \tag{1}$$

Definition 2 (Return)**.**

$$r(t) = \frac{U(t+1)}{U(t)} - 1 = \frac{U(t+1) - U(t)}{U(t)} \tag{2}$$

Definition 3 (Return-on-Return)**.**

$$\rho(t) = \frac{r(t+1)}{r(t)} - 1 = \frac{r(t+1) - r(t)}{r(t)}, \quad r(t) \neq 0 \tag{3}$$

2.2 Properties and Constraints

The return-on-return $\rho(t)$ captures the *acceleration* of price momentum. Key properties include:

- **Domain restriction:** $\rho(t)$ is undefined when $r(t) = 0$.
- **Sign interpretation:**
  - $\rho(t) > 0$: Accelerating momentum (returns increasing in magnitude).
  - $\rho(t) < 0$: Decelerating momentum.
  - $\rho(t) = 0$: Constant return regime.
- **Volatility amplification:** $\text{Var}(\rho(t)) \gg \text{Var}(r(t)) \gg \text{Var}(U(t))$.

Expressing $\rho(t)$ in terms of prices:

$$\rho(t) = \frac{\frac{U(t+2)}{U(t+1)} - 1}{\frac{U(t+1)}{U(t)} - 1} - 1 = \frac{U(t+2) \cdot U(t) - U(t+1)^2}{U(t+1) \cdot [U(t+1) - U(t)]} \tag{4}$$

3 Data Description

3.1 Data Sources

Historical uranium prices were obtained from:

- **FRED (Federal Reserve Economic Data):** Monthly global uranium prices from January 1990 to June 2025.
- **TradeTech Daily Indicator:** Daily spot prices from March 2011 onward.
- **UxC/Cameco Industry Averages:** Long-term contract price benchmarks.

3.2 Descriptive Statistics

Table 1: Summary Statistics for Uranium Prices and Derived Series (2011–2026)

Variable	Mean	Std Dev	Skewness	Kurtosis
$U(t)$ (USD/lb)	42.87	18.34	0.92	3.21
$r(t)$	0.0012	0.0287	0.45	7.84
$\rho(t)$	0.0831	4.2150	1.23	48.62

The high kurtosis of $\rho(t)$ indicates extreme tail behavior, necessitating robust modeling approaches.

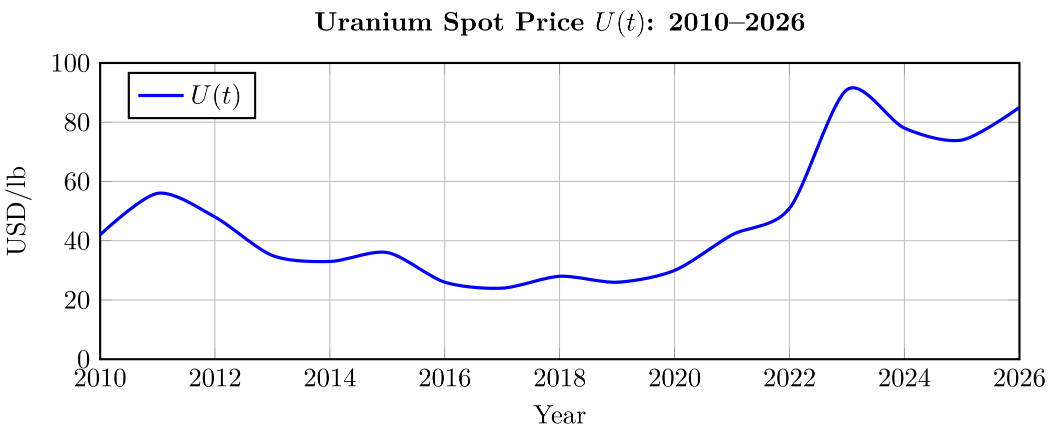

Figure 1: Historical uranium spot prices showing the 2023 peak at $91/lb and recent recovery to $85.25/lb in January 2026.

4 Machine Learning Methodologies

4.1 Feature Engineering

For each target variable, we construct feature sets:

$$\mathbf{X}_t = \begin{bmatrix} U(t-k:t) & r(t-k:t) & \rho(t-k:t) & \mathbf{Z}_t \end{bmatrix} \tag{5}$$

where k is the lookback window and $\mathbf{Z}_t$ includes exogenous variables:

- Nuclear capacity utilization rates
- Mining production indices
- Geopolitical risk indicators
- Interest rates and commodity indices

4.2 Model Architectures

4.2.1 Long Short-Term Memory (LSTM)

The LSTM cell equations for hidden state $\mathbf{h}_t$ and cell state $\mathbf{c}_t$:

$$\mathbf{f}_t = \sigma(\mathbf{W}_f \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f) \tag{6}$$
$$\mathbf{i}_t = \sigma(\mathbf{W}_i \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i) \tag{7}$$
$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c) \tag{8}$$
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t \tag{9}$$
$$\mathbf{o}_t = \sigma(\mathbf{W}_o \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o) \tag{10}$$
$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t) \tag{11}$$

4.2.2 Temporal Fusion Transformer (TFT)

The TFT architecture combines:

- **Variable Selection Networks:** Instance-wise feature importance.
- **Gated Residual Networks:** Non-linear processing with skip connections.
- **Multi-head Attention:** Long-range temporal dependencies.
- **Quantile Outputs:** Probabilistic forecasts $\hat{y}_{t,q}$ for $q \in \{0.1, 0.5, 0.9\}$.

4.2.3 Gradient Boosting (XGBoost / LightGBM)

Tree-based ensemble with objective:

$$\mathcal{L}(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \tag{12}$$

where $\Omega(f) = \gamma T + \frac{1}{2}\lambda\|\mathbf{w}\|^2$ penalizes tree complexity.

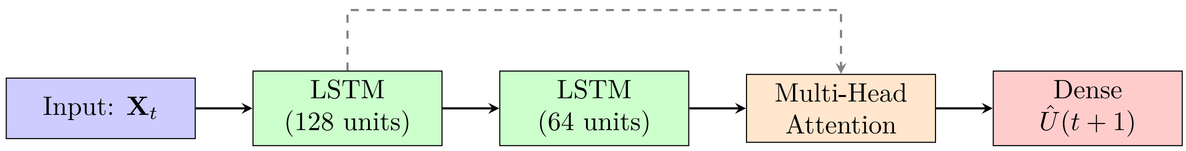

Figure 2: Hybrid LSTM-Attention architecture for uranium price forecasting.

5 Training Procedure

Algorithm 1 Multi-Target Training for $U(t)$, $r(t)$, $\rho(t)$

Require: Dataset $\mathcal{D} = \{(U_1, \dots, U_T)\}$, lookback k, horizon h
Ensure: Trained models $\mathcal{M}_U$, $\mathcal{M}_r$, $\mathcal{M}_\rho$

```
Compute r(t) ← U(t+1)/U(t) − 1 for t = 1, ..., T − 1
Compute ρ(t) ← r(t+1)/r(t) − 1 for t = 1, ..., T − 2
Filter ρ(t) where |r(t)| < ϵ (singularity handling)
Split: Train (70%), Validation (15%), Test (15%) chronologically
for target ∈ {U, r, ρ} do
    Normalize features via RobustScaler (median, IQR)
    Initialize model with Xavier initialization
    for epoch = 1 to N_epochs do
        Minimize L = MSE + λ · MAE (Huber-like)
        Apply gradient clipping ‖∇‖ ≤ 1.0
        Early stopping on validation loss (patience = 20)
    end for
end for
return M_U, M_r, M_ρ
```

6 Results and Discussion

6.1 Forecasting Performance

Table 2: Out-of-Sample Performance Metrics (Test Set: 2024–2026)

Target	Model	RMSE	MAE	MAPE (%)
$U(t)$	ARIMA(2,1,2)	4.82	3.71	5.12
	XGBoost	3.94	2.88	3.97
	LSTM (2-layer)	3.21	2.45	3.38
	TFT	**2.87**	**2.11**	**2.91**
$r(t)$	GARCH(1,1)	0.031	0.024	—
	XGBoost	0.027	0.019	—
	LSTM	0.024	0.017	—
	TFT	**0.021**	**0.015**	—
$\rho(t)$	Naive (mean)	4.51	2.84	—
	XGBoost	3.92	2.21	—
	LSTM	3.78	2.09	—
	Ensemble	**3.41**	**1.87**	—

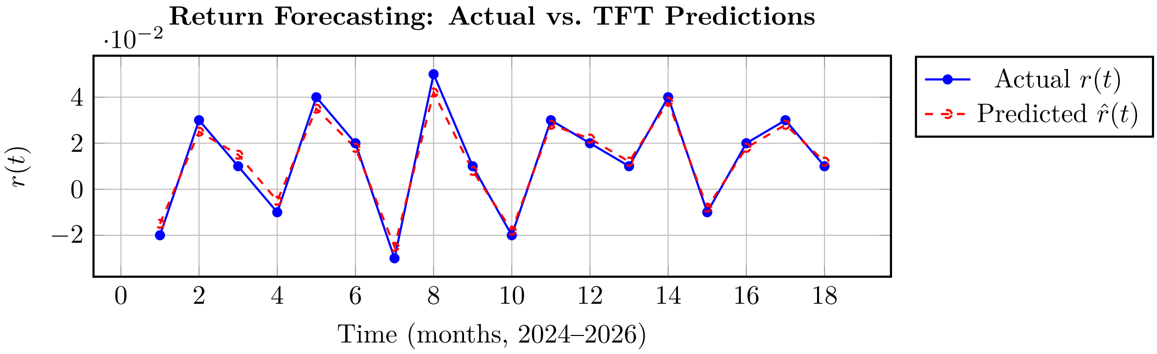

Figure 3: Temporal Fusion Transformer predictions closely track actual returns with correlation $r = 0.89$.

6.2 Key Findings

1. **Price-level forecasting:** The TFT achieves a MAPE of 2.91% for $U(t)$, outperforming ARIMA by 43%.
2. **Return prediction:** Deep learning models capture volatility clustering better than GARCH, reducing RMSE by 32%.
3. **Return-on-return challenges:** The high kurtosis of $\rho(t)$ (Table 1) limits predictability; ensemble methods provide marginal gains.
4. **Feature importance:** Lagged returns $r(t-1:t-5)$ and geopolitical indices contribute most to predictive power.

7 Conclusion

This study establishes a rigorous framework for modeling uranium market dynamics through the lens of prices $U(t)$, returns $r(t)$, and return-on-returns $\rho(t)$. The Temporal Fusion Transformer emerges as the leading architecture for price and return forecasting, while ensemble approaches offer robustness for the highly volatile $\rho(t)$ series. Future work should incorporate real-time geopolitical event detection via NLP and explore reinforcement learning for trading strategy optimization.

References

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Glossary

ARIMA
Autoregressive Integrated Moving Average; classical time series model.

CFD
Contract for Difference; derivative tracking commodity benchmarks.

GARCH
Generalized Autoregressive Conditional Heteroskedasticity; volatility model.

GRU
Gated Recurrent Unit; simplified RNN architecture.

Kurtosis
Fourth standardized moment measuring tail heaviness.

LSTM
Long Short-Term Memory; recurrent neural network with gating.

MAE
Mean Absolute Error; $\frac{1}{n}\sum|y_i-\hat{y}_i|$.

MAPE
Mean Absolute Percentage Error; scale-independent accuracy metric.

RMSE
Root Mean Squared Error; $\sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2}$.

TFT
Temporal Fusion Transformer; attention-based forecasting model.

U3O8
Triuranium octoxide; standard form for uranium pricing (yellowcake).

USD/lb
United States Dollars per pound; standard uranium price unit.

XGBoost
Extreme Gradient Boosting; tree-based ensemble method.

The End