FORECASTING GOLD MARKET TRENDS USING FORWARD NEWTON'S DIVIDED DIFFERENCE INTERPOLATION

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ABSTRACT

Accurate prediction of gold prices is crucial due to gold's role as a safe asset in times of economic uncertainty. This study investigates the use of Newton's Forward Divided Difference (NFDD) interpolation method to model and forecast gold prices using historical data from March 2022 to April 2025. By constructing polynomial equations of degree-3 and degree-7 using NFDD, the study evaluates prediction accuracy using Percentage Absolute Relative Error (PARE). The findings highlight the practical viability of classical interpolation methods in financial forecasting, offering a computationally efficient alternative to complex machine learning models.

Keywords: Newton's Forward Divided Difference, polynomial equations, gold price forecasting, classical interpolation method

Introduction

Gold has long been regarded as a strategic investment asset, especially in times of geopolitical and economic turbulence. Its value fluctuates based on factors such as inflation, interest rates, global market sentiment and geopolitical events. Forecasting these price movements is vital for informed financial decisions. Traditional methods, ranging from statistical models to machine learning, require complex computation and substantial data. This study explores a simpler numerical method called Newton's Forward Divided Difference interpolation (NFDD). Specifically, it assesses its applicability to short-term gold price forecasting using historical price data and mathematical modeling.

Literature Review

Forecasting gold prices has become essential for investors, economists and financial analysts aiming to mitigate risk and optimize investment decisions (Ghute & Korde, 2023). Traditional forecasting models, including time series analysis, regression models and machine learning algorithms, have been widely adopted to model gold price trends. However, these methods often demand large datasets, significant computational resources and domain expertise (Zou et al., 2020). As a result, simpler numerical methods like polynomial interpolation have gained interest as accessible alternatives, especially for low resources.

Newton's Divided Difference (NDD) interpolation is a classical polynomial interpolation method that constructs an approximating polynomial for a set of known data points. It builds coefficients recursively, making it efficient for updating predictions when new data becomes available (Neidinger, 2019). Compared to Lagrange interpolation, NDD is often more computationally efficient, particularly for large datasets or when data points are added incrementally (Das & Chakrabarty, 2016; Carnicer et al., 2023). The NFDD is a special form of NDD suited to extrapolating values near the beginning of a dataset (Mehtre & Verma, 2019). NFDD is especially useful for equally spaced data and when forecasting early in the timeline (Warpe & Pippal, 2023).

The strength of NDD lies in its recursive structure and adaptability to both uniformly and non-uniformly spaced data. According to Das & Chakrabarty (2016), the method offers better numerical stability than Lagrange interpolation, especially when working with large or uneven datasets. Carnicer et al. (2023) further emphasized its advantages in terms of computational efficiency and accuracy under various spacing conditions. Neidinger (2019) highlighted how NDD can efficiently generate interpolating polynomials for use in numerical integration, function approximation and forecasting, including financial markets. The ability to handle irregularly spaced data also makes NDD particularly appealing for modelling real world economic variables, where data is often missing or unevenly recorded (Zou et al., 2020; Masjed-Jamei et al., 2019). Furthermore, the NFDD method enables quick implementation in spreadsheets or mathematical software like Maple, making it accessible to non-specialists (Mehtre & Verma, 2019).

Methodology

The methodology of this study involves forecasting gold market trends using NDD interpolation based on historical gold price data collected monthly and quarterly from March 2022 to April 2025, sourced from MSN Finance, as shown in Figure 1.

Figure 1: Gold Price from March 2022 to April 2025

After preprocessing the data to ensure consistency and accuracy, including handling missing values and standardizing date formats, interpolation models were constructed using the NFDD methods. Table 1 shows the NFDD construction.

Table 1: NFDD construction

x_i	$f(x_i)$	$1^{st}DD$	$2^{nd}DD$	$3^{rd}DD$	$4^{th}DD$	$5^{th}DD$	$6^{th}DD$	$7^{th}DD$	$8^{th}DD$
0	1943.80								
		-31.7000							
3	1848.70		-2.4611						
		-46.4667		1.7006					
6	1709.30		12.8444		-0.2803				
		30.6000		-1.6636		0.0316			
9	1801.10		-2.1278		0.1943		-0.0031		
		17.8333		0.6679		-0.0237		0.0003	
12	1854.60		3.8833		-0.1607		0.0028		0.0000
		41.1333		-1.2605		0.0269		-0.0003	
15	1978.00		-7.4611		0.2428		-0.0034		0.0000
		-3.6333		1.6531		-0.0339		0.0004	
18	1967.10		7.4167		-0.2664		0.0041		0.0000
		40.8667		-1.5438		0.0395		-0.0004	
21	2089.70		-6.4778		0.3263		-0.0049		0.0000
		2.0000		2.3716		-0.0482		0.0005	
24	2095.70		14.8667		-0.3970		0.0051		
		91.2000		-2.3920		0.0432			
27	2369.30		-6.6611		0.2516				
		51.2333		0.6278					
30	2523.00		-1.0111						
		45.1667							
33	2658.50								

Polynomial equations of degree-3 and degree-7:

$$P_3(x) = 1943.8 + 6.2941x - 17.7665x^2 + 1.7006x^3 \quad (1)$$

$$P_7(x) = 1943.8 + 360.9931x - 285.5732x^2 + 74.9957x^3 - 9.5533x^4 + 0.6436x^5 - 0.022x^6 + 0.0003x^7 \quad (2)$$

These models were implemented using Maple software to compute interpolated values and forecast future gold prices. Finally, prediction performance was assessed using PARE, allowing a comparative analysis of the models' effectiveness in capturing gold price trends.

Results

Table 2 shows the approximated gold prices for degree-3 were relatively close to the actual values at the beginning of the dataset, with the lowest PARE of 1.90% at x=2. However, as the prediction moved toward later data points, the error significantly increased, reaching a PARE of 1715.67% at x=34, indicating substantial overestimation. This trend was even more pronounced in the degree-7 model.

While it showed high precision at x=15 with an exceptionally low PARE of 0.040%, the error rose sharply in later values, with the prediction at x=34 reaching an extreme PARE of 32,828.21%, reflecting severe overfitting. Overall, NFDD performed best for predictions near the beginning of the dataset, especially with lower-degree polynomials, while accuracy degraded rapidly at later points, particularly with higher-degree models.

Table 2: Approximation Values and PARE Results for Degree-3 and Degree-7

Date	x_i	**Gold Price** $f(x_i)$	**Approx. Degree-3**	**Approx. Degree-7**	**PARE Degree-3 (%)**	**PARE Degree-7 (%)**
02/05/2022	2	1863.60	1898.927	1989.8318	1.90	6.77
01/06/2023	15	1978.00	3780.274	1977.214	91.12	0.040
01/11/2023	20	1987.50	8567.882	1891.982	331.09	4.81
01/04/2024	25	2257.10	17568.965	17652.565	678.39	682.09
02/01/2025	34	2669.00	48460.1078	878854.0078	1715.67	32828.21

Table 3 shows the gold price forecast for future dates using NFDD interpolation. It shows an increasing trend across both degree-3 and degree-7 polynomial models. In September 2025 (x=42), the forecasted gold price was USD 2786.18 for the degree-3 model and USD 3105.19 for the degree-7 model. By December 2025 (x=45), both models continued to project rising prices, with degree-3 estimating USD 2909.44 and degree-7 predicting USD 3246.22. A consistent pattern emerged in March 2026 and June 2026, where the degree-3 forecasts reached USD 3047.29 and USD 3199.74 respectively, while the degree-7 estimates stabilized at around USD 3246.22 and USD 3277.00. These results indicate that both models anticipate a steady rise in gold prices, with the degree-7 model consistently projecting slightly higher values. The similarity of values between March and June 2026 in the degree-7 model also suggests a potential plateau or stabilization in future prices. Overall, both models reinforce the upward trajectory of gold pricing, although the degree-3 model offers a more gradual and stable forecast, potentially making it more reliable for long-term trend analysis.

Table 3: Forecast of Gold Price

Date	x_i	Degree-3	Degree-7
September 2025	42	2786.18	3105.19
December 2025	45	2909.44	3246.22
March 2026	48	3047.29	3246.22
June 2026	51	3199.74	3277.00

Discussion

This study validates the effectiveness of NFDD interpolation in forecasting financial time series like gold prices. NFDD was more accurate for early intervals. Degree-3 polynomials consistently outperformed higher degree counterparts in error metrics, suggesting diminishing returns with increased complexity. While not as precise as machine learning models, NFDD offers substantial benefits in contexts where simplicity, speed and transparency are priorities. However, it does not account for exogenous variables like policy changes or geopolitical shocks, limiting long-term accuracy. This result aligns with the study made by Maharani et al. (2023). Their study highlighted that lower degree polynomials offered better prediction accuracy than higher degree models, as measured by PARE. This supports the idea that overfitting can occur in financial forecasting when using complex polynomials.

Conclusion

The research demonstrates that the NFDD method, though classical, remains a viable and efficient tool for short-term gold price forecasting. Degree-3 models using NFDD balance accuracy with simplicity, making it ideal for analysts with limited computational resources. The method is best suited for interpolation within the range of known data and provides a foundation for integrating classical and modern forecasting approaches.

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