

Research on Defi Lending Forecasting based on GRA and Rolling GM(1,N) Model

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Abstract. This paper investigates the short-term dynamics of decentralised lending conditions on Aave, a leading DeFi pooled lending protocol whose rapid TVL growth has made its variable interest-rate mechanism systemically relevant for on-chain investors and risk managers. In contrast to traditional fixed-income markets, DeFi interest rates are endogenously determined by pool utilisation and are observed over relatively short and highly volatile time series, which poses challenges for conventional econometric models. To address this, we develop a grey-system forecasting framework tailored to the USDC pool on Aave v3. Weekly data from January to November 2025 are collected on the utilisation rate (U), total value locked (TVL) and the Crypto Fear & Greed Index (FG). Grey relational analysis (GRA) is first employed to screen explanatory factors; both TVL and FG exhibit relational grades above 0.7 with respect to U (0.7138 and 0.7673, respectively), confirming that on-chain liquidity and market sentiment jointly drive utilisation. On this basis, a multivariate rolling GM(1,3) model is specified, estimated over an 8-week moving window and used to generate one-step-ahead forecasts of weekly utilisation. The resulting pseudo out-of-sample forecasts for 46 weeks achieve a mean absolute percentage error of 5.97%, with a posterior error ratio $C=0.6475$ and small error probability $P=0.7632$, indicating acceptable forecasting accuracy under standard grey-model criteria. The model successfully reproduces the medium-term high-utilisation regime (around 0.8–0.88) that places the USDC pool near the kink of Aave's dual-slope interest-rate curve, implying frequent transitions into a high-rate environment for borrowers while offering attractive yields to liquidity suppliers. By linking grey-based utilisation forecasts to the protocol's endogenous rate formula, the paper provides an interpretable and data-efficient tool for anticipating Aave's interest-rate conditions and supporting lending, borrowing and arbitrage decisions in DeFi.

Keywords: Defi forecasting, GRA, GM, grey system.

1. Introduction

In March 2023, Silicon Valley Bank was forced into bankruptcy and liquidation amid a bank run. The primary cause was traced to its asset allocation errors, which ultimately triggered the mandatory liquidation [1]. This episode indicates that, under the current financial architecture, the risks inherent in banks' deposit-taking and lending activities remain non-negligible — a development that has driven lenders to seek safer, higher-yielding investment havens. Meanwhile, as blockchain technology and community governance improve, DeFi has entered the broader public discourse. AAVE is one of the most representative flagship projects in DeFi, making it especially valuable for study. According to community disclosures, AAVE's Total Value Locked (TVL) has grown from USD 5 billion in October 2023 to USD 45 billion in October 2025 — representing an average annual growth rate (CAGR) of 450% and indicating that the project is in a phase of rapid expansion. This growth can be attributed to the transparency and efficiency inherent in its decentralized lending mechanism, as well as the continuous refinement of its multiple risk-control models. More importantly, AAVE employs a dual-slope design that dynamically adjusts collateral ratios and interest rates, effectively balancing supply and demand and enhancing system stability [2]. DeFi's variable interest rate mechanisms not only influence the repayment and deposit planning of borrowers and lenders but also the behavior of short-horizon on-chain arbitrageurs [3]. Given the scarcity of research on interest-rate forecasting, it will be of substantial significance to forecast these rates.

The existing foreign research can be roughly divided into three branches. The first branch focuses on system overviews and functional frameworks, explaining how smart contracts reconstruct core processes such as clearing, custody, and settlement in an open environment. For example, Schär provides a systematic survey of DeFi's structure and underlying logic [4]. The second branch examines the interest-rate mechanisms of "pooled lending facilities (PLFs)" cross-protocol interactions, and market efficiency. Gudgeon, *et al* analyze the interest-rate curves and liquidity responses of protocols such as Compound, Aave, and dYdX, employing time-series/error-correction models to characterize cointegration among rates while assessing market liquidity, efficiency, and interdependence [5]. The third centers on leverage, funding liquidity, and liquidation risk. Heimbach and Huang identify typical wallet-level leverage ranges, showing how borrowing costs and LTV constraints drive leverage, and document potential liquidation cascades and vulnerabilities under market stress; Regulators and international organizations likewise highlight risk factors from macroprudential and financial-stability perspectives [6]. Nguyen, *et al* recently provide empirical evidence on the determinants of funding-liquidity risk in decentralized lending, pushing the discussion toward micro-level drivers [7]. On the domestic front, survey and policy studies on the digital economy, blockchain security, and fintech have continued to accumulate. Jia, *et al* summarize smart-contract security vulnerabilities, scam types, and detection techniques, offering a macro perspective and technical tools for DeFi risk sensing and supervisory technology [8].

According to the aforementioned literatures, it can be seen that quantitative research on the "predictability" of on-chain lending and the "operational boundaries" of strategies remains relatively limited, especially regarding robust modeling under "small samples and incomplete information". To fill these gaps, our work focuses on forward-looking measurement and interpretable forecasting of AAVE interest rates. Under conditions of short on-chain time series, pronounced heteroskedasticity, and frequent structural breaks, the grey modeling methods GRA and RGM(1,N) are introduced to accommodate settings characterized by grey informational uncertainty [9], thereby enriching the methodological toolkit for DeFi forecasting. Those models are parts of the grey system theory, which is proposed by Deng (1982) and designed for system with small samples, sparse information, and strong uncertainty. Those models feature parsimonious structure and strong interpretability and are frequently used for short-term trend prediction; Subsequent research has extended grey models to multivariate and structurally enhanced forms, with empirical applications to financial time series including interest and exchange rates [10]. The purpose of this paper is threefold: (1) This study contributes by transferring grey model from its conventional domain to Defi forecast, where data scarcity and high volatility is prevalent. By introducing GRA and RGM(1,N), we extend the applicability boundary of grey system and provide an interpretable and deployable framework for Defi Lending. (2) This study serves on-chain participants managing risk by providing users and market makers with forward-looking cost and risk boundaries; (3) It supplies quantitative inputs for protocol-governance parameters (e.g., interest-rate curves, LTV ratios, and penalties), helping to furnish verifiable empirical evidence for protocol governance and policy discussions and thereby offering clear academic and practical value [11].

The paper is organized as follows. In section 2, the GRA and RGM(1,n) model are described briefly. In section 3, we study the relationship among the Utility, the TVL and the Crypto Fear & Greed Index. based on on-chain data, a simulation of the tendency to Utility is been created, which shows the result of GRA and RGM(1,n) for predicting weekly utility and interest rate. In section 4, it's about the conclusion of this forecast and some suggestion for investor who involved in AAVE.

2. Methodology

2.1. Grey relational analysis

In this study, the explained variable is denoted by the reference time series $\{u^{(0)}(k)\}_{k=1}^T$, where $k = 1, 2, \dots, T$ indexes the discrete time period and T is the total number of observations.

The candidate explanatory variables are denoted by

$\{x_i^{(0)}(k)\}_{k=1}^T$, where $i = 1, 2, \dots, p$ indexes the different variables and p is the total number of candidates. Grey relational analysis (GRA) is employed to measure the geometric similarity between the reference series $u^{(0)}(k)$ and each comparative series $x_i^{(0)}(k)$ in a normalized space (Deng, 1989; Kuo *et al.*, 2008). Based on the resulting relational grades, a subset of variables is selected and will later be incorporated into a rolling GM(1,n) model.

2.1.1. Normalization

Because the variables may be measured in different units and scales, the original data are first normalized. A common “larger-is-better” linear scaling is adopted for the reference series:

$$\tilde{u}(k) = \frac{\{u^{(0)}(k) - \min_{1 \leq \tau \leq T} u^{(0)}(\tau)\}}{\{ \max_{1 \leq \tau \leq T} u^{(0)}(\tau) - \min_{1 \leq \tau \leq T} u^{(0)}(\tau) \}}, \quad k = 1, 2, \dots, T \quad (1)$$

Similarly, for each candidate explanatory variable $\{x_i^{(0)}(k)\}$, the normalized series is defined by

$$\tilde{x}_i(k) = \frac{\{x_i^{(0)}(k) - \min_{1 \leq \tau \leq T} x_i^{(0)}(\tau)\}}{\{ \max_{1 \leq \tau \leq T} x_i^{(0)}(\tau) - \min_{1 \leq \tau \leq T} x_i^{(0)}(\tau) \}}, \quad i = 1, 2, \dots, p, k = 1, 2, \dots, T \quad (2)$$

The normalized sequences $\tilde{u}(k)$ and $\tilde{x}_i(k)$ are dimensionless and bounded in $[0, 1]$, which facilitates a fair comparison across different variables.

2.1.2. Absolute deviation sequence

For each comparative series i , the absolute deviation between the reference and the comparative series at time k is defined as

$$\Delta_i(k) = |\tilde{u}(k) - \tilde{x}_i(k)|, \quad i = 1, 2, \dots, p, k = 1, 2, \dots, T \quad (3)$$

Here, $\Delta_i(k)$ is the absolute difference between the normalized reference value and the normalized value of variable i at the same time period k .

In the subsequent construction of the grey relational coefficient,

Δ_{min} represents the **minimum** value of $\Delta_i(k)$ taken over all variables i and all time periods k , and Δ_{max} represents the corresponding **maximum** value of $\Delta_i(k)$ over all i and k .

2.1.3. Grey relational coefficient

The grey relational coefficient between $\tilde{u}(k)$ and $\tilde{x}_i(k)$ at time k is then defined as

$$\xi_i(k) = \frac{\{\Delta_{min} + \rho \Delta_{max}\}}{\{\Delta_i(k) + \rho \Delta_{max}\}}, \quad 0 < \rho \leq 1, i = 1, 2, \dots, p, k = 1, 2, \dots, T \quad (4)$$

where ρ is the distinguishing coefficient controlling the contrast of relational coefficients. Following common practice, ρ is set to 0.5 unless otherwise specified.

2.1.4. Grey relational grade and variable selection

The overall grey relational grade for variable $x_i^{(0)}(k)$ is given by the arithmetic mean of $\xi_i(k)$ over all time points:

$$\gamma_i = \frac{1}{T} \sum_{k=1}^T \xi_i(k), \quad i = 1, 2, \dots, p \quad (5)$$

A larger γ_i indicates that the trajectory of $x_i^{(0)}(k)$ is more similar to that of $\xi_i(k)$ in the normalized space, and thus variable x_i is more strongly associated with the reference series.

All candidate variables are ranked in descending order of γ_i . In line with the structure of the GM(1,n) model, we select $(n - 1)$ explanatory variables with the highest relational grades, where n denotes the **total number of series** in the GM(1,n) model (one dependent series plus $(n - 1)$ selected explanatory series). These selected explanatory variables are relabeled as $x_j^{(0)}(k)$, with $j = 1, 2, \dots, n - 1$, for use in the subsequent modelling.

2.2. Construction of the GM(1,n) model

After variable selection, we construct a first-order multivariate grey model with one dependent series and $(n - 1)$ explanatory series, denoted as GM(1,n). The dependent series is $u^{(0)}(k)$, and the selected explanatory series are $x_j^{(0)}(k)$ for $j = 1, 2, \dots, n - 1$. The time index $k = 1, 2, \dots, T$ is the same as in the GRA step.

2.2.1. Accumulated generating operation (AGO)

The one-order accumulated generating operation (AGO) is applied to the dependent series:

$$u^{(1)}(k) = \sum_{\tau=1}^k u^{(0)}(\tau), \quad k = 1, 2, \dots, T \quad (6)$$

For each selected explanatory variable $x_j^{(0)}(k)$, the corresponding AGO series is defined as

$$x_j^{(1)}(k) = \sum_{\tau=1}^k x_j^{(0)}(\tau), \quad j = 1, 2, \dots, n - 1, k = 1, 2, \dots, T \quad (7)$$

Here, τ is a running index used inside the summation, while k continues to denote the current time point.

2.2.2. Grey differential equation

The continuous grey differential equation of the GM(1,n) model is specified as

$$\frac{\{d u^{(1)}(t)\}}{\{dt\}} + a u^{(1)}(t) = \sum_{j=1}^{n-1} b_j x_j^{(1)}(t) \quad (8)$$

where

- a is the **development coefficient**, reflecting the self-decay or self-growth speed of the system;
- b_j ($j = 1, 2, \dots, n - 1$) are the **driving coefficients**, measuring the impact of the explanatory variables on $u^{(1)}(t)$.

To discretize equation (8), a background value $z^{(1)}(k)$ is introduced for the dependent AGO series:

$$z^{(1)}(k) = \frac{1}{2} \left(u^{(1)}(k) + a z^{(1)}(k) \right), \quad k = 2, 3, \dots, T \quad (9)$$

Using the standard grey system approximation (Deng, 1989; Wu and Chen, 2005), the discrete form of equation (8) becomes

$$u^{(0)}(k) + a z^{(1)}(k) = \sum_{j=1}^{n-1} b_j x_j^{(1)}(k), \quad k = 2, 3, \dots, T \quad (10)$$

2.2.3. Parameter estimation

Equation (10) can be written in matrix form as

$$Y = B\theta \quad (11)$$

where Y is the $(T - 1) * 1$ vector of original observations (from period 2 to T):

$$Y = \begin{bmatrix} u^{(0)}(2) \\ u^{(0)}(3) \\ \vdots \\ u^{(0)}(T) \end{bmatrix} \quad (12)$$

(B) is the $(T - 1) * n$ design matrix constructed from the background values and AGO explanatory variables:

$$B = \begin{bmatrix} -z^{(1)}(2) & x_1^{(1)}(2) & x_2^{(1)}(2) & \cdots & x_{n-1}^{(1)}(2) \\ -z^{(1)}(3) & x_1^{(1)}(3) & x_2^{(1)}(3) & \cdots & x_{n-1}^{(1)}(3) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ -z^{(1)}(T) & x_1^{(1)}(T) & x_2^{(1)}(T) & \cdots & x_{n-1}^{(1)}(T) \end{bmatrix} \quad (13)$$

and θ is the $n * 1$ parameter vector:

$$\theta = \begin{bmatrix} a \\ b_1 \\ b_2 \\ \vdots \\ b_{n-1} \end{bmatrix} \quad (14)$$

The parameter vector θ is estimated by the ordinary least squares (OLS) solution:

$$\hat{\theta} = (\hat{a}, \hat{b}_1, \hat{b}_2, \dots, \hat{b}_{n-1})^T = (B^T B)^{-1} B^T Y \quad (15)$$

Substituting $\hat{a}$ and $\hat{b}_j$ ($j = 1, 2, \dots, n - 1$) back into equation (8) yields the fitted grey differential equation for the system under study.

2.2.4. Time response and inverse AGO

The solution (time response) of equation (8) with the estimated parameters can be expressed as

$$u^{(1)}(t) = e^{-\hat{a}(t-1)} u^{(1)}(1) + \int_1^t e^{-\hat{a}(t-\tau)} \left(\sum_{j=1}^{n-1} \hat{b}_j x_j^{(1)}(\tau) \right) d\tau \quad (16)$$

In practical implementations, the integral term in equation (16) is approximated numerically (for example, using a rectangular or trapezoidal rule over each interval $[k, k + 1]$, and thus one-step-ahead predictions of $u^{(1)}(k + 1)$ can be obtained recursively for $k = 1, 2, \dots$

The corresponding prediction of the original series is then given by the inverse AGO:

$$\hat{u}^{(0)}(k + 1) = \hat{u}^{(1)}(k + 1) - \hat{u}^{(1)}(k), \quad k = 1, 2, \dots \quad (17)$$

2.3. Rolling GM(1,n) forecasting scheme

Classical grey prediction models are typically estimated once based on an initial sample and then used to forecast all future observations. However, in rapidly changing environments, the data-generating mechanism may evolve over time, and a static model can quickly become outdated. To capture new information, we adopt a rolling GM(1,n) scheme (Chang et al., 2005; Tang and Yin, 2012).

Let m be the window size with $m \geq n + 1$ to ensure sufficient degrees of freedom for parameter estimation. For each rolling step r , we define the sample window

$$W_r = \{k: k = r, r + 1, \dots, r + m - 1\},$$

where $r = 1, 2, \dots, T - m$. At step r , only data within W_r are used to estimate the local parameters of GM(1,n) and to produce a one-step-ahead forecast for period $r + m$.

Within each window W_r , the original series are re-indexed locally. For the dependent series:

$$u_r^0(h) = u^0(r + h - 1), \quad h = 1, 2, \dots, m \quad (18)$$

For each selected explanatory series $x_j^{(0)}(k)$, the local re-indexed series is

$$x_{j,r}^{(0)}(h) = x_j^{(0)}(r + h - 1), \quad j = 1, 2, \dots, n-1, h = 1, 2, \dots, m \quad (19)$$

Here, h indexes the position within the current window W_r , while r indexes the rolling step.

The corresponding AGO series $u_r^0(h)$, $x_{j,r}^{(0)}(h)$ and the background values $z_r^{(1)}(h)$ are then constructed within each window in the same way as in Section 2.2.1, but restricted to $h = 1, 2, \dots, m$.

2.3.1. Local parameter estimation and one-step-ahead forecast

Within window W_r , the discrete GM(1,n) equations analogous to equation (10) are written as

$$u_r^{(0)}(h) + a_r z_r^{(1)}(h) = \sum_{j=1}^{n-1} b_{j,r} x_{j,r}^{(1)}(h), \quad h = 2, 3, \dots, m \quad (20)$$

where a_r and $b_{j,r}$ ($j = 1, 2, \dots, n-1$) are the window-specific parameters for the r -th rolling step.

The parameter vector for window W_r is

$$\theta_r = (a_r, b_{1,r}, b_{2,r}, \dots, b_{n-1,r})^T \quad (21)$$

and is estimated via OLS as

$$\hat{\theta}_r = (B_r^T B_r)^{-1} B_r^T Y_r, \quad (22)$$

where Y_r and B_r are constructed from the windowed AGO data in the same way as in equations (12)–(15), but using only the $m-1$ observations within window W_r .

Given $\hat{\theta}_r$ and the explanatory variables observed at time $m+1$, we compute the predicted accumulated value $\hat{u}^{(0)}(m+1)$ by applying the local time response of GM(1,n) over the window $[1, m+1]$, and then recover the one-step-ahead prediction of the original series as

$$\hat{u}^{(0)}(r+m) = \hat{u}_r^{(1)}(m+1) - \hat{u}_r^{(1)}(m) \quad (23)$$

Moving from window W_r to W_{r+1} , the oldest observation at time r is discarded and the new observation at time $r+m$ is added. Parameters are re-estimated based on the updated sample, so that the model always reflects the most recent information in the data.

The sequence of rolling forecasts

$\{\hat{u}^{(0)}(m+1), \hat{u}^{(0)}(m+2), \dots, \hat{u}^{(0)}(T)\}$ is obtained by repeating the above procedure for $r = 1, 2, \dots, T-m$.

2.4. Forecast accuracy evaluation

To evaluate the forecasting performance of the proposed rolling GM(1,n) model, we compare the predicted values $\hat{u}^{(0)}(k)$ with the actual observations $u^{(0)}(k)$ over the out-of-sample horizon. Standard error measures are adopted, including:

Mean absolute percentage error (MAPE):

$$\text{MAPE} = \frac{100\%}{N} \sum_{k \in \mathcal{K}} \left| \frac{u^{(0)}(k) - \hat{u}^{(0)}(k)}{u^{(0)}(k)} \right| \quad (24)$$

Root mean squared error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{k \in \mathcal{K}} (u^{(0)}(k) - \hat{u}^{(0)}(k))^2} \quad (25)$$

where $\mathcal{K}$ denotes the set of evaluation periods and $N = |\mathcal{K}|$ is the number of observations in the evaluation set.

For robustness, the rolling GM(1,n) model can be further compared with its non-rolling counterpart and with standard benchmark models (e.g., naïve forecast or exponential smoothing), but this lies beyond the core methodological focus of this paper.

3. Simulation and result

3.1. Data Description

In this reasearch, to apply the proposed grey rolling model to the Aave lending market, we need those following data. Weekly observations on the utilisation rate (U), total value locked (TVL) and the crypto Fear & Greed index (FG) are collected from *Aave subgraph* [12], *DeFiLlama* [13], and *Alternative*[14].*me* for the period from [2025.1.1] to [2025.11.19]. The main variables and their data sources are summarised in Table 1. From the perspectives of stability and compliance, we chose the U of USDC to represent the whole situation. All series are transformed into dimensionless form where necessary (for example, TVL is normalised by its sample mean) to avoid numerical scaling problems in the grey modelling.

Table 1. USDC weekly U, TVL and FG

Week	U	TVL	FG	Week	U	TVL	FG
1 (2025-01-01 -> 2025-01-08)	0.8388	20.27	70	24	0.7719	25.559	52
2	0.7932	20.897	70	25	0.8278	24.764	66
3	0.8355	21.689	84	26	0.8494	24.45	63
4	0.7336	20.991	72	27	0.8392	26.492	66
5	0.637	19.772	54	28	0.8087	30.277	70
6	0.6055	19.304	46	29	0.8402	33.264	74
7	0.6613	19.635	44	30	0.8474	34.049	74
8	0.6334	19.176	21	31	0.8778	34.416	54
9	0.5819	18.214	20	32	0.8515	40.177	73
10	0.5469	17.046	34	33	0.8428	35.609	44
11	0.5696	17.714	32	34	0.8255	39.799	51
12	0.6591	19.286	47	35	0.7947	38.588	55
13	0.6892	17.809	44	36	0.8549	39.666	49
14	0.6452	16.356	18	37	0.8446	40.968	53
15	0.6626	17.823	29	38	0.8432	39.938	44
16	0.6181	18.861	72	39	0.7834	43.332	49
17	0.672	19.718	56	40	0.7679	44.865	60
18	0.7329	20.413	67	41	0.7417	41.212	34
19	0.824	25.222	73	42	0.7663	38.414	25
20	0.8495	24.371	70	43	0.782	38.983	51
21	0.8453	25.426	71	44	0.8873	32.483	23
22	0.8461	25.143	62	45	0.8437	32.585	24
23	0.8503	26.443	72	46 (2025-11-12 -> 2025-11-19)	0.8376	31.992	15

3.2. Factor Screening and Validation

From the perspective of DeFi lending theory, the utilisation rate of a lending pool is primarily driven by two dimensions: **on-chain liquidity conditions** and **market risk appetite**. On the one hand, the total value locked (TVL) in the pool reflects the amount of capital supplied and therefore constrains how much can be borrowed at a given point in time. On the other hand, investors' risk appetite affects their willingness to lever up or de-lever, which is closely related to the borrowing demand for stablecoins.

In light of this economic intuition, we focus on two representative explanatory variables in the empirical model: the pool-level TVL and the Crypto Fear & Greed Index (FG). Rather than

performing an exhaustive search over a wide set of macro and market variables, we deliberately restrict attention to these two factors so as to keep the grey model parsimonious and to avoid over-parameterisation given the limited sample size.

To statistically validate the relevance of TVL and FG for Aave’s utilisation dynamics, we employ grey relational analysis (GRA). The weekly utilisation rate U is taken as the reference sequence $X_0(k)$, while the two factor sequences TVL and FG are treated as comparison sequences $X_1(k)$ and $X_2(k)$. All three series are normalised according to the procedure described in Section 2, with the distinguishing coefficient set to $\zeta=0.7$. Using those equations, we compute the grey relational coefficients and the corresponding relational grades between U and each factor.

The results show that the relational grade for FG is **0.7673**, while that for TVL is **0.7138**. Both values exceed the conventional threshold of 0.7, indicating a strong association with the utilisation rate. Moreover, FG exhibits a slightly higher relational grade than TVL, suggesting that short-term variations in market sentiment play a somewhat more prominent role than changes in locked liquidity in explaining the week-to-week movements of U . These findings support the use of **TVL and FG as the two explanatory variables** in the subsequent RGM(1,3) model.

3.3. Rolling GM(1,3) Forecasts

The sample consists of 46 weekly observations on U , TVL and FG from 1 January 2025 to 19 November 2025. Before estimation, the original utilisation series $U^{(0)}(k)$ is transformed into its first-order accumulated generating operation (1-AGO) sequence $U^{(1)}(k)$. As shown in Figure 1., the accumulated series displays a smooth, approximately exponential upward trend, satisfying the basic requirement for applying a first-order grey model.

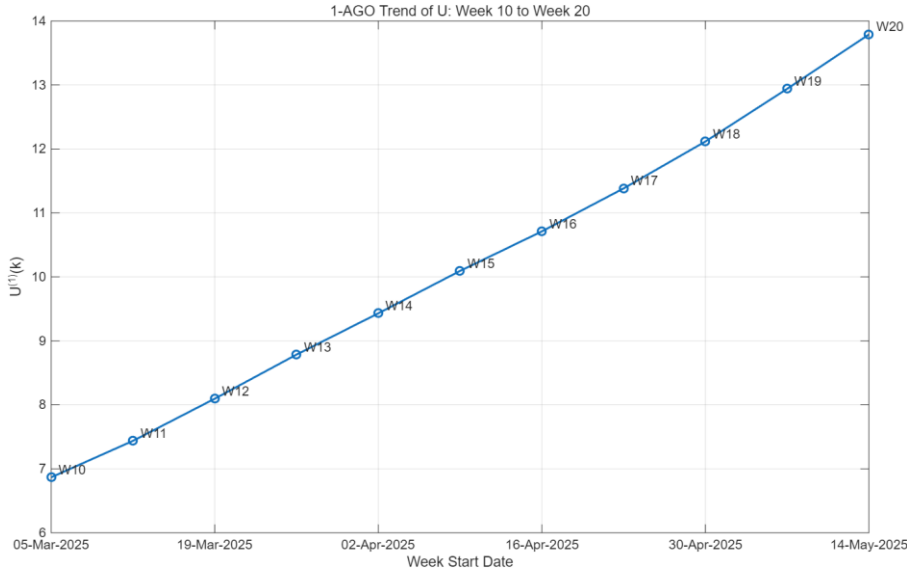


Figure 1. 1-AGO Trend of U: Week 10 to Week 20

To investigate the short-term predictive performance in a more realistic setting, we implement a rolling GM(1,3) forecasting scheme. A rolling window of 8 consecutive weeks is used to estimate the model parameters. For each window, the estimated GM(1,3) is then used to generate a one-step-ahead forecast for the utilisation rate in the following week. The window is shifted forward by one week until the end of the sample, producing a sequence of pseudo out-of-sample forecasts for weeks 9–46.

Figure 2. displays the actual utilisation rate together with the rolling GM(1,3) forecasts. The rolling model closely tracks the level and direction of U over most of the sample. In particular, it captures the sustained high-utilisation regime between weeks 20 and 35, and it reproduces the mild decline in utilisation around weeks 38–42. However, the forecasts tend to slightly under-predict the utilisation at local peaks (e.g. around weeks 22–24 and 31–32) and slightly over-predict some troughs (around weeks 40–42), which is typical for first-order grey models when faced with abrupt regime shifts.

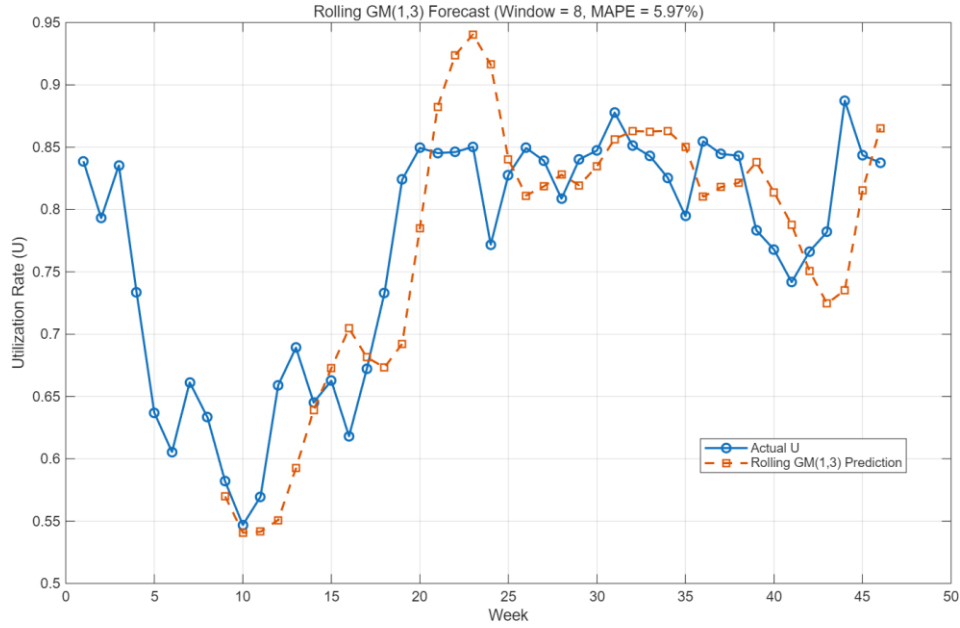


Figure 2. Rolling GM(1,3) Forecast

Over the evaluation sample, the mean absolute percentage error (MAPE) is 5.97% and the Root mean squared error (RMSE) is 0.0603, while the grey posterior error ratio and small error probability are $C=0.6475$ and $P=0.7632$, respectively. According to the standard grey-forecasting criteria, the model meets the requirement for at least moderate forecasting accuracy, with a relatively small average percentage error but a posterior error ratio slightly above the threshold for Grade III. This reflects the trade-off between capturing the overall trend and reacting to abrupt short-term shocks.

3.4. Discussion

Several empirical insights emerge from the above analysis. First, both the GRA results and the RGM(1,3) estimates confirm that on-chain liquidity (TVL) and market sentiment (FG) are strongly associated with the utilisation dynamics of Aave’s USDC lending pool. Weeks with high TVL and elevated Fear & Greed scores are typically accompanied by higher utilisation ratios, indicating increased leverage and borrowing activity in the DeFi lending market.

Second, despite the small sample size of only 46 weekly observations and the well-known volatility of DeFi markets, the rolling GM(1,3) model achieves a MAPE below 6% and reproduces the medium-term evolution of the utilisation rate with acceptable accuracy. This suggests that, within local windows of about ten weeks, the utilisation series exhibits a quasi-exponential pattern that is well suited to grey modelling.

Third, the model’s main limitation lies in its response to sudden structural breaks. Around sharp turning points—such as the rapid increase in utilisation in weeks 19–22 or the short-lived dip around weeks 40–42—the rolling GM(1,3) forecasts lag behind the actual series and generate larger errors, which is reflected in the relatively high posterior error ratio C . In practice, this issue could be mitigated by further shortening the rolling window, incorporating regime-switching information (e.g. major governance decisions or liquidity mining campaigns), or combining the grey model with complementary approaches such as ARIMAX or machine-learning-based predictors.

Overall, the empirical results indicate that the proposed rolling GM(1,3) framework provides a simple yet effective approach to modelling and forecasting DeFi lending utilisation under data-scarce conditions. It can serve as a lightweight risk-monitoring tool for protocol designers and regulators, while leaving room for future work to extend the model to higher-order or nonlinear grey structures and to other DeFi platforms and asset classes.

From an interest-rate perspective, the utilisation forecasts derived from the rolling GM(1,3) model translate directly into predictions for Aave v3’s endogenous borrowing and lending rates. In Aave v3,

the variable borrow rate is a piecewise linear function of utilisation: below the asset-specific optimal utilisation U_{opt} , the rate increases gradually with slope 1, whereas above U_{opt} it rises much more steeply with slope 2 in order to discourage further borrowing and restore liquidity.[15] Formally, for USDC this can be written as $r_b(U) = r_0 + \left(\frac{U}{U_{opt}}\right) \cdot s_1$ when $U \leq U_{opt}$, and $r_b(U) = r_0 + s_1 + \left[\frac{U - U_{opt}}{1 - U_{opt}}\right] \cdot s_2$ when $U > U_{opt}$, where r_0 is the base rate and s_1, s_2 are the two slopes chosen by Aave governance. Supplier returns (the liquidity rate) are funded by borrower interest net of the reserve factor, and are therefore an increasing function of both U and $r_b(U)$. Given that the realised and predicted utilisation of the USDC pool in our sample mostly fluctuates around 0.8–0.88, i.e. close to or slightly above the optimal utilisation used for high-liquidity stablecoins in Aave v3, the model implies that the corresponding borrow rates frequently operate in the kinked segment of the curve where marginal changes in utilisation are amplified into disproportionately large changes in interest costs. For leveraged investors this means that small forecasted increases in U can signal a transition into a high-rate regime, making variable-rate borrowing substantially more expensive and strengthening the incentive either to deleverage or to switch into stable rates. For liquidity providers, periods in which the predicted utilisation remains persistently near or above U_{opt} correspond to an environment of elevated lending yields, which can attract additional deposits and crowd in carry-trade or yield-farming strategies that fund positions on Aave with cheaper liquidity obtained elsewhere. Conversely, when the grey model anticipates a decline in utilisation away from the optimal region, it points to a forthcoming compression of both borrowing costs and deposit yields, reducing the profitability of such strategies and potentially motivating liquidity providers to reallocate capital to alternative protocols. In this way, the utilisation forecasts produced by the rolling GM(1,3) model can be re-interpreted as a forward-looking indicator of the Aave v3 interest-rate environment, with direct relevance for borrowing, lending and cross-platform arbitrage decisions in the DeFi ecosystem.

4. Conclusion

This study set out to construct and evaluate a parsimonious, interpretable forecasting framework for decentralised lending conditions on Aave, motivated by the scarcity of robust interest-rate prediction tools under short, noisy on-chain time series. Building on grey-system theory, we combined grey relational analysis with a rolling GM(1,3) specification to model the weekly utilisation dynamics of Aave v3’s USDC lending pool. Utilisation was taken as the reference variable, while TVL and the Crypto Fear & Greed Index were selected as candidate drivers representing on-chain liquidity and market sentiment, respectively. The GRA results confirmed that both factors are strongly associated with utilisation, with relational grades above the conventional 0.7 threshold and a slightly higher grade for FG, suggesting that short-term sentiment shocks exert at least as much influence as changes in locked capital.

Using these two variables as inputs, we implemented a rolling GM(1,3) model with an 8-week estimation window to generate one-step-ahead forecasts across the 46-week sample. The empirical results show that the rolling grey model is capable of tracking the level and direction of utilisation with a MAPE below 6% and satisfactory small-error probability, although the posterior error ratio indicates that forecast errors increase around local peaks and troughs where regime shifts are abrupt. In particular, the model captures the sustained high-utilisation regime observed in the middle of the sample and the subsequent modest decline, thereby reproducing the medium-term behaviour that is most relevant for protocol risk monitoring and liquidity planning.

Interpreted through the lens of Aave v3’s dual-slope interest-rate formula, these utilisation forecasts translate directly into expectations about future borrowing and lending rates. When predicted utilisation remains near or above the optimal threshold, the implied borrowing costs move into the steep segment of the rate curve, signalling tighter funding conditions for leveraged borrowers and higher yields for liquidity suppliers. Conversely, forecast declines in utilisation point to an easing of rates and a compression of carry-trade opportunities. In this sense, the grey rolling model offers not

only a prediction of pool utilisation but also a forward-looking indicator of Aave's rate environment, which can support risk management for users, liquidity providers and protocol governors by providing quantitative guidance on the timing of leverage adjustments, deposit allocation and parameter calibration.

At the same time, several limitations warrant further research. The analysis is based on a single pool and a relatively short weekly sample, and the linear first-order grey structure responds sluggishly to sudden structural breaks. Extending the framework to multi-asset settings, incorporating richer governance and macro-market indicators, exploring nonlinear or regime-switching grey models, and modelling interest rates directly alongside utilisation are promising avenues for future work. Nonetheless, the evidence presented here suggests that grey rolling GM(1,3) models can serve as a useful and operational building block for DeFi forecasting under data-scarce conditions, bridging the gap between grey-system theory and decentralised lending practice.

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