

Research on Copper Procurement Risks and Strategies in the New Energy Vehicle Industry Chain Based on Multi-Model Prediction

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Abstract: In the context of the expansion of the new energy vehicle industry and the growth in copper demand, fluctuations in copper prices directly affect the procurement costs and budget stability of enterprises. This paper uses the COMEX copper futures prices from July 20, 2016 to July 10, 2026, the US dollar index, and WTI crude oil prices to construct a rolling forecast for the next 20 trading days, comparing Naive, rolling mean, ARIMA, random forest, HistGradientBoosting, and combined models. Further, using the ARIMA prediction interval and 5,000 Monte Carlo paths, the price uncertainty is converted into the distribution of procurement costs, and the Cost at Risk concept is borrowed to construct the Purchase Cost Risk Value (PCaR). The results show that the complex machine learning models do not outperform the simple benchmark; the MAE of the ARIMA development period is \$259.0 per ton, slightly better than the 260.3 per ton of Naive, but the error in the independent test period significantly increases, with the 80% and 95% coverage rates being only 69.5% and 87.6%. Under the assumption of uniform procurement of 1,000 metric tons in the next 20 trading days, the expected cost is approximately \$1,392,000, and the 95% PCaR is approximately \$93,000, accounting for 6.7% of the expected cost. Based on this, this paper proposes three levels of risk signals (routine, attention, and review), as well as batch procurement, budget buffer, and dynamic manual review mechanisms. The research value lies in connecting short-term price prediction, uncertainty, and procurement budget risk into an interpretable decision support process, rather than pursuing the lowest deterministic price prediction.

Keywords: New energy vehicle industry chain; Copper; Price forecast; Purchase cost risk value; Purchase decision

Online publication: September 30, 2026

1. Introduction

The power batteries, electric drive systems, high-voltage wiring, charging facilities, and distribution equipment of new energy vehicles all have a high demand for copper. The copper price is influenced by various factors such as global supply and demand, the US dollar, energy prices, trade policies, and geopolitical events. Price fluctuations will be transmitted to procurement budgets, inventory capital occupation, and procurement

schedules. Therefore, what enterprises truly need is not only “what the future price will be,” but also how much budget pressure may be caused by unfavorable price deviations, and when it is necessary to adjust or re-evaluate the procurement plan.

This paper proposes to establish an analytical process of “short-term prediction–uncertainty assessment–procurement cost risk–conditional strategy–dynamic review” under the condition of public market data. The research focus is to test whether the complex model can stably provide incremental information and convert the prediction distribution into a budget risk that enterprises can understand. At the same time, this paper does not estimate the causal effect of the expansion of new energy vehicles on copper prices, but only serves as an application scenario for copper procurement ^[1].

2. Data and research methods

2.1. Prediction model and evaluation

This paper sets Naive and 20-day rolling average returns as simple benchmarks, and compares ARIMA, Random Forest, and HistGradientBoosting. Naive assumes that future prices will remain at the level of the prediction starting point; ARIMA takes the first-order difference of the logarithmic sequence of copper prices and selects the combination of orders that converge normally from the candidate models with p and q not exceeding 2 at the beginning of each development period using AIC. Random Forest adopts a direct multi-step structure and trains models for the next 1–20 days separately; HistGradientBoosting uses the prediction period as an additional feature and predicts cumulative returns of different periods using the same model ^[2].

2.2. Procurement risk assessment

The copper price risk is first transmitted to the budget through the formula “purchase cost = unit price × purchase quantity”; when the actual purchase price is higher than the budget price, the budget deviation will increase proportionally with the purchase volume. Due to the lack of data on enterprise demand, inventory, warehousing, delivery, and contracts, this paper only quantifies the budget risk caused by market prices and does not calculate the optimal inventory or the optimal purchase ratio. After selecting the model, this paper uses the joint prediction distribution of the main model to generate 5,000 future 20-day price paths, and assumes that the enterprise purchases 1,000 metric tons of electrolytic copper uniformly within this window ^[3].

3. Empirical results

3.1. Comparison of development period models

The median COMEX copper price during the sample period was approximately \$8,036 per ton, with a range of \$4,562 to \$14,721 per ton. During the development period, 72 starting points resulted in a total of 1,440 future 1–20-day predictions. Among them, the overall MAE of ARIMA was the lowest at \$259.0 per ton, but it was only about 0.5% lower than Naive’s \$260.3; Random Forest and HistGradientBoosting were \$264.7 and \$276.2 per ton, respectively, and Rolling Mean 20 was \$339.3 per ton. In the 20-day average price MAE, ARIMA was \$225.6 per ton, and Naive was \$227.2 per ton ^[4]. See **Tables 1 and 2**.

Table 1. COMEX copper price during the development period

Model	Development period MAE	20-day average price (MAE)
ARIMA	259.0	225.6
Naive	260.3	227.2
Random Forest	264.7	230.7
HistGradientBoosting	276.2	238.9
Rolling Mean 20	339.3	309.4

The results of the time interval analysis further demonstrate that the advantages of ARIMA are not stable: the MAE on the 1st day and the 20th day were 92.5 and 388.4 US dollars per ton, respectively, both slightly higher than the 91.9 and 387.8 of Naive; only on the 5th day and the 10th day was it slightly better than Naive.

Table 2. COMEX copper price during different forecast periods

Forecast period	Naive	ARIMA	Random Forest	HistGradientBoosting
Day 1	91.9	92.5	92.4	112.2
Day 5	193.3	192.4	199.2	204.8
Day 10	266.8	266.6	270.6	285.2
Day 20	387.8	388.4	404.9	412.3

2,000 bootstrap samples show that the confidence intervals of the starting-level errors of ARIMA, Random Forest, and HistGradientBoosting relative to Naive all include 0, indicating that their improvement directions are not stable. The overall MAE of the three types of combined models constructed based on low, medium, and high fluctuation states is approximately 261 US dollars/ton, which is also not higher than ARIMA; the adaptive weights are mostly concentrated in the range of 24–27%, suggesting that historical errors and fluctuation states are not sufficient to form a stable distinction ^[5].

3.2. Model selection

Before the test, ARIMA was set as the main model, while Naive, Random Forest, and HistGradientBoosting were regarded as the challenging models. The combined model maintained an exploratory status. During the independent testing period, 19 starting points resulted in a total of 380 predictions. The equal-weight, state contraction, and global adaptive combined MAE were \$581.4, \$581.5, and \$581.7 per ton, respectively; Random Forest was \$583.6, ARIMA was \$588.2, Naive was \$595.1, and HistGradientBoosting was \$595.9. Although the combined model ranked higher in the short term, it did not show an advantage during the development period. Therefore, the main model cannot be changed based on the test results afterward. 5,000 bootstrap iterations also did not show a stable error improvement compared to Naive or ARIMA for each model ^[6]. See **Figure 1**.

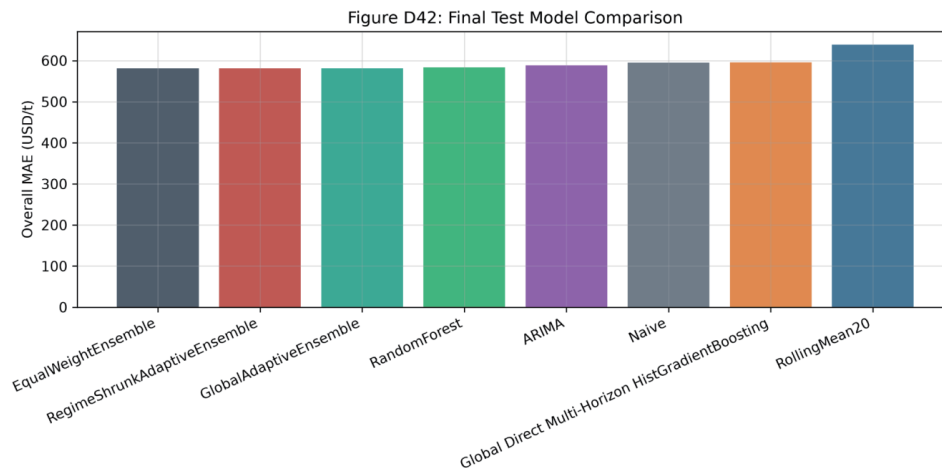


Figure 1. Overall model comparison during independent testing period

3.3. Prediction for the next 20 trading days

Starting from July 10, 2026, the copper price was \$13,854.95 per ton. The ARIMA model predicts that the prices on July 13, 2026, July 24, 2026, and August 7, 2026 would be approximately \$13,857, \$13,907, and \$13,962 per ton, respectively. The 20-day average is approximately \$13,910 per ton, with the central path showing a generally stable upward trend. The 20th day has risen by approximately 0.8% compared to the starting point. See **Figure 2**.

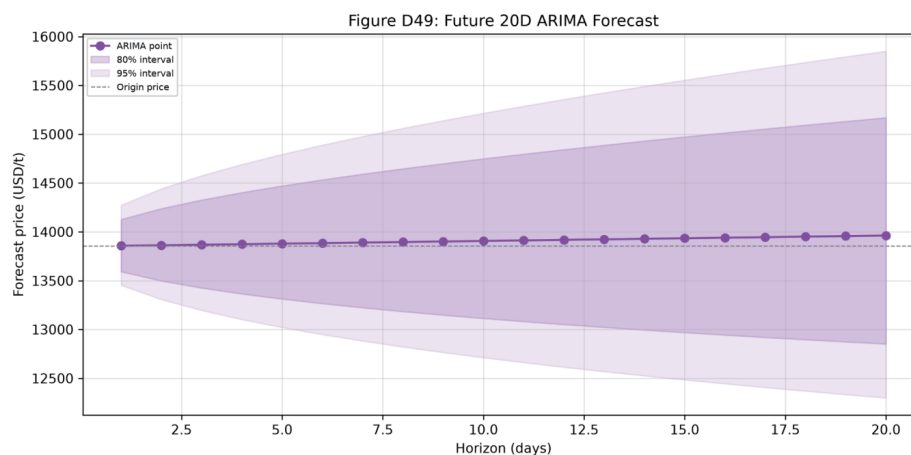


Figure 2. ARIMA forecast and confidence interval for the next 20 trading days

4. Procurement risks and strategies

4.1. Scenario costs and PCaR

Based on 5,000 ARIMA joint simulation paths, under the assumption of uniform purchase of 1,000 metric tons over the next 20 trading days, the 20-day average copper price scenarios of price decline Q20, expectation, and price increase Q95 are approximately \$13,456, \$13,922 and \$14,850 per ton respectively, corresponding to purchase costs of approximately \$13.46 million, \$13.92 million and \$14.85 million. Compared with the

expected cost, the downside scenario can reduce costs by approximately \$470,000, while the upside scenario increases costs by approximately \$930,000, indicating that the adverse cost deviation is significantly greater than the potential savings ^[7]. See **Table 3**.

Table 3. Scenario costs and PCaR

Situation	Average copper price (USD/ton)	Procurement cost	The difference from expectations
Q20 Downstream	13,456	Approximately 13.46 million US dollars	- \$470,00
Expectation	13,922	Approximately 13.92 million US dollars	—
Q95 Upstream	14,850	Approximately 14.85 million US dollars	\$930,00

This result indicates that even if the central forecast shows only a slight upward trend, enterprises may still face tail risks in their budgets. PCaR is not the upper limit of procurement costs; approximately 5% of the simulation results are still higher than the 95th percentile cost; at the same time, this value relies on ARIMA, 5,000 paths, and 1,000 metric tons assumptions, and does not take into account exchange rates, transportation, warehousing, spot premiums and discounts, supplier quotations, and contract terms. This is for budget buffer reference only, and does not provide a definite cost boundary ^[8]. See **Figure 3**.

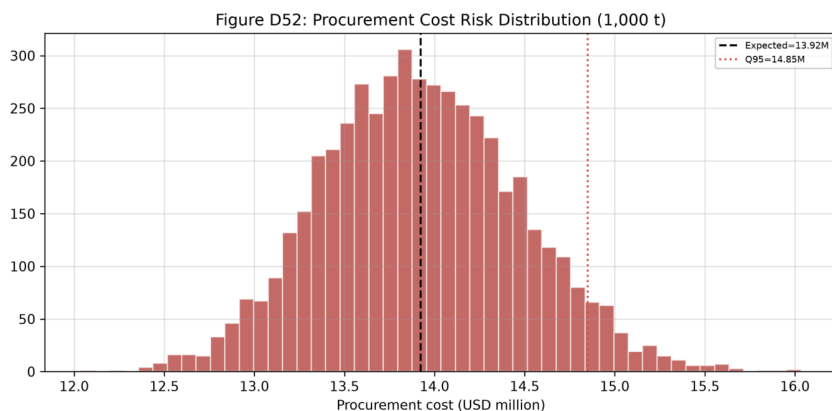


Figure 3. Simulation distribution of 1,000 ton purchase cost and PCaR

4.2. Risk signals

This article classifies risk signals into three levels. The regular signal indicates that the predicted changes are small, the actual price remains within the predicted range, and the error is stable. In this case, the original batch purchasing schedule should be maintained. The attention signal indicates a continuous increase in price, the price approaching the upper limit of the range, or an increase in PCaR. At this time, the inventory, remaining purchase quantity, and budget space should be rechecked. If inventory permits, partial purchases can be appropriately advanced. The review signal indicates that the actual price exceeds the predicted range or the recent error continues to expand. At this time, mechanical adjustments should be suspended to ensure the necessary purchases for production and wait for manual review. See **Table 4**.

Table 4. Risk signals

Signal	Main conditions	Suggested action
Conventional	The price is within the range and the error is stable.	Maintain the original batch purchasing plan
Pay attention	Trend is rising, approaching the upper limit or PCaR is increasing	Review the budget and inventory, and make appropriate advance purchases for some items.
Recheck	Continuous crossing of boundaries or significant expansion of errors	Reduce the model weights, ensure necessary purchases, and conduct manual reviews

4.3. Strategy

Procurement risk management should adopt a closed-loop process of “data update–rolling forecast–error monitoring–anomaly review–model update.” Enterprises can incorporate the latest copper prices, US dollar index, and WTI data daily to generate a new 20-day forecast. At the same time, they should regularly record the MAE and interval coverage of the forecast values and actual values. Manual review is used to handle policy, geopolitical events, and sudden supply disruptions that are difficult for historical numerical models to reflect in a timely manner.

5. Conclusion

This paper takes copper procurement in the new energy vehicle industry chain as the scenario and constructs a decision support process for rolling price prediction, prediction uncertainty, PCaR, and procurement risk signals. The study shows: First, the copper price has a thick-tailed distribution and periodic high-volatility characteristics, and a single average trend is insufficient to represent the procurement risk; Second, in the sample comparison, complex machine learning and combined models did not exceed Naive and ARIMA in stability. Although ARIMA has the lowest error during the development period, its advantage is very small, and the error increases significantly during the testing period, so the complexity of the model cannot be equated to the prediction reliability; Third, after converting the prediction distribution into procurement costs, the risk information prediction has more management significance. In the 1,000-ton scenario, the 95% PCaR is approximately \$930,000, accounting for 6.7% of the expected cost, indicating that there may still be a relatively high budget risk; Fourth, the three-level risk signals and dynamic manual review can convert the prediction results into conditional procurement management information. The three-level signals proposed in this paper still need to be tested by enterprises over the long term. In the future, it can be connected to internal enterprise data to establish an enterprise procurement optimization model and verify the reliability of the model through long-term tracking data.

Disclosure statement

The author declares no conflict of interest.

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