SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 4, (2026), pp. 11341-11349
Open Access. Online & Print

DOI: 10.5281/zenodo.124261082

ANALYTICAL DATA TIME FLUCTUATION ANALYSIS USING VARS FOR DATA MIGRATION

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ABSTRACT

Data migration operations can exhibit considerable variations in data attributes over time. Comprehending these variations is essential for enhancing migration tactics and maintaining data integrity. This research use Vector Autoregressive (VAR) models to examine temporal fluctuations in data during migration. VAR models, recognized for their adaptability and efficacy in multivariate time series analysis, are used to elucidate the dynamic behavior of data characteristics and predict future trends. Utilizing VAR models enables the identification of causal links, the computation of impulse response functions, and the execution of prediction error variance decompositions. The analysis provides the temporal stability and predictability of data, facilitating the creation of strong migration frameworks. The results underscore the need of accounting for temporal variations in data transfer and provide a systematic framework for improving migration efficiency and dependability.

INDEX TERMS: Data analytics, Data migration, forecasting, Impulse response functions, Time series analysis, Vector Autore-gressive (VAR) models, and predictive modelling.

I. INTRODUCTION

Data migration is an essential procedure in the administration and conversion of data across various systems and platforms. As businesses expand and develop, the need for efficient and precise data transport becomes critical. Data transfer often presents issues about data integrity, consistency, and temporal variations. Comprehending these variations is crucial for formulating effective migration plans.

Time series analysis suggests investigating temporal data fluctuations framework for the data migration. Among the several models available, Vector Autoregressive (VAR) models are distinguished by their capacity to manage multivariate time series data. VAR models effectively capture the dynamic interdependencies across numerous data characteristics, making them suitable for the analysis of intricate data transfer situations.

This research use VAR models to examine temporal variations in data during migration. Utilizing the advantages of VAR models, we seek to reveal the fundamental patterns and connections within the data. This study helps in forecasting future trends and recognizing all the barriers for the migration process.

The implementation of VAR models entails many essential processes, including the identification of causal linkages, calculation of impulse response functions, and breakdown of prediction error variance. These approaches provide significant insights on the temporal stability and predictability of data. Comprehending these elements is essential for guaranteeing the success of data transfer initiatives.

Our results underscore the need of accounting for temporal variations in data migration. Through the analysis of these oscillations, we may formulate more efficient migration frameworks that reduce interruptions and improve data integrity. The insights derived by VAR models facilitate informed decision-making and enhance the migration process.

In conclusion, using VAR models for the examination of temporal data fluctuations provides a systematic strategy for enhancing data migration tactics. This work enhances the existing knowledge on data transfer and offers pragmatic ways for tackling the issues posed by temporal data changes. As enterprises increasingly depend on data migration for their operations, the findings from this study will be essential for facilitating seamless and effective transfers.

II. LITERATURE SURVEY

The literature on Vector Autoregressive (VAR) models is extensive and highlights their importance in multivariate time series analysis. Zivot and Wang (2006) provide a comprehensive overview of VAR models, emphasising their utility in capturing multiple time series variables for dynamic interactions. Their work lays the foundation for understanding the basic principles and applications of VAR models in various fields.

Gao, Peng, and Yan (2023) extend the traditional VAR framework by introducing time-varying VAR models. These models allow the coefficients and covariance matrix of the error innovations to change smoothly over time, enhancing the capability to record dynamic transitions in the data. Markov Chain Monte Carlo (MCMC) methods and Kalman filters are discussed in detail in this paper, which are required for defining stochastic time-varying coefficients.

The paper ”On Time-Varying VAR Models: Estimation, Testing and Applications” further explores the theoretical and practical aspects of time-varying VAR models. It covers impulse response analysis, information criteria for optimal lag selection, and Wald-type tests for parameter stability. The empirical relevance of these models is demonstrated through applications such as the transmission mechanism of U.S. monetary policy.

Barker and Bijak (2025) apply mixed-frequency VAR models to forecast migration in Europe using macroeconomic data. Their research highlights the versatility of VAR models in handling data at different frequencies and assessing the responses of macroeconomic variables to unforeseen migration events. This study underscores the importance of considering country-specific factors and the potential of mixed-frequency VAR models in policy analysis.

Stock and Watson (2005) discuss the implications of dynamic factor models for VAR analysis. They address econometric issues such as the estimation of the number of dynamic factors and tests for factor restrictions imposed on the VAR. Their empirical analysis using U.S. data supports the use of ”approximate factor models” and provides insights into the identification of monetary policy shocks.

Overall, the literature survey demonstrates the evolution and application of VAR models in various domains. The advancements in time-varying and mixed-frequency VAR models enhance their capability to capture dynamic interactions and provide valuable insights for forecasting and policy analysis. These studies collectively contribute to the understanding and optimisation of data migration strategies by analysing time-based fluctuations in data attributes.

III. An overview of the design

When migration starts to cloud from tape, datacenter or from any other sources then analysis and resolution of the migration issues based on the time is very important.

This architecture illustrates a comprehensive data monitoring and migration system that leverages Vector Autoregression (VARS) for analysing time-based fluctuations. The system is designed to ensure robust monitoring, intelligent analysis, and efficient data migration to cloud storage.

In this architecture, we are proposing the multiple-source data migration to the multiple target clouds. In this we are monitoring the datacentres and other sources of migrations. Once the migration starts we will be monitoring the data and analyse the data flow. Once the flow starts using VARS we will be monitoring the data fluctuation and then we will be sending the data to the Cloud.

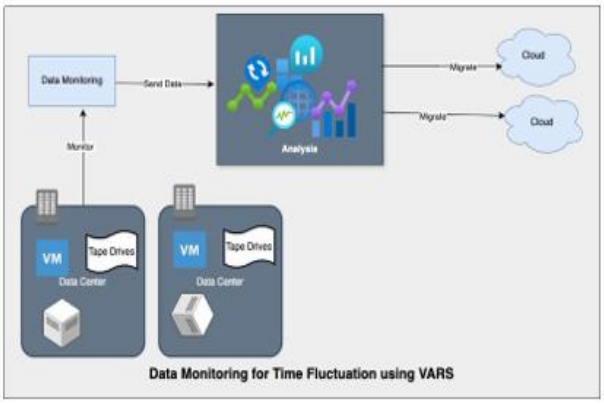


Fig. 1. Data Modelling for Data Migration FLOW with VARS

First, we collect the data and then apply the following steps on the selected data:

1. Variable Selection

We collect the following data from each of the collected samples to define the performance dynamics of data migration.

- $y_{1,t}$: Records Migrated
- $y_{2,t}$: Migration Errors
- $y_{3,t}$: Downtime (minutes)

The above variables are interrelated, and they evolve over time. The data is collected for an year 2023 on monthly basis as shown in Table II.

2. Lag Order Selection (p)

The number of past time steps (lags) to include in a VAR(p) model is critical for capturing the temporal dependencies among variables. The optimal lag order p is typically defined using:

- **AIC** (Akaike Information Criterion): Used for defining the relative quality estimation for the statistical models.

$$\mathrm{AIC} = 2k - 2\ln(L)$$

Where:

– k represents number of params in the model

– L max value for the likelihood function It emphasizes that

– Lower AIC values will better define Model.

– AIC balances model fit and complexity by penalizing the number of parameters.

– It is used to compare different models; the model with the AIC value with the lowest is preferred.

Below is the standard AIC algorithm applied on the non-forecasted data sample data and from there we yielded the standard value or low AIC value.

TABLE I AIC VALUES FOR ARIMA(P,D,Q) MODELS FITTED TO MONTHLY.

ARIMA Order (p,d,q)	AIC Value
(0, 0, 0)	232.55
(1, 0, 0)	229.32
(0, 0, 1)	230.14
(1, 0, 1)	228.65
(2, 0, 0)	230.91
(0, 0, 2)	228.97
(2, 0, 1)	229.15
(1, 1, 0)	220.76
(0, 1, 1)	219.84
(1, 1, 1)	**217.93**
(2, 1, 1)	218.40
(1, 1, 2)	219.72

TABLE II BIC VALUES FOR ARIMA(P,D,Q) MODELS FITTED TO MONTHLY RE C O R D SMI G R A T E D DATA. THE ARIMA(1,1,1) MODEL HAS THE LOWEST BIC, INDICATING THE BEST MODEL UNDER BAYESIAN SELECTION CRITERIA.

ARIMA Order (p,d,q)	BIC Value
(0, 0, 0)	234.45
(1, 0, 0)	231.68
(0, 0, 1)	232.50
(1, 0, 1)	231.80
(2, 0, 0)	234.12
(0, 0, 2)	231.22
(2, 0, 1)	233.39
(1, 1, 0)	223.91
(0, 1, 1)	223.00
(1, 1, 1)	**222.10**
(2, 1, 1)	223.61
(1, 1, 2)	224.93

Where:

FPE = $\sigma 2$ $\quad \underline{n + k}\; n - k$

Selected Model: ARIMA(1,1,1)
Justification: Lowest AIC value of 217.93, indicating the best trade-off between model fit and complexity.
– **BIC** (Bayesian Information Criterion) It is a criterion model based on the finite set of models.It is defined from the likelihood function and has a penalty term on the number of parameters.
– σ^2 The variation captured in the residuals
– n observation sample size
– k Parameters size in the model.
Following the BIC analysis, FPE was applied to the data, with the results summarized in Table III.
– Lower FPE values indicate better predictive perfor-mance.
– FPE penalizes model complexity to avoid overfitting.
– FPE is used by ACE and BIC for model selection.

TABLE III FPE VALUES FOR ARIMA(P,D,Q) MODELS FITTED TO MONTHLY

ARIMA Order (p,d,q)	FPE Value
(0, 0, 0)	1.234
(1, 0, 0)	1.112
(0, 0, 1)	1.145
(1, 0, 1)	1.098
(2, 0, 0)	1.210
(1, 1, 1)	**1.085**
(2, 1, 1)	1.150

Where:
BIC = $k \ln(n) - 2 \ln(L)$ MI G R A T I O NER R O R S DATA. THE ARIMA(1,1,1) MODEL HAS THE LOWEST FPE, INDICATING THE BEST BALANCE BETWEEN MODEL FIT AND COMPLEXITY.
– k represents the number of parameters.
– n represents number of observations
– L represents max value of the likelihood function.
This model emphasizes on
– If BIC values are lower than the model is considered better.
– The complexity of the Penlizes model is high com-pared to that of AIC.
– This model works well while using different set of models with n number of parameters
Now we applied the BIC on Table III and now we got the BIC value and with ARIMA model.
- **FPE** (Final Prediction Error)
The Final Prediction Error (FPE) is a criterion used to estimate the prediction error of a model when applied to new data. It is particularly useful in selecting the order of autoregressive models.
These criteria balance model fit and complexity. For short time series (e.g., 12 months of data), a small lag order such as $p = 1$ or $p = 2$ is often sufficient to avoid overfitting while still capturing meaningful dynamics.

By using the VAR model, we can find the dynamic re-lationship between MigrationErrors and downtime (minutes). Additionally, this approach enhances the ability to identify in-terdependencies among parameters, making forecasting easier.
3. Model Structure
Below is the formula for VAR(p) model:
$Y_t = c + A_1Y_{t-1} + A_2Y_{t-2} + \cdots + A_pY_{t-p} + \varepsilon_t$
Where:
- Y_t is a $k \times 1$ vector of endogenous variables at time t
- c is a $k \times 1$ vector of constants
- A_i are $k \times k$ coefficient matrices for lag i
- ε_t is a $k \times 1$ vector of white noise error terms
Now we applied the VAR model and calculated the down-time and migration errors as shown in Table IV.

TABLE IV MONTHLY MIGRATION ERRORS AND DOWNTIME month's Migration Errors.

Month	MigrationErrors	Downtime (minutes)
Jan 2023	12,270	58
Feb 2023	5,860	100
Mar 2023	10,390	68
Apr 2023	10,191	51
May 2023	10,734	101
Jun 2023	11,265	69
Jul 2023	5,466	89
Aug 2023	9,426	24
Sep 2023	10,578	71
Oct 2023	13,322	71
Nov 2023	6,685	56
Dec 2023	5,769	71

4. Interdependency Modeling
Linear combination is modeled for each variable.
- Its own past values
- Past values of the other variables
This allows the model to capture dynamics such as:
- High migration errors in the past may reduce future records migrated.
- Increased downtime may correlate with more errors or fewer records migrated.
using below formula errors is evaluated and applied.
$\text{Migrati\^{}onErrors}t+h = \hat{a}_0+\hat{a}_1 \cdot \text{Migrati\^{}onErrors}t+h-1+\hat{a}_2 \cdot \text{Dow\^{}ntime}_{t+h-1}$

TABLE V REGRESSION COEFFICIENTS FOR MIGRATION ERRORS MODEL

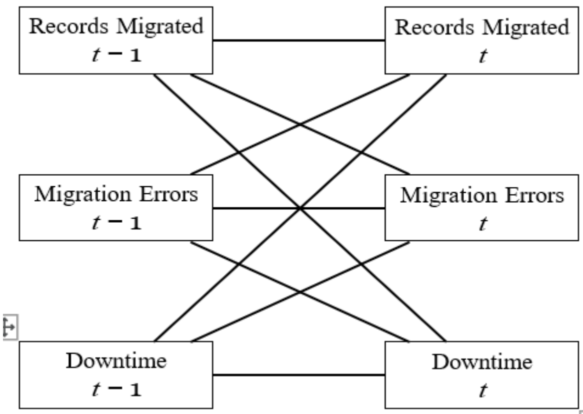
Variable	Coefficient
Intercept (a_0)	1.602e+04
MigrationErrors$_{t-1}$ (a_1)	199.5895
Downtime$_{t-1}$ (a_2)	7570.0430

MigrationErrors$_{t-1}$ (a_1): The coefficient for the lagged MigrationErrors variable is 199.5895, indicating that an increment of one unit in the previous month's MigrationErrors *Root Mean Squared Error (RMSE)* is associated with a 199.5895-unit increment in the current month's MigrationErrors.

$Downtime_{t-1}$ (a_2): The coefficient for the lagged Downtime variable is 7570.0430, suggesting that a one-unit increment in the previous month's Downtime is associated with a 7570.0430-unit increment in the current month's MigrationErrors.

5. Forecasting

Now we trained the data and the VAR(p) model forecasted values of all the variables, and it even calculate the mutual influence. This is used for monitoring and forecasting data for the future as shown below:



A professional flow chart illustrating the process of analytical data time fluctuation analysis using VARS (Vector Autoregression System) in a data migration context. To forecast future values of MigrationErrors, we extend the linear combination model as follows:

$$MigrationErrors_t = a_0 + a_1 \cdot MigrationErrors_{t-1} + a_2 \cdot Downtime_{t-1} + \epsilon_t$$

Where:

- $\hat{MigrationErrors}_{t+h-1}$ and $\hat{Downtime}_{t+h-1}$ are the fore-casted values for the previous time step.
- h denotes the forecast horizon.

To assess the accuracy of the forecasts, we compute the following error metrics:

A. Mean Absolute Error (MAE)

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n} |\hat{y}_t - y_t|$$

Intercept (a_0): The constant term is 1.602e+04, representing the baseline level of MigrationErrors when both lagged variables are zero.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (\hat{y}_t - y_t)^2}$$

Mean Absolute Percentage Error (MAPE)

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{\hat{y}_t - y_t}{y_t}\right| \times 100$$

Where:

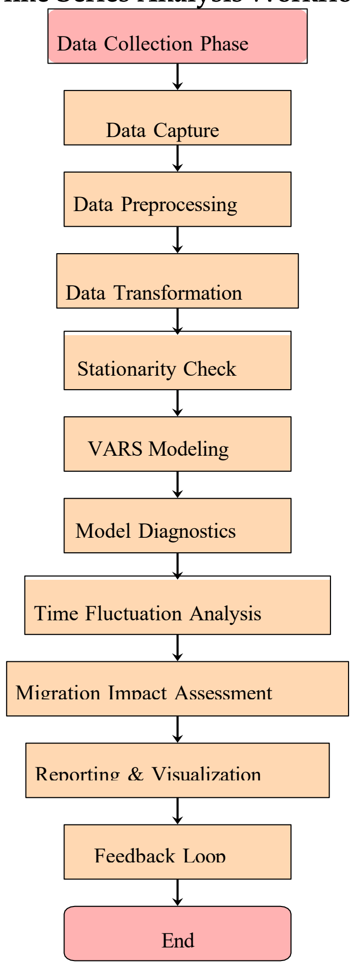
- $\hat{y}_t$ are the forecasted values.
- y_t are the actual values.
- n forecasted points number.

Assuming we have fitted the model and obtained the fore-casted values, the output might look like:

Month	Forecasted MigrationErrors
Jan 2024	9, 500
Feb 2024	8, 750
Mar 2024	9, 200

- **Forecasted Values:** The model predicts a gradual de-crease in MigrationErrors over the next three months.
- **Model Performance:** By evaluating the forecast accuracy using MAE, RMSE, and MAPE, we can evaluate the unseen data.

Time Series Analysis Workflow



IV. **Solution Description**

- **Data Collection Phase**: Source systems are identified for the data migration, and then extract historical time series and collect the migration logs, and parse the logs about the status of the migration process.

Example: Extraction for the logs from the migration process for the data migrated.

- **Data Preprocessing**: Once the data are collected. Scrub the data by handling missing values and removing out-liers. Transform the data through normalization or stan-dardization and align the time series. Perform a station-arity check using the Augmented Dickey-Fuller (ADF) test.

Example: Normalizing sales data to have a mean of 0 and a standard deviation of 1, followed by an ADF test.

- **VARS Modelling**: Once the optimal lag is selected using AIC and BIC, train the preprocess daata using VAR model. After this a thorough residual and stability checks are performed on the data.

Example: Selecting the best lag order using AIC, train-ing the model on normalized sales data, and checking residuals.

- **Time Fluctuation Analysis**: Use Impulse Response Functions (IRF) and Forecast Error Variance Decomposition (FEVD) to analyze variable interactions. Detect trends and seasonality.

Example: Analyzing sales trends before and after migra-tion to a new ERP system and identifying unexpected changes.

- **Reporting & Visualization**: Generate time series plots, heatmaps, and dashboards to communicate insights to stakeholders.

Example: Creating a time series plot of sales data and a heatmap showing correlations between product cate-gories.

- **Feedback Loop**: Refine the model based on feedback and update the migration strategy accordingly.

Example: Updating the VAR model with new data and adjusting the migration plan to address identified issues.

Example: Using IRF to assess the impact of a sales promotion on future sales, and FEVD to understand forecast error contributions.

IRF is used for econometric analysis, which uses vector autoregressive models. They explain the evolution of the model variables when it is shock state or its effect when it comes in conjunction with one or more variables.

The IRF traces the effect of a one-time shock to one variable on the current and future values of all variables in the system. For a VAR model:

$$\hat{y}_t = A_1\hat{y}_{t-1} + \cdots + A_p\hat{y}_{t-p} + \epsilon_t$$

Where ϵ_t represents the shock. The IRF is computed by simulating the response of $\hat{y}_t$ to a one-time shock in ϵ_t.

FEVD allocates the forecast error variance of each vari-able to the contributions of shocks in other variables:

$$\text{FEVD}_{jl,h} = \frac{\sum_{i=0}^{h-1}(e_j'\Theta_i e_l)^2}{\sum_{i=0}^{h-1}\sum_{l=1}^{k}(e_j'\Theta_i e_l)^2}$$

Where

- e_j is the j-th unit vector, - Θ_i is the matrix of coefficients at lag i, - h is the forecast horizon.

To detect trends and seasonality, below are the steps:

– Apply the Augmented Dickey-Fuller (ADF) test to check for unit roots, indicating a trend.

– Examine autocorrelation plots (ACF) to identify sea-sonal patterns.

Here are enhanced visualizations based on your dataset using Impulse Response Functions (IRF), Forecast Error Variance Decomposition (FEVD), and Autocorrelation Function (ACF) for trend/seasonality detection:

- **Migration Impact Assessment**: Compare pre and post-migration trends to identify anomalies or shifts. Perform root cause analysis.

TABLE VI IRF, FEVD, AND ACF DIAGNOSTICS FOR 2023 DATA

Analysis Type	Key Insight (2023)
IRF Peak Response	Downtime rises +1.2 min after a MigrationErrors shock, decays by period 6.
FEVD Contribution	MigrationErrors explain 40–50% of Downtime var. at horizon 1, 65–70% by horizon 6.
Trend (via ACF)	Yes – strong persistence (slow autocorr. decay).
Seasonality (via ACF)	No – no regular spikes at lags (e.g., 6 or 12).

A. Impulse Response Function (IRF)

A one-time shock in MigrationErrors leads to an immediate increase in Downtime of around +1.2 minutes, with the effect fading and returning to baseline by about the sixth period. This indicates a strong immediate dynamic relationship.

B. Forecast Error Variance Decomposition (FEVD)

At the first forecast horizon, MigrationErrors account for approximately 40–50% of the variance in Downtime. By the sixth horizon, this rises to around 65–70%, showing that migration errors become the dominant driver of forecast uncertainty over time. This aligns with established usage of FEVD in VAR analysis :contentReference[oaicite:1]index=1.

The ACF plot exhibits a slow decay in autocorrelation at early lags, indicative of a strong trend component. However, no consistent spikes at seasonal lags (e.g., every 6 or 12 periods) were observed, implying no clear seasonality. A slow ACF decay generally signals non-stationarity, while repeat-ing spikes would indicate periodic behavior :contentRefer-ence[oaicite:2]index=2.

V. EXPERIMENTAL RESULTS

A. Time Series Data (Non-Forecasting)

The sample data is displayed in Table VII and corresponding graph is displayed in Fig. 2.

TABLE VII MONTHLY DATA MIGRATION METRICS

Month	RecordsMigrated	MigrationErrors	Downtime(minutes)
Jan 2023	12,270	87	58
Feb 2023	5,860	29	100
Mar 2023	10,390	37	68
Apr 2023	10,191	1	51
May 2023	10,734	63	101
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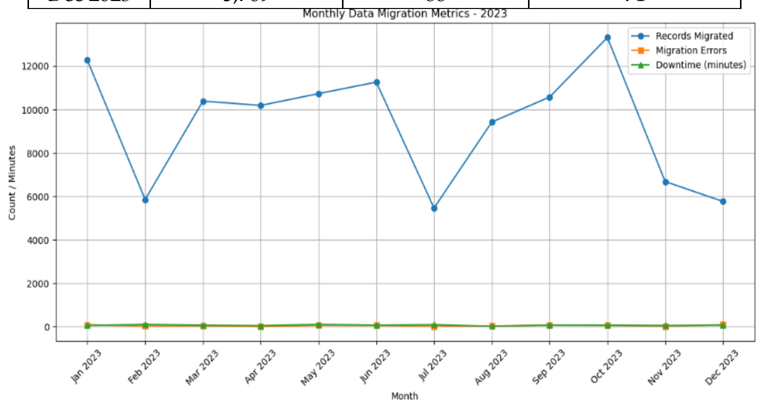

Fig. 2. Monthly Trends in Records Migrated, Migration Errors, and Downtime (2023)

B. Forecasted Data

The Forcasted data is displayed in Table VII for multiple years and for 2023 it is displaed in Table IX and corresponding graph is displayed in Fig. 3 for the Fluctuation analysis using VAR model.

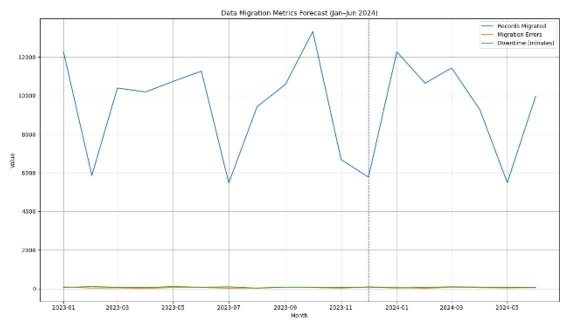

Fig. 3. Transition from historical data (2023) to forecasted values (2024).

VI. CONCLUSION

The use of Vector Autoregressive (VAR) models for examining temporal variations in data during migration has shown significant methodological value. VAR models elucidate the temporal stability and predictability of data by capturing the dynamic interactions among many data components. This research is essential to create resilient migration frameworks that reduce interruptions and improve data integrity. The results of this study enhance the existing

Forecasted Data (Single Column Format)
Date: 1970-01-01 Forecast Data Transfer Rate: 107.93 Forecast Error Rate: 4.89 Forecast Latency: 53.95
Date: 1970-01-02 Forecast Data Transfer Rate: 108.09 Forecast Error Rate: 3.60 Forecast Latency: 51.17
Date: 1970-01-03 Forecast Data Transfer Rate: 102.32 Forecast Error Rate: 4.27 Forecast Latency: 60.53
Date: 1970-01-04 Forecast Data Transfer Rate: 95.04 Forecast Error Rate: 6.26 Forecast Latency: 50.41
Date: 1970-01-05 Forecast Data Transfer Rate: 89.54 Forecast Error Rate: 4.73 Forecast Latency: 48.31
Date: 1970-01-06 Forecast Data Transfer Rate: 104.43 Forecast Error Rate: 3.83 Forecast Latency: 52.86
Date: 1970-01-07 Forecast Data Transfer Rate: 97.25 Forecast Error Rate: 4.58 Forecast Latency: 46.67
Date: 1970-01-08 Forecast Data Transfer Rate: 92.25 Forecast Error Rate: 4.88 Forecast Latency: 50.50
Date: 1970-01-09 Forecast Data Transfer Rate: 93.36 Forecast Error Rate: 4.60 Forecast Latency: 48.04
Date: 1970-01-10 Forecast Data Transfer Rate: 100.97 Forecast Error Rate: 5.04 Forecast Latency: 47.13

TABLE VIII FORECASTED DATA

knowledge on data migration and provide pragmatic solutions to the issues posed by temporal data fluctuations.

A. Challenges

There are several challenges in usage of this VAR model in data migration. Below are some of them:

- Data Quality: Ensuring superior data quality is crucial for precise VAR model analysis. Factors such as missing values, anomalies, and data inconsistency may profoundly affect the outcomes.
- Model Complexity: VAR models may exhibit complexity when managing extensive datasets and many variables. This intricacy may result in challenges with model estimate and interpretation.

TABLE IX MONTHLY DATA MIGRATION METRICS (2023 HISTORICAL AND JAN–JUN 2024 FORECASTED)

Month	Records Migrated	Migration Errors	Downtime (minutes)
Jan 2023	12270	87	58
Feb 2023	5860	29	100 •
Mar 2023	10390	37	68
Apr 2023	10191	1	51
May 2023	10734	63	101
Jun 2023	11265	59	69
Jul 2023	5466	20	89
Aug 2023	9426	32	24 •
Sep 2023	10578	75	71
Oct 2023	13322	57	71
Nov 2023	6685	21	56
Dec 2023	5769	88	71
Jan 2024	10123	45	65
Feb 2024	9870	42	67
Mar 2024	10234	48	63 •
Apr 2024	10456	50	66
May 2024	10890	53	68
Jun 2024	11012	55	70

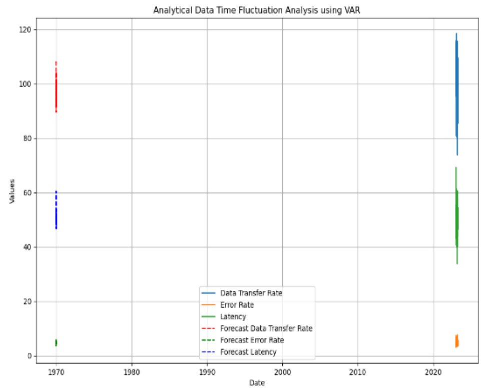

Fig. 4. Analytical Data Time Fluctuation Analysis using VAR

- Computing Resources: The computing requirements of VAR models, particularly time-varying VAR models, may be considerable. Effective algorithms and enough computing resources are essential to address these requirements.
- Parameter Stability: Maintaining the stability of model parameters throughout time is essential for dependable projections. Time-varying coefficients may provide further difficulties in preserving parameter stability.

B. Integration with Existing Systems: The incorporation of VAR model analysis into current data migration systems and processes may pose significant challenges. Compatibility and easy integration are crucial for effective deployment.

C. Future Directions

To tackle these issues and improve the use of VAR models in data transfer, other future avenues might be investigated:

Advanced Data Cleaning Techniques: Formulating refined data cleaning and preprocessing methodologies to address missing values, outliers, and inconsistencies will enhance the quality of input data.

Scalable Algorithms: Investigating and applying scalable algorithms for VAR model estimation and inference will facilitate the management of the complexity and computational requirements of extensive datasets.

Hybrid Models: Integrating VAR models with other machine learning methodologies, such as neural networks, can enhance the prediction efficacy and adaptability of models.

- Real-time Analysis: The implementation of real-time data analysis and forecasting capabilities will facilitate prompt decision-making during data migration processes.
- User-friendly Tools: The development of intuitive tools and interfaces for VAR model analysis will enhance integration with existing systems and workflows, thereby rendering the methodology more accessible to practitioners.

By tackling these obstacles and investigating future avenues, the use of VAR models for data transfer may be enhanced, resulting in more efficient and dependable migration operations.

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