Enhancing External Debt Nowcasting: A Data-Driven Approach Using Advanced Analytics

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Background

Why external debt projection important?

1. External debt is one of the Indonesian primary financing sources.

2. The substantial share of external debt in financing highlights the importance of debt sustainability monitoring (including accurate projection).

3. Projections for external debt disbursements and repayments is a part of foreign exchange supply-demands projection, which are critical for Bank Indonesia’s objective of achieving and maintaining Rupiah exchange rate stability.

4. Due to the dependency on corporate report which still lack of good disbursement dan repayment projection, private external debt projection needs improvement in methodology.

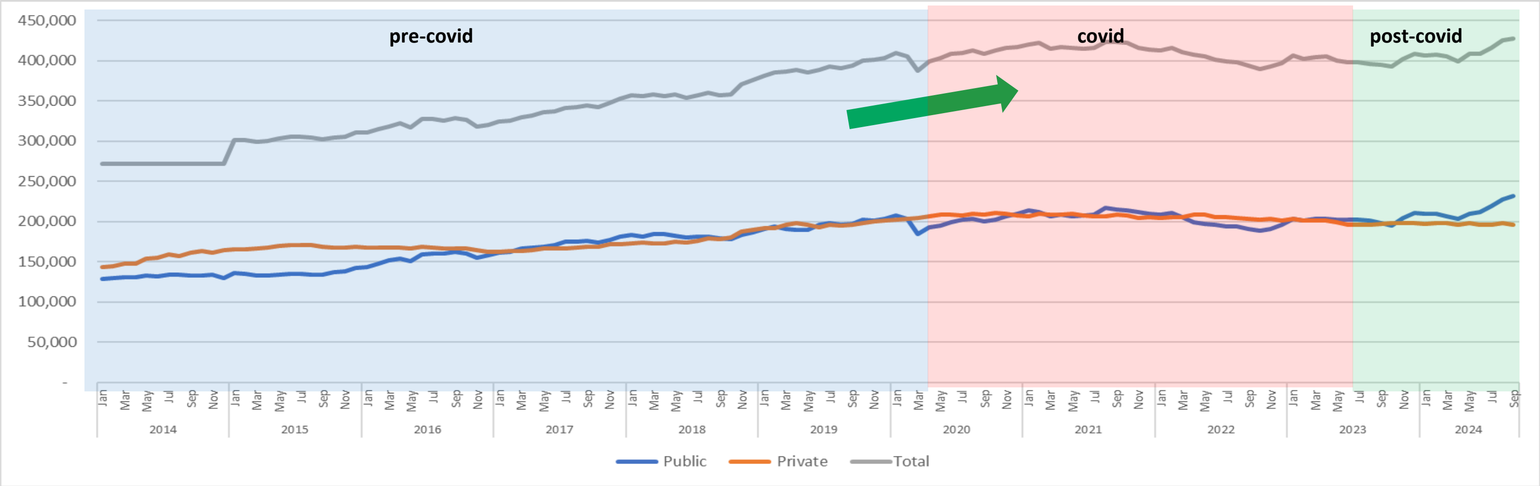
5. This research attempt to use data driven approaches (clustering-decomposition, and time series analysis) for private external debt disbursements and repayments projection.

Background

Indonesia's external debt has grown over the past decade

Indonesian External Debt

million of USD



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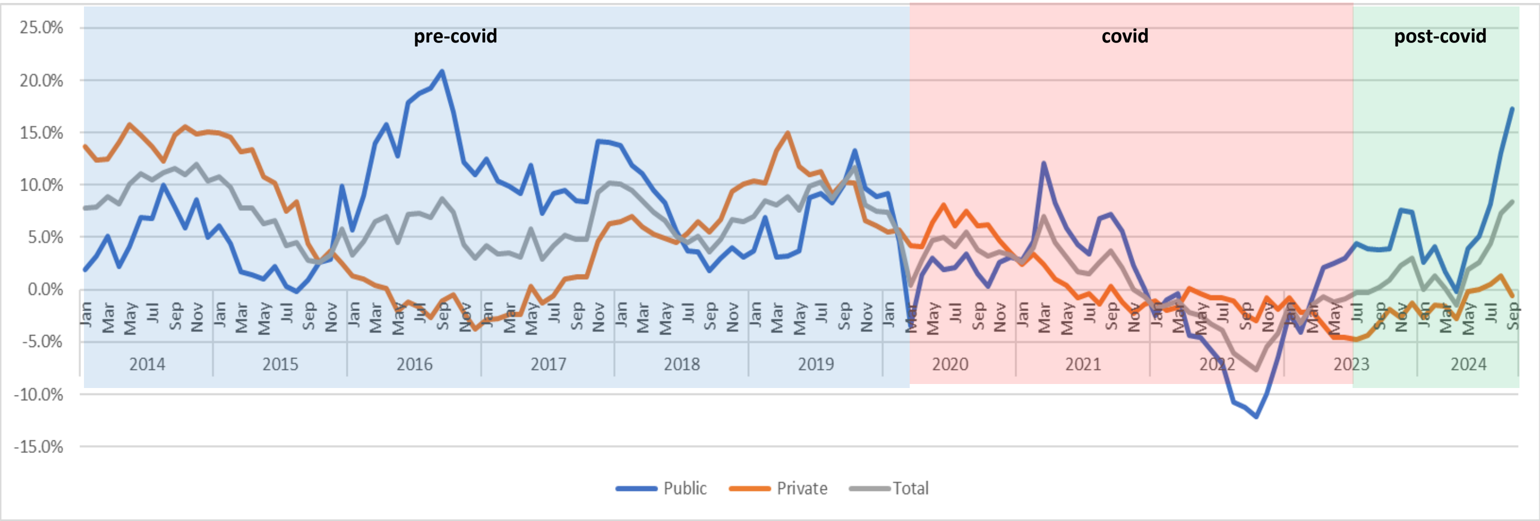


Indonesia's external debt grew from USD 293.8 billion at the end of 2014 to USD 427.8 billion by the end of third quarter 2024. This growth stems from increases in both public and private external debt.

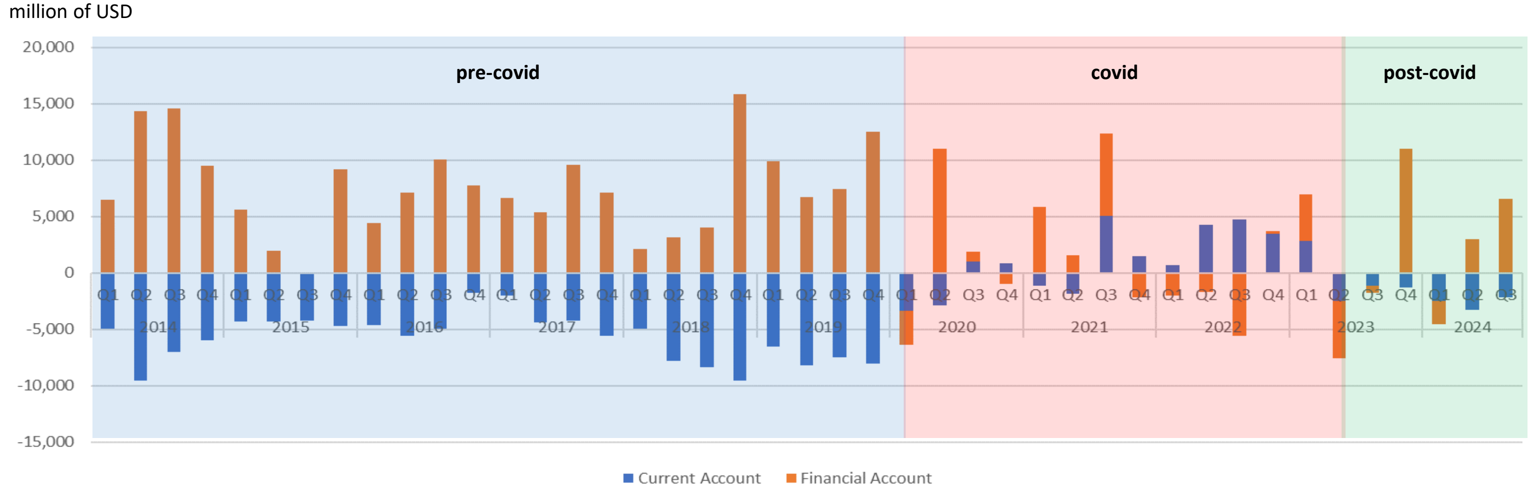
This growth stems from increases in both public and private external debt, with an average annual growth rate of 4.4% (y-o-y). After a contraction during the COVID-19 period (Q1 2020 - Q2 2022), Indonesia's external debt has resumed growth post-pandemic. However, private external debt growth still under pre-pandemic growth, this affected by post-pandemic economic growth that has not yet fully recovered.

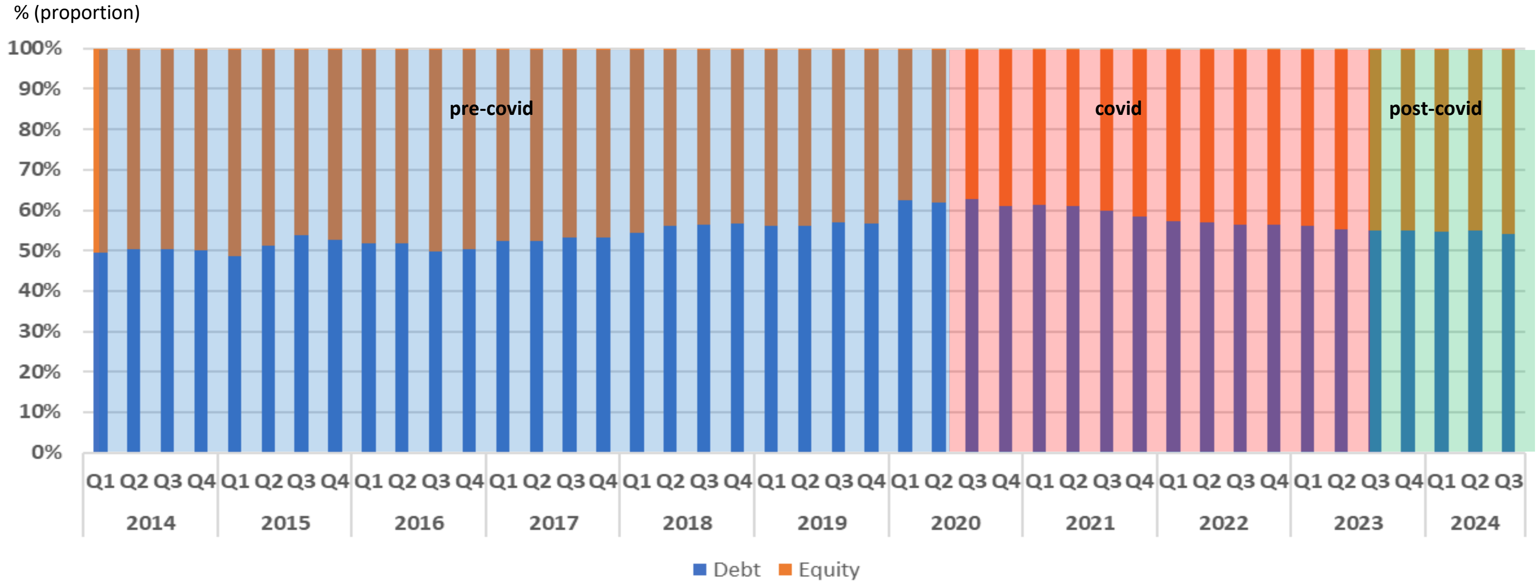
Source: Indonesian External Debt Publication period: September 2024

Background

External debt played important role as part of Indonesia Balance of Payment (BoP)

Indonesian Balance of Payment (BoP) and International Investment Position (IIP)





Indonesia's current account deficit was offset by financial account surplus. This trend reversed slightly during the pandemic, as the current account recorded a surplus driven by reduced imports due to the decline in economic activity. This anomaly ended post-pandemic, with current account returning to deficit, balanced by surplus in financial account.

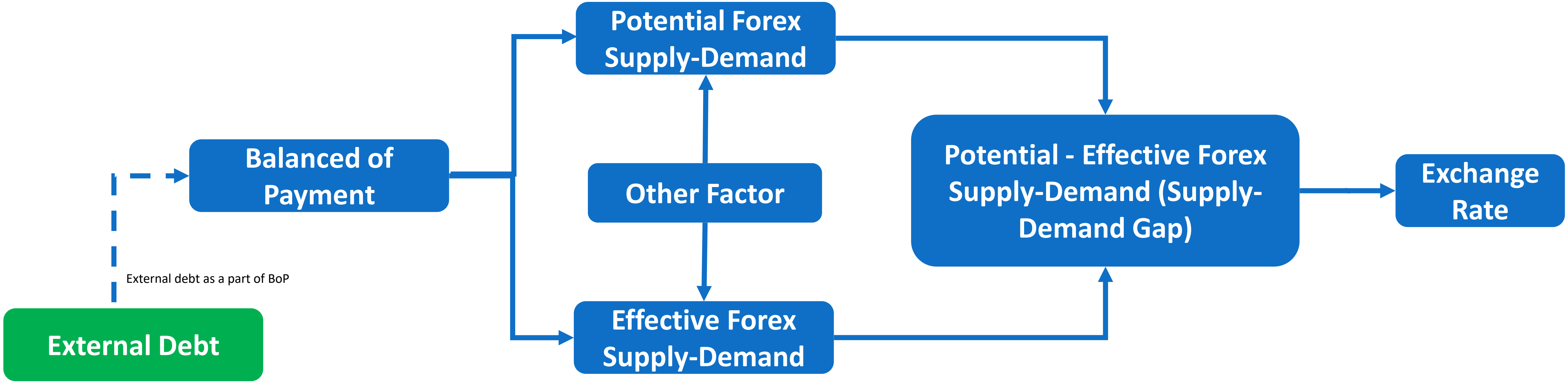
Indonesian external debt also plays an essential role in the Balance of Payments (BoP) and International Investment Position (IIP), especially in financial liability. External debt forms approximately 55% of financial account liabilities position.

Source: Indonesian Balance of Payment and International Investment Position Publication, period: Q3-2024

Background

External Debt can affect Foreign Exchange (Forex) Supply and Demand

- Forecasting foreign exchange demands aligns with the role of Bank Indonesia as the central bank, whose primary objective is to achieve and maintain Rupiah stability. Rupiah stability implies price stability of goods and services as well as rupiah exchange rate stability. To achieve the objective of maintaining rupiah exchange rate stability, Bank Indonesia conduct various strategies that require reliable information, including projections of foreign exchange supply-demands.
- Bank Indonesia projections for external debt disbursements and repayments is an important part of foreign exchange supply-demands projection.



Framework: Working Paper (Piter, 2016)

Research Question

Is alternative methodology using data-driven approach is suitable for private external debt projection?

How accurate is data-driven approach (clustering and time series) in projecting private external debt disbursement and repayment?

What are the advantages in using data-driven approach (clustering-decomposition and time series) for private external debt projection?

Limitation

This paper is limited to the projection of private external debt, specifically for trade credit and other loan. The other loan type, such as loan agreement and debt securities, needs more deep research on its projection method, including adding external variable such as economic growth, external rate, etc.

Lorem Ipsum Dolor Sit

Methods: Data Sources

- **Indonesia External Debt** — Joint publication Ministry of Finance (MoF) and Bank Indonesia (Central Bank)
  - **Public**
    - **Government** ← Ministry of Finance
    - **Central Bank** ← Bank Indonesia
  - **Private** ←
    - External Debt Reporting System
    - Bank Report
    - Data Provider
    - Anecdotal Information

Methods:
Research Stages

Data Analysis

This step includes exploring the collected external debt data to identify patterns and relationships that can be used in the development of the nowcasting model. The main objective is to understand the basic behavior of external debt transactions.

Data Preprocessing

This stage focuses on preparing raw data before modelling. In the context of this paper, these steps include cleaning up external debt data, handling missing or inconsistent values, and normalizing the dataset. This stage also select perpetrators based on the Pareto 80/20 principle. Only actors who account for 80% of the total contribution (based on historical data) are prioritized for further analysis.

Data Modelling

In this step, the clustering-decomposition method and time series analysis are combined to develop a hybrid nowcasting model. Clustering-decomposition is used to organize debt data into homogeneous groups, thus allowing the application of a specific time series model for each group. This hybrid approach aims to improve prediction accuracy by leveraging the power of both methods.

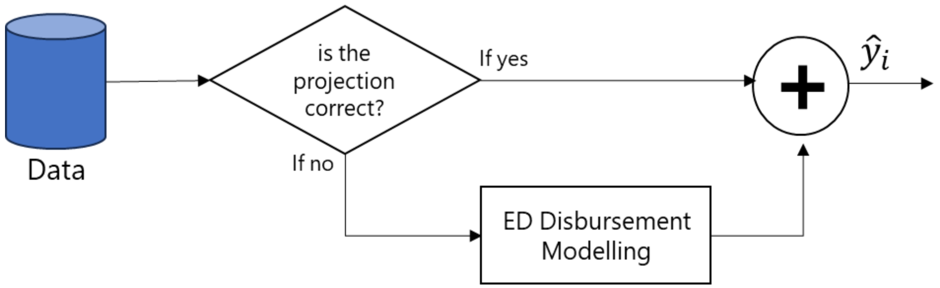
Evaluation

The last stage is evaluation. This stage assesses the performance of the nowcasting model using metrics such as mean absolute percentage error (MAPE). This evaluation ensures that the model is able to provide accurate short-term and medium-term predictions for external debt disbursement and repayment.

Methods

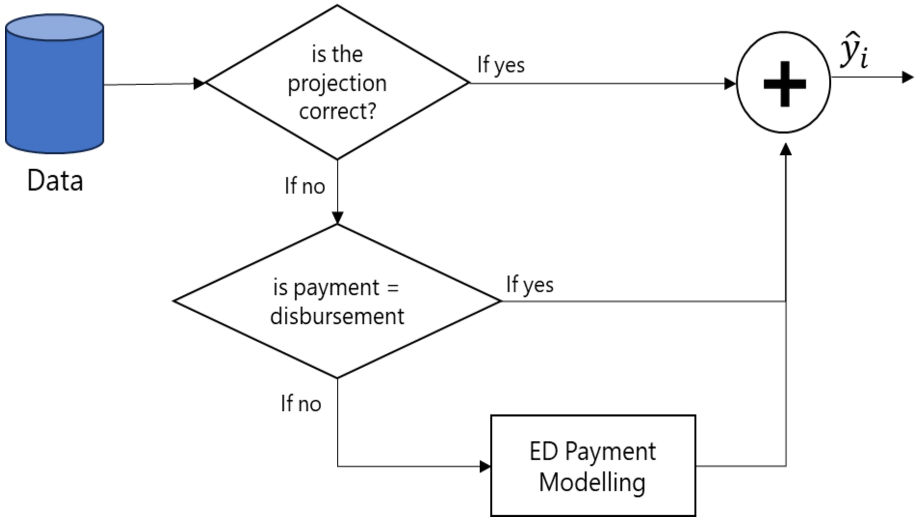
Data analysis:
company selection

Disbursement



- First step is to decide whether the "projection/plan" data reported by company are correct.
- If correct, then use the "projection". If not, then the company is selected to be used in modeling stage.

Repayment

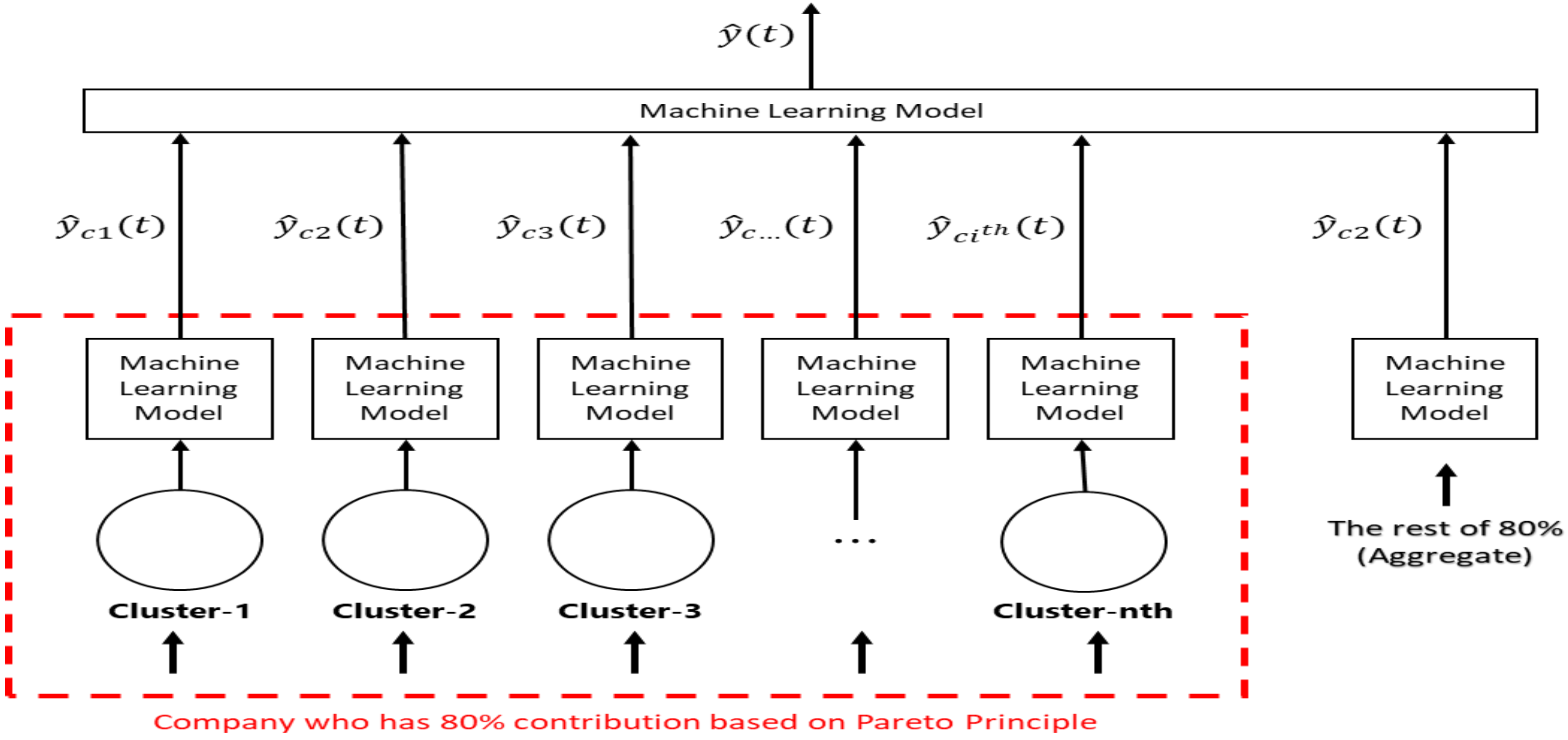


- First step is to decide whether the "projection/plan" data reported by company are correct.
- If correct, then use the "projection". If not, then decide whether the payment is mirroring the disbursement in the same period.
- If correct, then use the disbursement data for repayment. If not, then the company is selected to be used in modeling stage.

Methods

Data preprocessing and modelling:
clustering and time series analysis

Clustering and time-series analysis

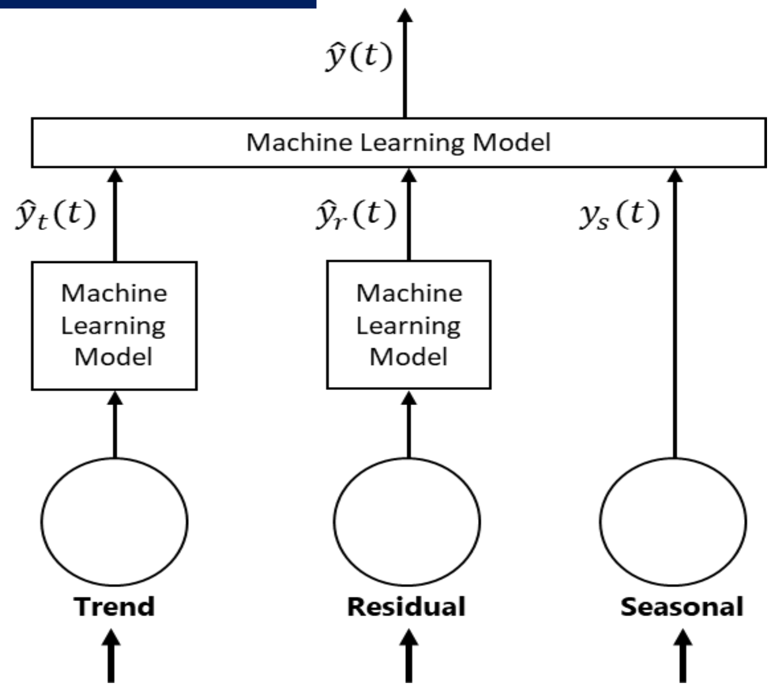


1. Select list of company that have 80% contribution based on nominal value.
2. Using machine learning to divide group of company into several cluster, based on their behaviour on external debt disbursement and repayment.
3. Construct machine learning model (time-series model) for each cluster.
4. Combining result from each model to produce a result.

Methods

Data preprocessing and modelling:
decomposition and time series analysis

Decomposition and time-series analysis



1. Divide the company population into 3 categories based on their behaviour in debt disbursement and repayment. The category are:
   - Trend, if there is a pattern on company disbursement and repayment
   - Seasonal, if company make disbursement and repayment in certain period.
   - Residual, other company that doesn’t have pattern on disbursement and repayment.
2. Construct machine learning model (time-series model) for each category.
3. Combining result from each model to produce a result.

Methods:

Evaluation

Mean Absolute Percentage Error (MAPE)

For evaluation we use mean absolute percentage error (MAPE). This evaluation ensures that the model is able to provide accurate short-term and medium-term predictions for external debt disbursement and repayment. The formula for the metric is as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100$$

$\hat{y}_i$: predicted value for i-th data point

y_i : actual value for the i-th data point

n : number of observations

In order to conclude whether the model is reliable or not, Lewis (1982) divide MAPE criteria as follows:

MAPE	Forecasting Power
<10%	Highly accurate forecasting
10% - 20%	Good forecasting
20% - 50%	Reasonable forecasting
>50%	Weak and inaccurate forecasting

Result

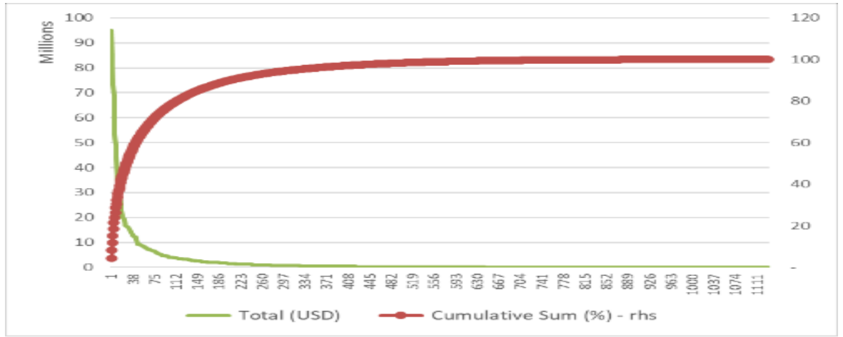
This research show that data-driven approach using clustering-decomposition and time series can project external debt disbursement and repayment specifically for trade credit and other loan

Result : Projection on Trade Credit

1. Data Analysis

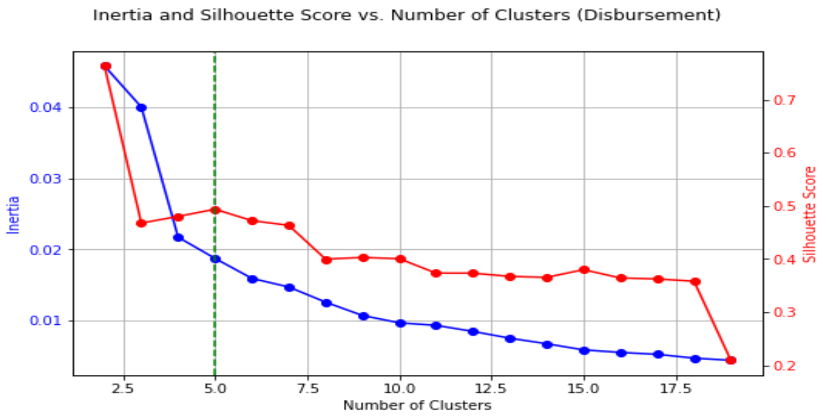
For the trade credit, we use clustering and time-series analysis. The first step is to identify if the projection from company reporting is correct. We found that for all company that have trade credit external debt, the projection reporting is not reliable. Next step, for repayment, we identified 13 company have identical repayment and disbursement patters. There are 4 (four) debtors from the Direct Investment-Trade Credit (DI-TC) group and 9 (nine) debtors from the Non-DI-TC group with such patterns.

2. Data Preprocessing



Example of DI-TC Disbursements

The first step of data preprocessing is to determine company who contribute 80% of the total external debt. The company contributing 80% for the DI-TC loan type (disbursement) are 113 debtors, Non-DI-TC (disbursement) are 115 debtors, DI-TC (payment) are 114 debtors, and Non-DI-TC (payment) are 115 debtors. After that, data normalization is performed to align variable scales to equalize, improve model performance, reduce bias, and facilitate analysis.



Example of Selecting the Optimal Number of Clusters for DI-TC Disbursement

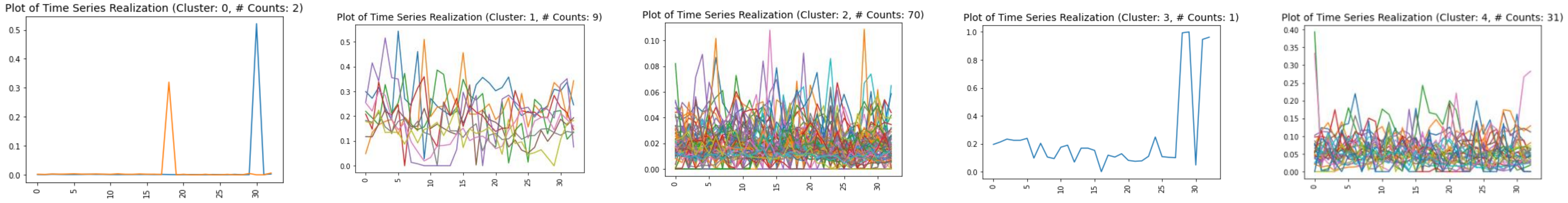
The next step is the clustering process using DTW, selected based on the Within-Cluster Sum of Squares (WCSS) and Silhouette Score values. The results for the WCSS and Silhouette Score TC are as follows:

		# Best Clusters	Silhouette Score	WCSS Score
Disbursement	DI-TC	5	0.4936	0.0187
	Non-DI-TC	4	0.7000	0.0007
Repayment	DI-TC	5	0.4206	0.0202
	Non-DI-TC	6	0.4668	0.0137

Result : Projection on Trade Credit

3. Data Modelling

In this stages, we use a clustering-based hybrid model to forecast Trade Credit (TC) Loans. This method involves grouping time series data using clustering algorithms to form clusters with similar characteristics. The clustering process aims to identify localized patterns within each cluster, enabling a more focused and customized analysis. In this modelling approach, we separate the data based on investment status (Direct Investment (DI) and Non-Direct Investment (Non-DI)) categories for further analysis.



Example of Clustering Results from DI-TC Disbursement

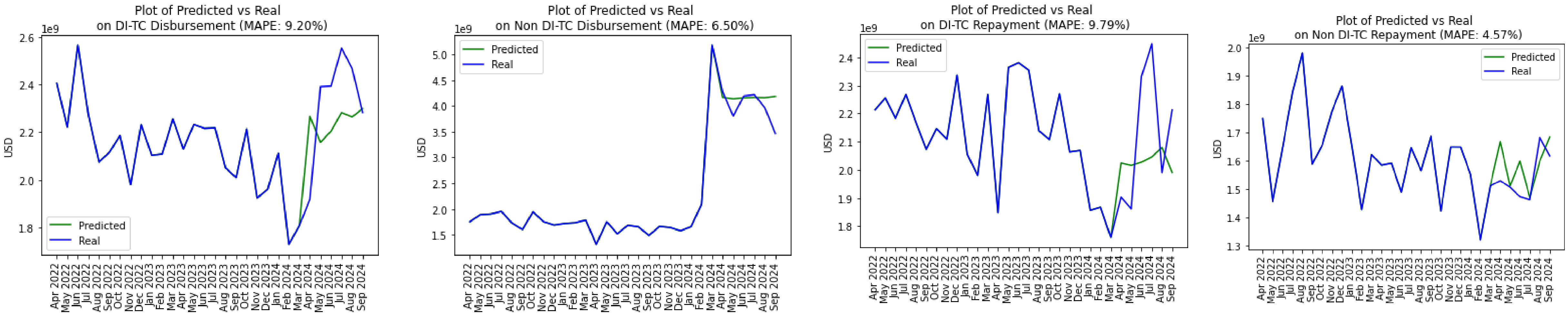
Five clusters were generated for DI-TC Disbursement, each with distinct pattern characteristics:

1. Cluster 0, exhibits a simple pattern where most values remain flat with a significant spike toward the end.
2. Cluster 1 displays a more complex and fluctuating pattern, with values rising and falling variably over time.
3. Cluster 2, shows highly volatile and seemingly random patterns, indicating significant variation within this cluster.
4. Cluster 3 stands out with its unique pattern, where values remain stable for most of the period before experiencing a sharp increase at the end.
5. Cluster 4 demonstrates relatively more organized fluctuations compared to Cluster 2, although variations are still present.

Result : Projection on Trade Credit

4. Data Modelling and Evaluation

Next, data modelling is performed for all cluster based on the results from the previous steps. Next, we combined result form each cluster for: 1) DI TC Disbursement; 2) Non-DI TC Disbursement; 3) DI TC Repayment; and 4) Non-DI TC Repayment.



Result of Projection on Trade Credit

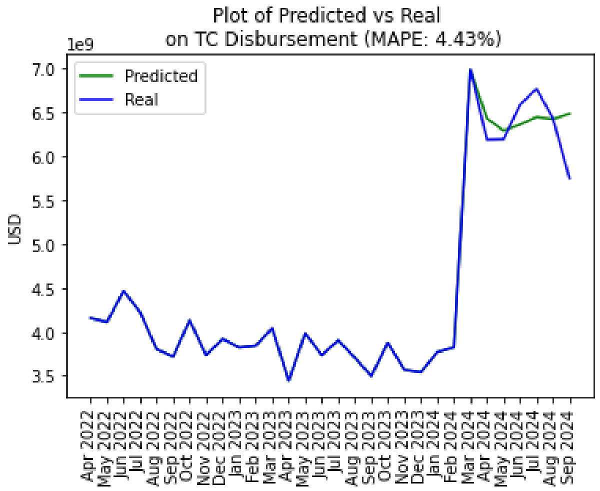
Final step is evaluation, this process use mean absolute percentage error (MAPE). The result is as follows:

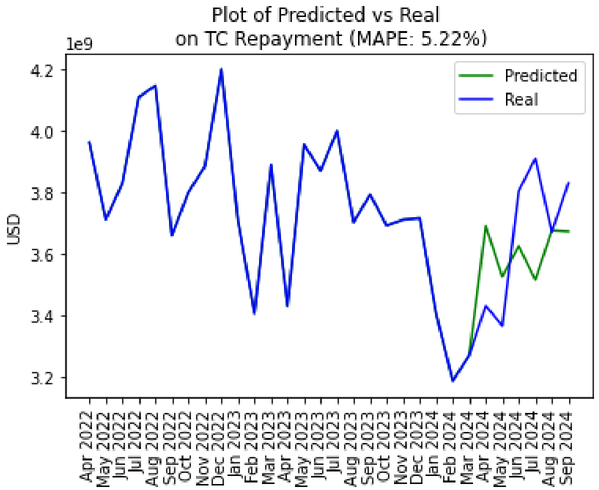
No	Loan Type	MAPE score	Description
1	DI TC Disbursement	9,20%	<10%, highly accurate forecasting
2	Non-DI TC Disbursement	6,50%	<10%, highly accurate forecasting
3	DI TC Repayment	9,79%	<10%, highly accurate forecasting
4	Non-DI TC Repayment	4,57%	<10%, highly accurate forecasting

Result : Projection on Trade Credit

5. Data Modelling and Evaluation

Furthermore, we tried to combined result form DI and Non-DI trade credit, both disbursement and repayment.





Result of Projection on Trade Credit

The combined result give better evaluation score. The evaluation use mean absolute percentage error (MAPE), as follows:

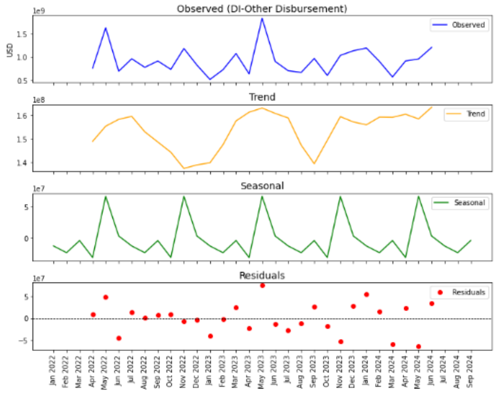
No	Loan Type	MAPE score	Description
1	TC Disbursement	4,43%	<10%, highly accurate forecasting
2	TC Repayment	5,22%	<10%, highly accurate forecasting

Result : Projection on Other Loan

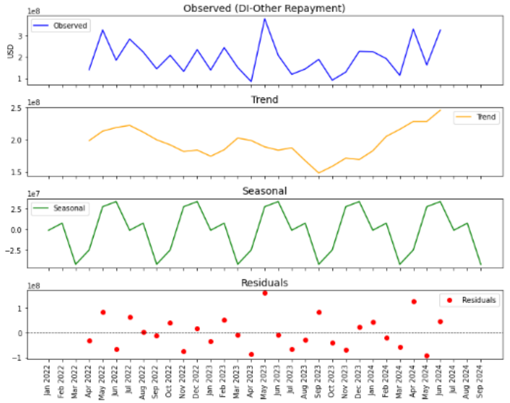
1. Data Analysis

For the other loan, we use decomposition and time-series analysis. Clustering is not used in this type of loan, because the behaviour of company in disbursement and repayment external debt often change over time. The first step is to identify if the projection from company reporting is correct. We found that for all company that have other loan external debt, the projection reporting is not reliable.

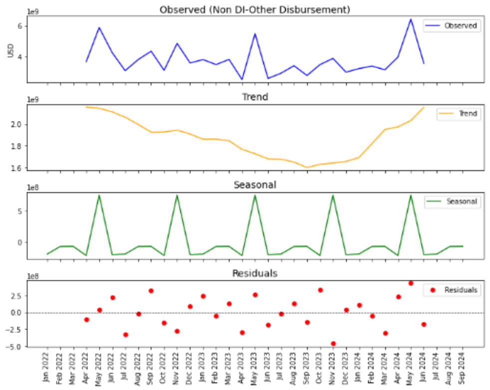
2. Data Preprocessing



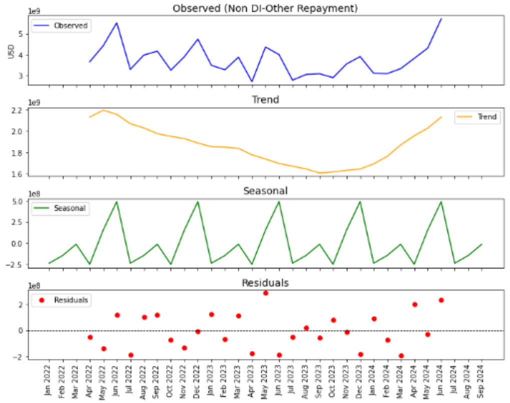
Decomposition results of DI Other Loan Disbursement



Decomposition results of DI Other Loan Repayment



Decomposition results of Non-DI Other Loan Disbursement



Decomposition results of Non-DI Other Loan Repayment

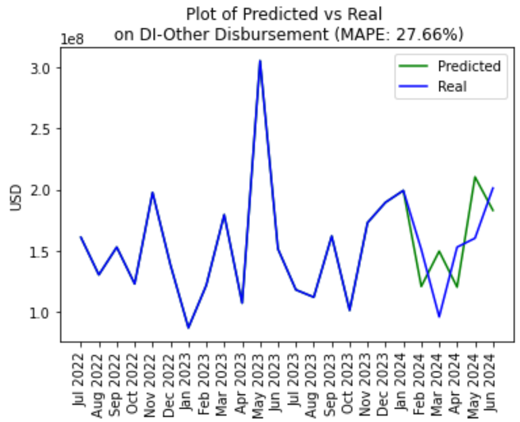
For each other loan type component (DI disbursement, DI repayment, non-DI disbursement and non-DI repayment), we formed 3 models which is trend, seasonal, and residual. The trend and residual components will be modelled separately, while the seasonal component will be studied for its seasonal pattern and directly added to the predictions of the trend and residual components. This approach is taken because the seasonal patterns formed through additive decomposition are already clear.

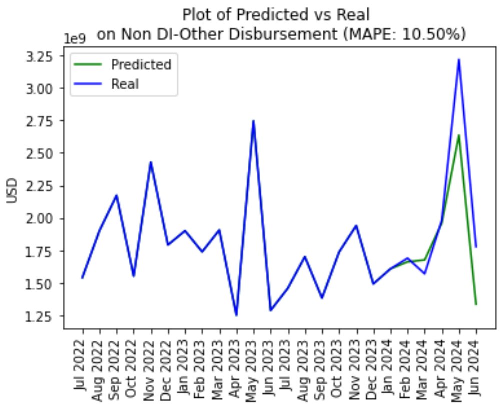
Example of Selecting the Optimal Number of Clusters for DI-TC Disbursement

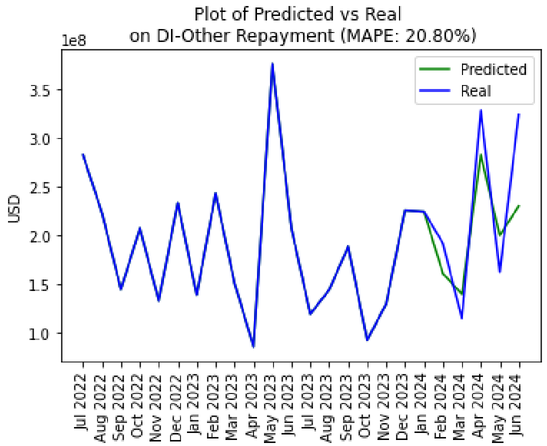
Result : Projection on Other Loan

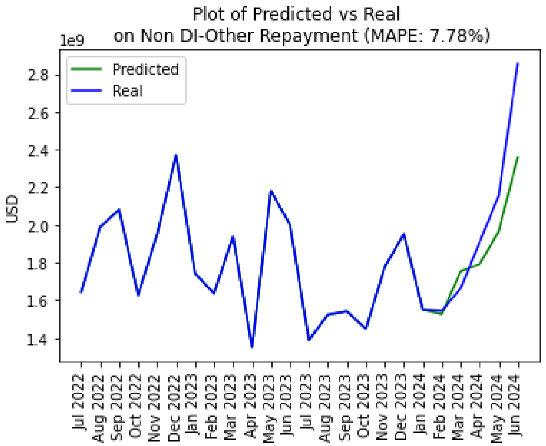
3. Data Modelling and Evaluation

Next, data modelling is performed for all category based on the results from the previous steps. Next, we combined result form each cluster for: 1) DI OL Disbursement; 2) Non-DI OL Disbursement; 3) DI OL Repayment; and 4) Non-DI OL Repayment.









Result of Projection on Trade Credit

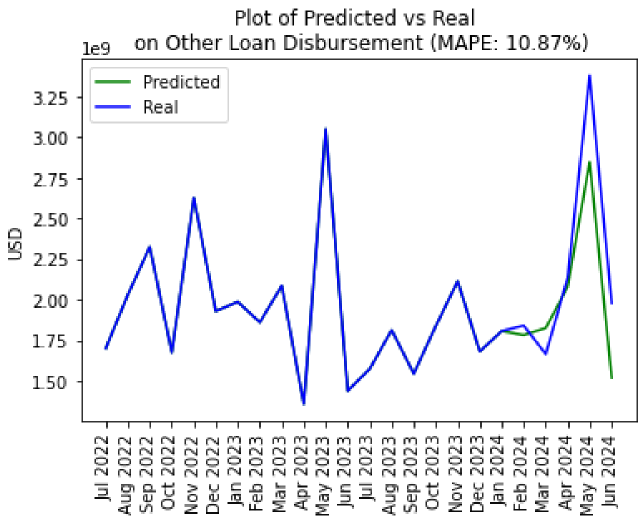
Final step is evaluation, this process use mean absolute percentage error (MAPE). The result is as follows:

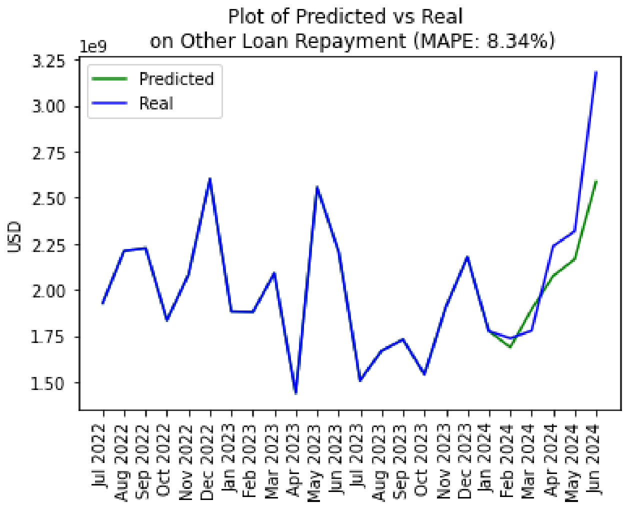
No	Loan Type	MAPE score	Description
1	DI OL Disbursement	27,66%	20-50%, Reseonable forecasting
2	Non-DI OL Disbursement	10,50%	10-20%, Good forecasting
3	DI OL Repayment	20,8%	20-50%, Reasonable forecasting
4	Non-DI OL Repayment	7,78%	<10%, highly accurate forecasting

Result : Projection on Other Loan

4. Data Modelling and Evaluation

Furthermore, we tried to combined result form DI and Non-DI other loan, both disbursement and repayment.





Result of Projection on Other Loan

The combined result give better evaluation score. The evaluation use mean absolute percentage error (MAPE), as follows:

No	Loan Type	MAPE score	Description
1	OL Disbursement	10,87%	10-20%, Good forecasting
2	OL Repayment	8,34%	<10%, highly accurate forecasting

Conclusion

- Advanced analytics, specifically clustering-decomposition and time series methodology **can be used for projecting** private external debt (trade credit and other loan) disbursement and repayment.

- Implementing clustering-decomposition and time series methodology increase **the reliability of projection**. This proves by projection evaluation using Mean Absolute Percentage Error (MAPE).

- Implementing advanced analytics for projection private external debt, **can increase work process efficiency**. This achieved by reducing dependencies to company reporting data, thus eliminating coordination process such as the data confirmation

THANK YOU