Methodology for Calculating and Predicting Ideal Votable Supply

--By Chain_L and Team

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Methodology:

The process for calculating and predicting IVS involves several interconnected steps, starting with historical analysis and ending with machine learning-based predictions. The methodology combines theoretical calculations, data normalization, and predictive modeling to ensure accurate results.

Methodology for Calculating Past Ideal Votable Supply (IVS)

1. Calculate Indexes

The initial step involves calculating the necessary indexes required for further analysis. These indexes act as foundational metrics for the votable supply calculations. Below are the indexes used and their respective details:

1.1 Liquidity Activity Ratio (LAR) – Directly Proportional

- **Definition:** Measures how actively a token is traded relative to its circulating supply, indicating market liquidity.
- **Reason:** Higher liquidity indicates broader token usage, reducing governance risk through active participation.
- **Impact:** A higher LAR increases the Ideal Votable Supply.
- **Formula:** Indicates the degree of liquidity or market activity relative to token availability.

$$Liquidity\ Activity\ Ratio\ (LAR) = \frac{Volume\ Traded\ (24h)}{Circulating\ Supply}$$

1.2 Participation Ratio (PR) – Inversely Proportional

- **Definition:** Measures the ratio of tokens actively participating in governance relative to circulating supply.
- **Reason:** More participation leads to stronger governance and higher inclusivity.
- **Impact:** A higher PR decreases the Ideal Votable Supply.
- **Formula:** Represents the percentage of tokens actively involved in governance compared to the total circulating supply.

$$PR = \frac{Votable\ Supply}{Circulating\ Supply}$$

1.3 Voting Power Index (VPI) / Actual Voting Power Index (AVPI) – Directly Proportional

- **Definition:** Represents actual voting power usage compared to theoretical power.
- **Reason:** Higher ratios reflect strong governance activity, indicating active and engaged participants.
- **Impact:** A higher VPI/AVPI increases the Ideal Votable Supply.

- **Formula:** Captures governance activity by reflecting how much of the votable supply is actively participating in governance.

$$Voting\ Power\ Index\ (VPI)\ = \frac{Votable\ Supply}{Volume\ Traded\ (30d)}$$

$$Actual\ Voting\ Power\ Index\ (AVPI)\ = \frac{Actual\ Votable\ Supply}{Volume\ Traded\ (30d)}$$

Actual Votable Supply (AVS):

- Represents the portion of votable supply actively used in governance over time.
- Determined by considering the votable supply contributed by participants on the last day of each proposal's voting period.
- The maximum observed votable supply during overlapping proposal periods is considered.

1.4 OP Token Price – Inversely Proportional

- **Definition:** Represents the market price of the OP token.
- **Reason:**
  - **Low Prices:** Tokens are cheaper to acquire, increasing the risk of governance capture. To counter this, votable supply is increased.
  - **High Prices:** Tokens are harder to acquire, reducing governance risk. In this case, votable supply is reduced.
- **Impact:** An increase in OP price reduces governance risk, thereby decreasing Ideal Votable Supply, and vice versa.

1.5 Price Stability Index (PSI) - Directly Proportional

- **Definition:** The Price Stability Index (PSI) measures the stability of the OP token price over a given period, emphasizing consistency and minimizing the effects of sudden price fluctuations.
- **Reason:**
  - Stable token prices reduce the risk of manipulation, ensuring that governance decisions are not disproportionately influenced by volatile market behavior. This stability fosters long-term governance engagement and trust among participants.
- **Impact:** A higher PSI indicates greater price stability, which enhances the robustness of governance. Consequently, the Ideal Votable Supply increases with higher PSI values.
- **Formula:** This formula captures the relative stability of the OP token by comparing its average price over the last 7 days to the current market price.

$$Price\ Stability\ \ Index\ (PSI)\ = \frac{Average\ Price\ (7\ days)}{Current\ Price}$$

2. Scale Parameters Using MinMaxScaler

To ensure consistency and comparability between parameters, Min-Max Scaling was applied to all relevant parameters, including OP_Price, AVPI, LAR, and PR. This transformation rescales values into a fixed range [0,1], ensuring that all parameters contribute proportionally to further analysis.

2.1 Min-Max Scaling Function

Min-Max Scaling is a widely used normalization technique in machine learning and statistical analysis. It rescales data based on the following formula:

$$X\_Scaled = \frac{X - Xmin}{Xmax - Xmin}$$

Where:

- ➢ X = Original parameter value
- ➢ $Xmin$ = Minimum observed value in the dataset
- ➢ $Xmax$ = Maximum observed value in the dataset
- ➢ X_Scaled = Scaled value in the range [0, 1]

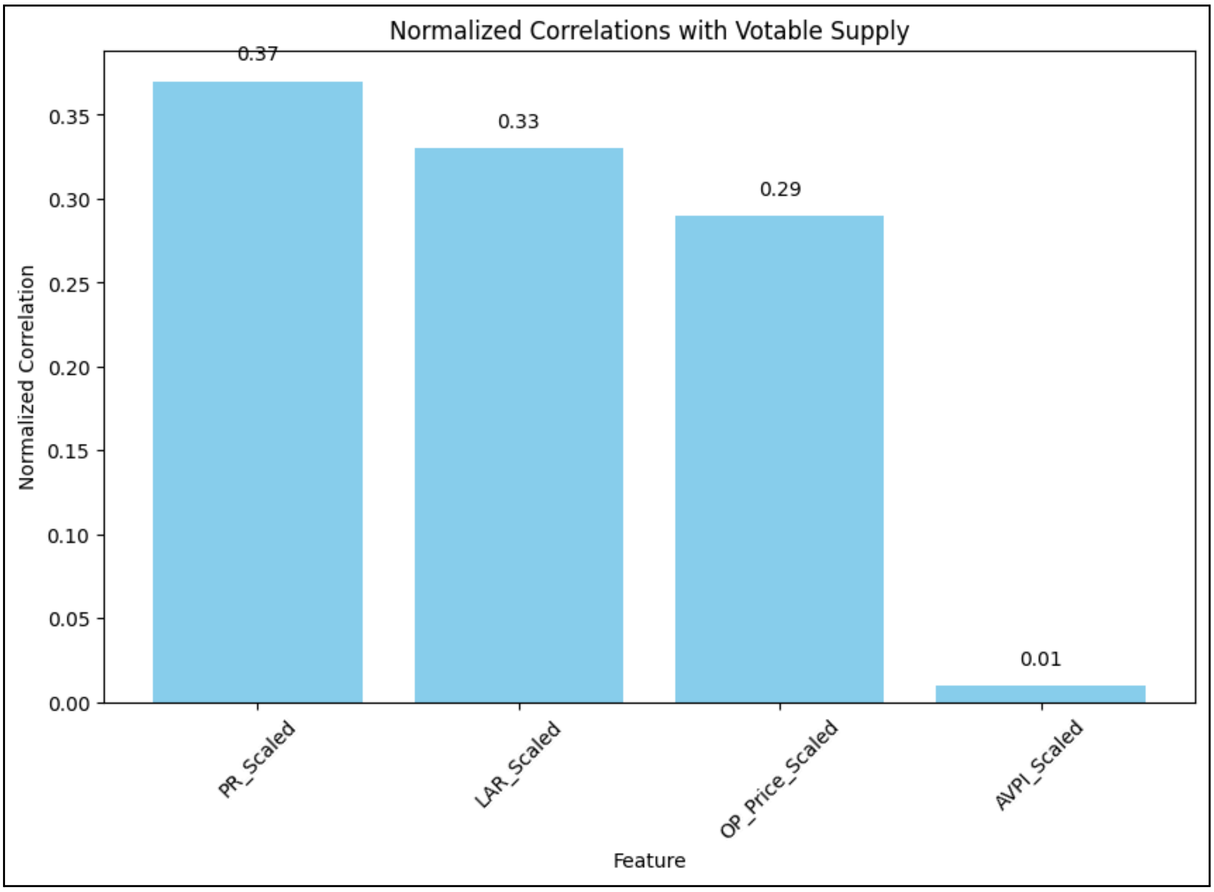
Impact of Min-Max Scaling:

- Brings all parameters to the same proportional range.
- Preserves relative relationship between values.
- Prevents any single parameter from dominating the analysis.

3. Identify the Weight Ranges of Parameters

To determine the significance of each parameter, the following sub-steps were performed:

1. **Calculate Correlations:**
   - The absolute correlation of each parameter with the original votable supply was calculated to understand the relationship between them.
2. **Normalize Correlations:**
   - The correlations were normalized so that the sum of all correlations equaled 1. This ensured that the weights derived from these correlations were proportionate.
   - Normalized Correlations:
     i. PR_Scaled - 0.37
     ii. LAR_Scaled - 0.33
     iii. OP_Price_Scaled - 0.29
     iv. AVPI_Scaled - 0.01

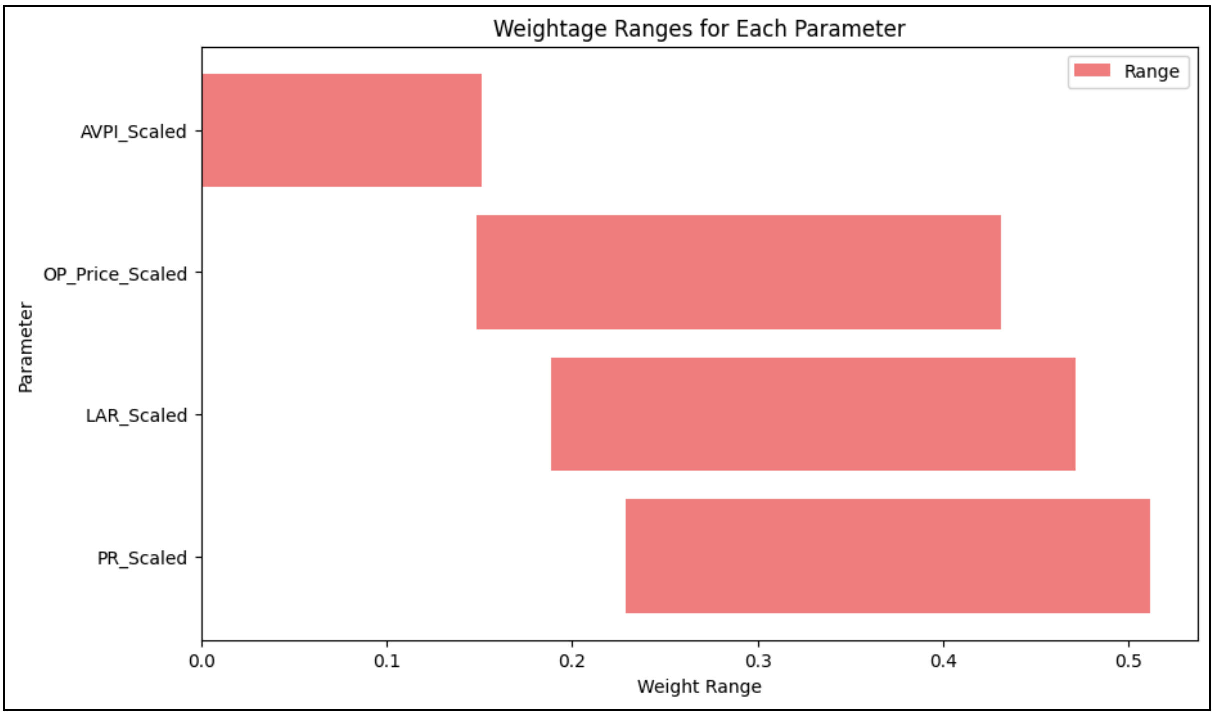


3. **Determine Weight Ranges:**
   - Using the normalized correlations, weight ranges for each parameter were calculated. These ranges guided the selection of valid weight combinations in the subsequent steps.

3.1 Method for Determining Weight Ranges

Weight ranges for each parameter were calculated using the standard deviation of the normalized weights. The method ensures flexibility while keeping the weights within a reasonable range.

- **Inputs:**
  - Normalized weights for each parameter.
  - k, a scaling factor that adjusts the width of the range based on the standard deviation.
- **Process:**
  1. Compute the standard deviation of all weights.
  2. Calculate the range for each parameter.
  3. Ensure that the lower bound of the range does not fall below 0.
- **Output:**
  - The range for each parameter's weight, expressed as a lower and upper bound, enabling the generation of valid weight combinations.
  - Weightage Ranges for Each Parameter:
    - PR_Scaled: [0.23, 0.51]
    - LAR_Scaled: [0.19, 0.47]
    - OP_Price_Scaled: [0.15, 0.43]
    - AVPI_Scaled: [0.00, 0.15]



4. Generate Weight Combinations and Calculate F Values

4.1 Generating Weight Combinations

1. **Define Constraints:**
   - Each weight must fall within a predefined range established in Step 3.
   - The weights must follow the condition: $w_1 > w_2 > w_3 > w_4$ to ensure relative importance of parameters.
   - The sum of all weights must be approximately 1 to maintain proportional contribution.
2. **Methodology:**
   - A step size of 0.01 was used to generate weight values within the specified ranges.
   - Iterative exploration of all possible weight values ensured that no valid combinations were overlooked.
   - A filtering mechanism retained only those combinations that met the predefined constraints.
3. **Outcome:**
   - A total of 5,066 valid weight combinations were generated, ensuring comprehensive coverage of possible parameter weightings.

4.2 Calculating F Values

To calculate the key metric F, the following formula was applied:

$$F = \left(\frac{1}{1 + (w1 * PR\_Scaled)}\right) * (1 + (w2 * LAR\_Scaled)) * \left(\frac{1}{1 + (w3 * OP\_Price\_Scaled)}\right) * (1 + w4 * AVPI\_Scaled)$$

Where:

- $w1$, $w2$, $w3$, $w4$ are the respective weights for each parameter, ensuring $w1 > w2 > w3 > w4$.
- OP_Price_Scaled = Scaled OP Token Price.
- $AVPI\_Scaled$ = Scaled Actual Voting Power Index.
- PR_Scaled = Scaled Participation Ratio.
- LAR_Scaled = Scaled Liquidity Activity Ratio.

5. Calculate the Ideal Votable Supply (IVS) for All Weight Combinations

After generating the weight combinations and computing the F values, the next step is to calculate the **Ideal Votable Supply (IVS)** for all weight combinations. This calculation is performed systematically across all datasets using the following approach:

5.1 Computing IVS for All Weight Combinations

Methodology:

The IVS is calculated as:

$$IVS = VS * (\beta + (e^{\alpha * (\frac{F - Fmin}{Fmax - Fmin})} - 1))$$

Where:

- **IVS** = Influence-Weighted Supply
- **VS** = Votable Supply
- **F** = Governance metric score for a given weight combination
- **Fmin, Fmax** = Minimum and maximum values of F in the dataset
- α **(alpha) =** Controls the rate of exponential growth
- β **(beta) =** Base multiplier to ensure a minimum IVS/VS ratio

5.2 Rationale for the IVS Calculation Approach

1. Scaling Between a Target Range:

- F values are normalized between F_min and F_max to ensure consistent behavior across different datasets.
- The exponential scaling ensures non-linearity, meaning higher F values increase IVS more rapidly while lower F values have a dampened effect.

2. Fine-Tuned Control Over IVS Growth:

- The **α** parameter controls how fast IVS increases with higher F.
- The **β** parameter ensures that **IVS/VS** doesn't drop too low, setting a minimum scaling factor.

3. Flexibility in Adjusting the IVS Range:

- **Higher α values** → IVS increases more aggressively.
- **Lower α values** → IVS increases more gradually.
- **Higher β values** → Raises the lower bound of IVS.
- **Lower β values** → Lowers the lower bound of IVS.
- **Higher F values** → IVS increases more rapidly due to exponential scaling.
- **Lower F values** → IVS remains closer to the base VS, preventing over-inflation.

- If future adjustments are needed, modifying **α** and **β** allows for precise tuning of the IVS range.

By setting **β = 1.35** and **α = 0.7**, the IVS effectively stays within the **1.5x - 2x** range, aligning with our desired assumptions while ensuring governance sensitivity and dynamic scaling.

6. Find the Ideal Weights

Once the **IVS** for all weight combinations are calculated find the ideal weights to calculate final IVS. The method for calculating the **IVS** and evaluating the weight combinations involves the following steps:

6.1 Calculating the Proportional Increase (Pincrease):

For each weight combination's dataset, the Proportional Increase is calculated as the ratio of the **Ideal Votable Supply (IVS)** to the original **Votable Supply (VS)**:

$$P_{increase} = \frac{IVS}{VS}$$

This metric quantifies how much the **IVS** deviates from the original votable supply for each time point, providing a measure of the ideal votable supply's increase compared to the original.

6.2 Performance Metrics Evaluation:

To assess each weight combination's effectiveness, the following performance metrics are calculated:

- **Monotonicity Score**: The monotonicity score measures the consistency of the **Pincrease** over time. Specifically, it represents the proportion of instances where **Pincrease** does not decrease between consecutive time points. The formula is:

  $$Monotonicity\ Score = \frac{Number\ of\ Non-Decreasing\ Instances}{Total\ Instances}$$

  A higher monotonicity score indicates smoother and more consistent growth in the **Pincrease**.

- **Average Proportional Increase**: This is the mean of all **Pincrease** values across the dataset:

  $$Average\ Proportional\ Increase = \frac{1}{n}\sum_{i=1}^{n} P_{increase}[i]$$

  Where **n** is the total number of data points. This metric represents the average ratio of the ideal votable supply to the original votable supply.

- **Standard Deviation of Proportional Increase**: This metric measures the variability in the **Pincrease** values:

  $$Standard\ Deviation = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (P_{increase}[i] - Average\ Proportional\ Increase)^2}$$

A lower standard deviation indicates stability, with fewer fluctuations in the **Pincrease**.

6.3 Calculating the Total Score:

The **Total Score** is a composite metric that combines the three performance metrics using a weighted formula:

$$Total\,Score = (Monotonicity\,Score * 0.5) - (Std.\ Deviation * 0.3) + (Average\,Increase * 0.2)$$

Where:

- **The Monotonicity Score** is weighted the highest at **0.5**, emphasizing the importance of consistent growth.
- **Standard Deviation** is penalized with a weight of **-0.3**, as high variability is undesirable.
- **Average Proportional Increase** is given a positive weight of **0.2**, rewarding higher average increases in **Pincrease**.

6.4 Ranking Weight Combinations

After calculating the Total Score for each weight combination, the combinations are ranked in descending order of their Total Score. The weight combination with the highest total score is considered the ideal weight combination, as it offers the best balance between consistent growth, higher average increase, and stability.

6.5 Results

Finally, the weight combinations are ranked based on their total scores, and the results are saved for further analysis. The weight combination with the highest total score is identified as the best set of weights for the given governance model.

Ideal Weights:

- Weights: w1=0.29, w2=0.28, w3=0.27, w4=0.15
- Monotonicity Score: 0.39
- Average Proportional Increase: 1.79
- Standard Deviation: 0.20
- Total Score: 0.49

Methodology for Predicting Future Ideal Votable Supply (IVS)

To ensure effective governance planning, predicting the **Ideal Votable Supply (IVS)** for future periods requires a systematic approach based on historical trends, key governance parameters, and predictive modeling techniques. The following methodology outlines the step-by-step process used to forecast IVS, including data preparation, parameter forecasting, and model selection.

1. Forecasting Future Data for Key Parameters

The first step in predicting IVS involves forecasting key governance-related parameters that influence voting activity and governance engagement. The parameters considered for this analysis include:

- **Liquidity Activity Ratio (LAR)**
- **Participation Ratio (PR)**
- **Actual Voting Power Index (AVPI)**
- **OP Token Price (OP_Price)**

These predictions are based on analyzing historical data and anticipating how these parameters might evolve in the future. This provides the necessary foundation for forecasting future IVS values.

2. Estimating Future Circulating Supply (CS)

To accurately estimate IVS, the future **circulating supply** must be projected. The process involves:

1. **Establishing the Baseline:**
    - The current circulating supply as of 30th November 2024 serves as the starting point.
2. **Projecting Supply for December 2024 - April 2025:**
    - Using the forecasted cumulative circulating supply for May 2024 - April 2025, the remaining supply to be distributed from December 2024 to April 2025 is calculated.
    - This supply is evenly distributed across the months, and daily projections are generated.
3. **Extending the Forecast to May 2025 - April 2026:**
    - The forecasted cumulative circulating supply for May 2025 - April 2026 is used to extend the projections beyond April 2025.
    - The supply from 30th April 2025 is taken as the baseline, and the remaining supply is distributed across the next 12 months.
4. **Finalizing the Forecasted Supply Dataset:**
    - The projections from December 2024 - April 2025 and May 2025 - April 2026 are merged into a single dataset to ensure continuity and consistency in the forecasted supply data.

Source of Forecasted Data

3. Predicting Future Votable Supply (FVS)

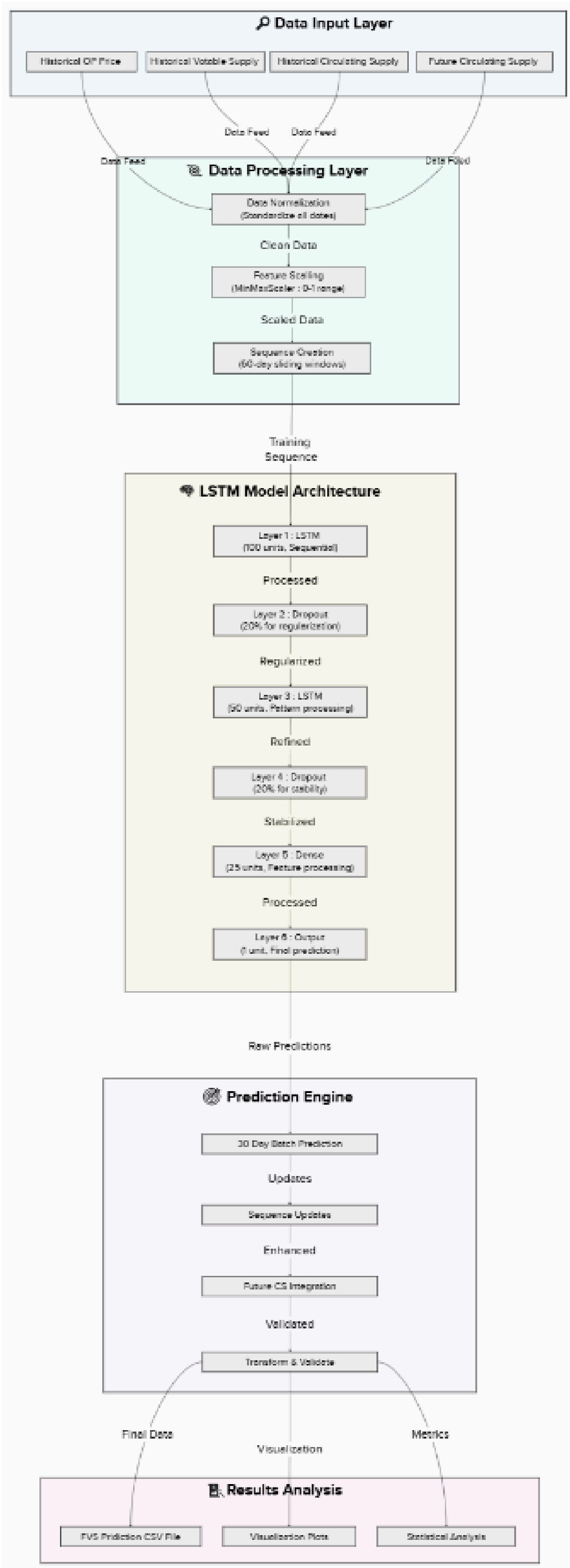
1. Approach Overview

The model follows a systematic, step-by-step methodology that includes:

- **Data Input:** Historical and future supply metrics, OP token price trends.
- **Learning Process:** Pattern identification through temporal analysis using historical data.
- **Prediction Method:** Batch-wise 30-day predictions utilizing a rolling window mechanism and dynamic circulating supply integration.
- **Model Update:** Continuous learning via adaptive updates during the prediction process.

2. Technical Implementation Details

Our implementation uses a sophisticated LSTM neural network architecture:



3. LSTM Neural Network Architecture

3.1 LSTM Neural Network Architecture

3.1.1 Architectural Components

- **Input Layer (LSTM - 100 Units):**
  - Processes sequential data patterns.
  - Retains long-term dependencies to track historical patterns.
  - Essential for identifying governance trends.
- **First Dropout Layer (20%):**
  - Reduces overfitting.
  - Ensures better generalization across unseen data.
- **Second LSTM Layer (50 Units):**
  - Refines pattern recognition from the initial layer.
  - Extracts high-level temporal features.
- **Second Dropout Layer (20%):**
  - Adds further regularization.
  - Mitigates noise in training data.
- **Dense Processing Layer (25 Units):**
  - Combines extracted features.
  - Prepares data for prediction.
- **Output Layer (Single Unit):**
  - Provides the final votable supply prediction.
  - Utilizes a linear activation function for precise output.

3.2 Key Technical Parameters

3.2.1 Computational Configuration

- **Sequence Length:** 60 days
    - Captures medium-term trends in the ecosystem.
- **Batch Size:** 30 days
    - Aligns with the governance cycle and ensures frequent updates.
- **Training Epochs:** 50 per batch
    - Facilitates robust learning without overfitting.

3.3 Data Processing Pipeline

3.3.1 Preparation Stage

- **Data Normalization:**
    - Standardizes timestamp formats and data scales.
- **Feature Scaling:**
    - Uses MinMaxScaler to convert data to a 0-1 range.
- **Sequence Generation:**
    - Generates overlapping windows for continuous learning.

3.3.2 Prediction Process

- **Rolling Window Update:**
    - Applies incremental learning from the most recent 60 days.
- **Dynamic Integration:**
    - Incorporates predicted future circulating supply into forecasts.

3.4 Training Strategy

- **Sequential Batch Training:**
  - Periodic retraining ensures adaptability to new trends.
- **Adaptive Learning Mechanisms:**
  - Adjusts to variations in governance metrics.

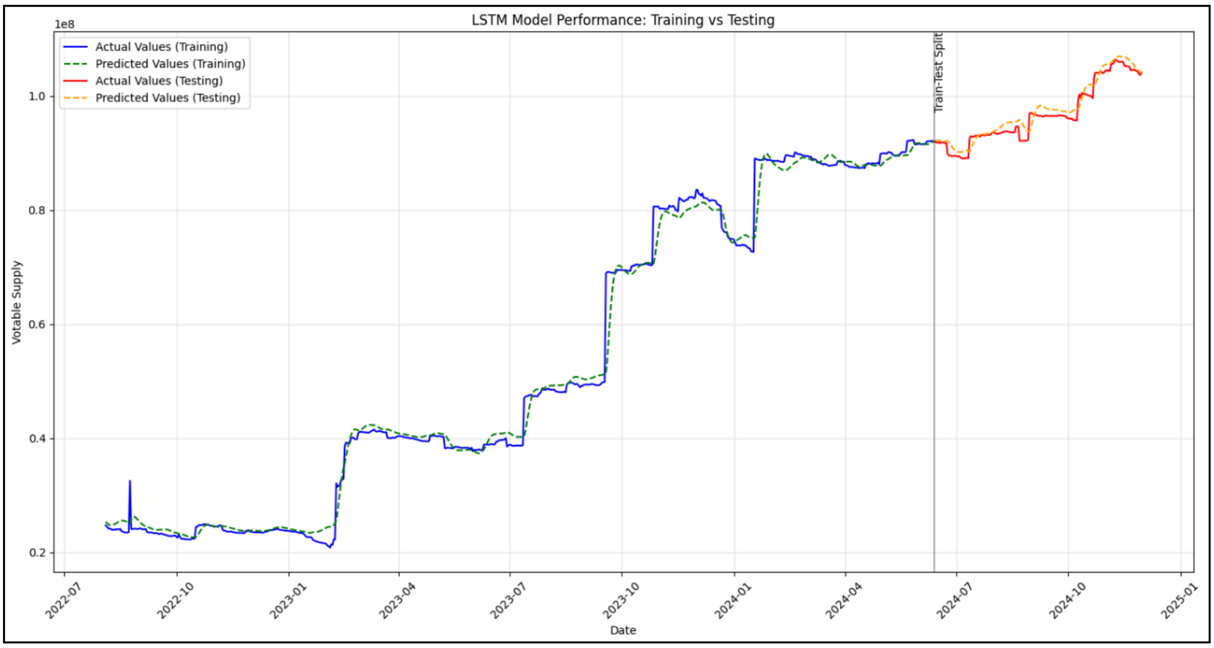
3.5 Validation and Output Mechanisms

- **Visual Trend Verification:**
  - Cross-checks predictions with historical patterns.
- **CSV Storage:**
  - Stores predictions for external analysis.
- **Statistical Analysis:**
  - Evaluates model performance using metrics like MAE and RMSE.

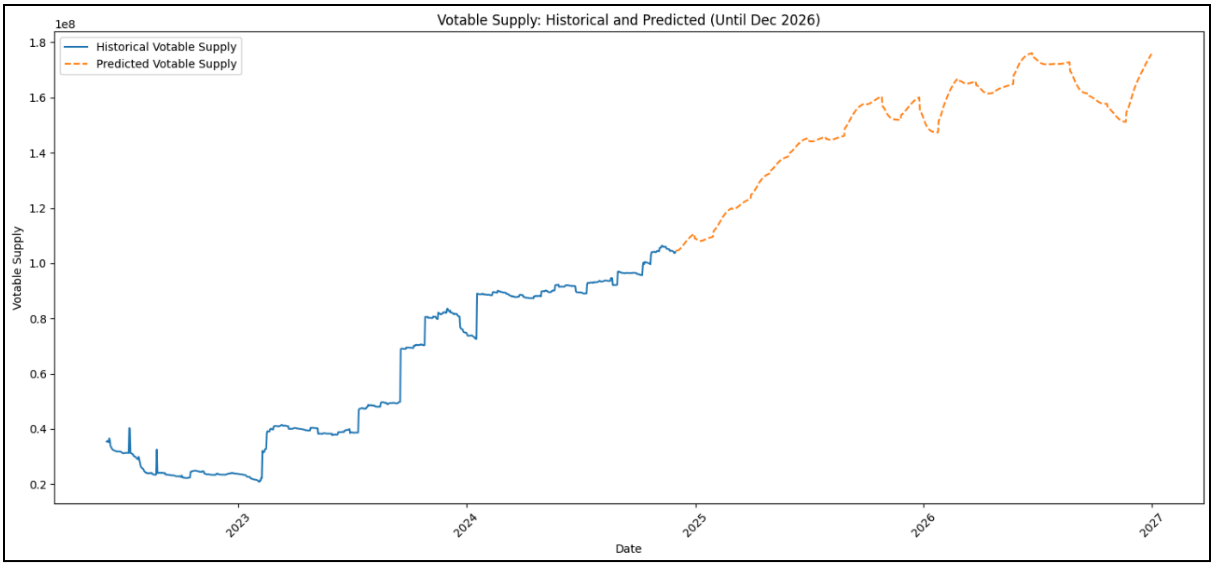
3.6 Model Performance and Visualization

To assess the accuracy and reliability of the LSTM model, two key performance graphs are included:

1. **LSTM Model Performance: Training vs Testing**



2. **Votable Supply: Historical and Predicted**



4. Computing the Future Adjustment Factor (F)

After obtaining FVS and the forecasted governance parameters, the adjustment factor (F) is computed. This process follows the methodology used in past calculations, ensuring consistency.

- The adjustment factor (F) is derived after determining the ideal weight combinations for governance parameters.
- Both historical and forecasted values for governance parameters are used in F calculation to account for governance trends.

5. Forecasting Future IVS Using Predictive Models

After predicting all relevant components, the **final step** is forecasting IVS.

To generate accurate predictions:

- A **polynomial regression model of degree 2** is used.
- This model captures **non-linear relationships** between governance parameters, circulating supply, and IVS.
- Parameters such as **VS, CS, and F** (from both historical and forecasted data) serve as **inputs to predict IVS**.

5.1 Parameters Used for Training the Models:

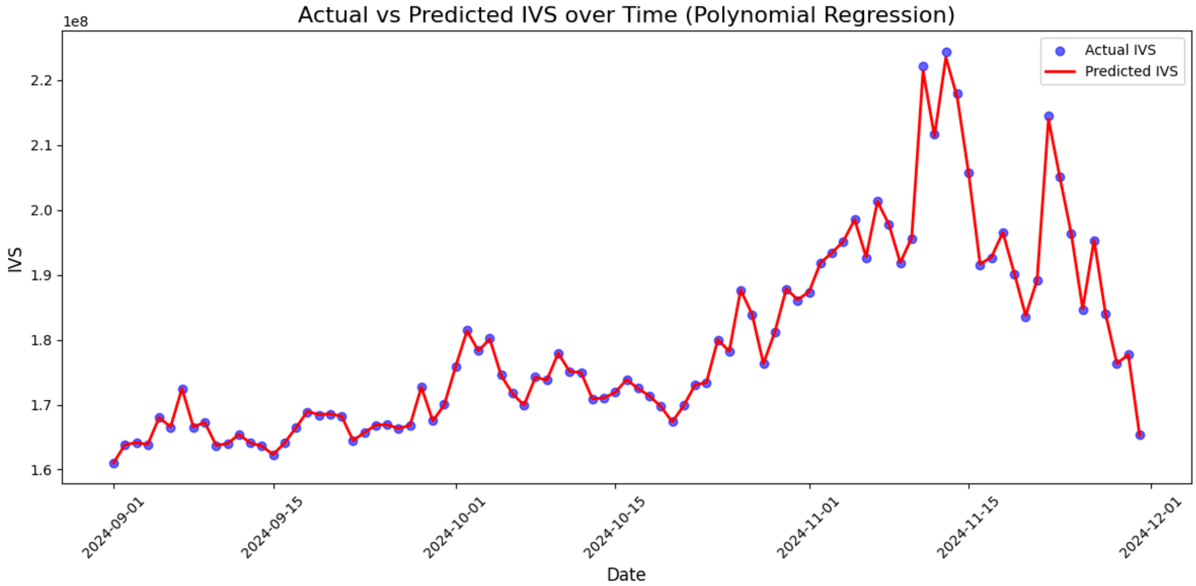
- **Votable Supply**: Votable supply.
- **Circulating Supply**: Circulating supply.
- **F**: Adjustment factor representing influences of governance parameters.
- **IVS**: Ideal Votable Supply (target variable).

5.2 Model Description:

- Polynomial regression effectively models non-linear relationships present in governance dynamics.
- Degree-2 polynomials provide sufficient flexibility without overfitting.
- The approach ensures that IVS predictions align with expected governance trends and supply evolution.

5.3 Model Performance (tested on 3 months data from September 2024 - November 2024):

- Polynomial Regression: Achieved near-perfect results with an R^2 score of 0.9999, indicating minimal error due to its ability to capture complex relationships.



5.4 Results (Monthly VS and Calculated_IVS and Predicted_IVS)