Interdisciplinary Social Studies
P-ISSN: 2808-0467
E-ISSN: 2808-5051
Volume 5
Number 4, 2026

Forecasting Intermittent Disbursements for Non-Routine Investment Budget Expenditures Using the TSB–Croston–ADIDA Model with Hierarchical Reconciliation: A Case Study of Disbursements at PLN UIP Sulawesi

Pricilia Maureen Poluan*, R. Mohamad Atok
Institut Teknologi Sepuluh Nopember, Indonesia
Email: maureen.pricilia85@gmail.com*, radenatok@gmail.com

Keywords:
intermittent disbursement; intermittent demand forecasting; hierarchical reconciliation

ABSTRACT

This research evaluates three Intermittent Demand Forecasting (IDF) methods Croston, TSB, and ADIDA for non-routine investment disbursement at PLN UIP Sulawesi, characterized by intermittent and lumpy patterns. Using a three-stage analytical approach (in-sample validation on 29 PRKs, rolling origin out-of-sample on 180 PRKs, and production forecast on 959 PRKs) with MASE, MAE, and ME metrics, ADIDA emerged as the best method with consistent win-rate dominance (58.6% in Phase 1; 64.2% in Phase 2). Hierarchical reconciliation using Weighted Least Squares (WLS) produced a coherent 2026 forecast of IDR 2,781.89 billion, outperforming Bottom-Up and Top-Down approaches in hold-out validation. These findings provide an empirical foundation for data-driven cash planning at PLN UIP Sulawesi, with the ADIDA–WLS pipeline offering a validated, auditable, and computationally efficient framework for Monthly Cash Budget preparation. The methodological framework's auditability particularly the traceability of WLS weight matrices to empirical error sources supports readiness for SAP S/4HANA Single Source of Truth (SSoT) Wave 3 implementation scheduled for October 2027, while the PRK-level forecast matrix enables hybrid statistical-expert judgment review to address administrative zero constraints. This research contributes theoretically by extending IDF literature beyond spare parts inventory into infrastructure investment cash management, and practically by providing operational tools for working capital optimization, KPI cascading, and systematic investment portfolio phasing within PLN's Transformation 2.0 agenda.

INTRODUCTION

PT PLN (Persero) enters the Transformation 2.0 phase as a continuation of the achievements of Transformation 1.0, with the vision of becoming a Global Top 500 company and the customer's first choice for energy solutions. This new phase of acceleration translates into Moonshots' portfolio focused on Growth, Digital, and Net Zero Emission (NZE). To realize this acceleration, two key Launchpads, namely Centralized Planning & Investment Optimization (CP) and Integrated Financial Management (IFM), are designed to close the gap in investment planning and financial governance that has been partial and manual. On the planning side, CP targets vertical-horizontal integration of investment programs by moving from single-criteria based prioritization (Generation 2) to multi-criteria value framework and optimization (Generation 4 in 2026). On the financial side, IFM integrates budgeting processes (Integrated Planning & Budgeting System/IPBS), payments (Integrated Payment Management

System/IPMS), debt management, reporting, and tax management into one traceable and auditable SAP-based data architecture. With this architecture, the planning–budgeting-payment to reporting processes become integrated, transparent, and auditable in line with the principles of single source of truth (SSoT) and Performance Management System (PMS) which are the stream from corporate strategy to unit goals through the cascading of KPIs from each employee of PT. PLN (Persero).

However, in execution, the pattern of realization of uneven non-routine investment payments (intermittent) is highly dependent on technical milestones, vendor billing schedules, and administrative completeness, which then becomes the main source of uncertainty for cash planning, working capital efficiency, compliance with payment SLAs, and absorption accuracy per period. Historical analysis at PLN UIP Sulawesi shows the magnitude of this challenge: about [33%] of the total monthly period experienced zero disbursement (high intermittency), while [70%] of the total annual realization was concentrated only in June, November and December reflecting an extreme lumpy pattern. This then has the potential to disrupt the Service Level Agreement (SLA) centralized payment, triggering late fines, and damaging relationships with vendors. The back-loaded budget absorption pattern also increases the risk of deviation from the periodic target and accumulates payment operational burdens in a short period of time. This gap shows that the success of Centralized Planning (CP) and Integrated Finance Management (IFM) demands precise disbursement forecasting capabilities, especially for data with many zero periods and lumpy value spikes.

Answering this need, this study proposes an intermittent disbursement forecasting approach based on Croston, TSB (Teunter-Syntetos-Babai), and ADIDA (Aggregate-Disaggregate Intermittent Demand Approach) methods that are specifically designed to handle intermittent characteristics and then be reconciled hierarchically using Weighted Least Squares (WLS) in the framework of optimal combination reconciliation (Hyndman et al., 2011, 2016) to be consistent from the project/contract level to the total unit portfolio. Hierarchical reconciliation ensures top-down and bottom-up coherence in line with cascading KPIs and Performance Management System (PMS) mechanisms so that forecasts at the aggregate level do not deviate from the sum of units further down (Hollyman 2024; Kumar 2025; Vespoli et al. 2026). The integration of forecast results into the IPBS and IPMS ecosystems is expected to produce reliable cash signals for cash planning, reduce cash idle arising from over-forecasting disbursement, improve the accuracy of periodic absorption targets, and in turn strengthen the company's financial sustainability.

From the perspective of capital budgeting and cash management, intermittent disbursement raises asymmetrical risks. The phased budgeting mechanism at PLN from RKAP as an annual plan, SKAI (Investment Budget Power of Attorney) as authorized by the Head Office, to AKB (Monthly Cash Budget) which is determined based on the actual physical progress of the contractor (PERDIR 0036/P/DIR/2016) requires verification of work minutes for each disbursement/payment, so that the risk of sudden cash shortfall is structurally minimal. The dominant risk is idle cash: when the AKB allocation is set too high relative to the actual physical realization, the funds that have been prepared are not absorbed productively and effectively, creating a real cost of carry. This research bridges capital budgeting (CP flow → phasing capex/RKAP) with cash management by producing more accurate and coherent disbursement forecasts across hierarchies to reduce over-forecasting and cash idle systematically. Thus, the focus of the thesis "Intermittent Disbursement Forecasting of Non-Routine Investment Budget Expenditure based on TSB-Croston-ADIDA with Hierarchical Reconciliation: A Case Study of PLN UIP Sulawesi" is right at the crucial point that connects the corporate transformation agenda (CP, IFM, and Centralized Payment) with the operational needs of the unit. This approach not only provides forecast accuracy for daily decision-making, but also provides the cross-level consistency needed to move financial strategies, plans, and realizations in unison while strengthening governance/prioritization and phasing investment portfolios systematically in the event of material deviations between plans and realizations.

Research on intermittent demand forecasting has developed rapidly since Croston (1972) introduced the first method specifically designed to handle data with many zero periods. The Croston method became the main foundation in IDF literature for several decades, with various developments and evaluations conducted by Syntetos and Boylan (2005) as well as Teunter et al. (2011) who produced the TSB method as an improvement over Croston's weakness in handling changes in demand probability. Nikolopoulos et al. (2011) then proposed the ADIDA approach which uses temporal aggregation to reduce the level of intermittency before the forecasting process is implemented. Comparative evaluations of these three methods have been widely conducted in the context of spare parts inventory management and supply chains (Kourentzes, 2014; Petropoulos & Kourentzes, 2015), with findings showing that no single method is universally superior method performance strongly depends on data characteristics such as Average Inter-Demand Interval (ADI) and coefficient of variation (CV^2) (Syntetos et al., 2005). In the realm of hierarchical forecasting, research by Hyndman et al. (2011) and Wickramasuriya et al. (2019) has developed an optimal combination reconciliation framework that ensures mathematical consistency across aggregation levels. This approach has been tested in various contexts such as retail demand forecasting, tourism, and energy (Athanasopoulos et al., 2017), but its application to financial data with intermittent characteristics remains very limited.

Although the IDF literature has matured in the operational domain, its application to cash flow forecasting and cash management is still rarely found. Research on disbursement forecasting for infrastructure projects, particularly in state-owned enterprises in developing countries, has not received much academic attention. In fact, the characteristics of infrastructure project payments that are highly intermittent and lumpy caused by administrative factors such as land acquisition, licensing, and completeness of payment documents present unique forecasting challenges that differ from the spare parts inventory context. This study addresses this research gap by testing and comparing IDF methods in the context of infrastructure investment disbursement forecasting at PLN, as well as integrating them with hierarchical reconciliation to ensure forecast coherence at the project, implementing unit, and corporate levels.

Based on the background that has been described, this study departs from the identification of a fundamental gap between the need for precise disbursement forecasting as a prerequisite for the success of Centralized Planning & Investment Optimization (CP) and Integrated Financial Management (IFM) and the reality of high uncertainty of payment realization due to intermittent patterns in non-routine investment spending. Intermittent patterns, characterized by the high frequency of zero disbursements interspersed with significant spikes in payments (lumpy pattern) at certain times, pose critical challenges in cash planning, working capital optimization, and the achievement of periodic budget absorption targets. This gap raises the urgent need to develop forecasting capabilities that are not only technically accurate, but also hierarchically consistent and integrated with the company's digital ecosystem. To answer this need, this study formulated two interrelated research questions designed to bridge the gap between intermittent forecasting theory and PLN's operational needs.

The formulation of the problems that will be analyzed in this study are: Selection of Forecasting Models. Which forecasting model is most suitable to handle the intermittent characteristics of non-routine investment expenditure disbursement at PLN UIP Sulawesi? This question requires in-depth investigation and research of systematic comparisons between three methods specifically designed for intermittent data: Croston (1972) as an established historical benchmark in the IDF literature, Teunter-Syntetos-Babai (TSB) as the most responsive development to changes in demand probability, and the Aggregate-Disaggregate Intermittent Demand Approach (ADIDA) as a framework that reduces the level of data intermittency through the incorporation of observation periods before the forecasting process is implemented. This comparison considers the specific characteristics of PLN UIP Sulawesi data, including the Average inter-Demand Interval (ADI) and demand square variability (CV^2), to determine the most reliable model in the context of SOE infrastructure.

Hierarchical Consistency. How to ensure consistency and coherence of forecasts across levels of the organizational hierarchy to support the Centralized Planning process? This question leads to the application of a hierarchical reconciliation method in the framework of optimal combination, using Weighted Least Squares (WLS) as a practical approach that has been proven to provide competitive accuracy (Hyndman et al., 2016) to ensure that the forecast at the aggregate level is mathematically consistent with the summation of the forecast at the aggregate level (per project or contract). This consistency is important to support the KPI cascading mechanism and vertical-horizontal integration within the Centralized Planning framework, given that forecast inconsistencies can lead to conflicts in prioritization and resource allocation.

The two research questions above are designed in an integrated manner: the first question builds a methodological basis through the identification of the best IDF method for PLN data characteristics, while the second question tests whether hierarchical reconciliation adds value over the underlying forecast generated. By answering these two questions comprehensively and systematically, the research is expected to make a significant practical contribution to PLN in accelerating the Transformation 2.0 agenda, as well as enriching the academic literature on the application of intermittent forecasting methods in the context of infrastructure investment in developing countries.

Broadly speaking, this study aims to develop an accurate, consistent, and integrated intermittent disbursement forecasting model for non-routine investment expenditure at PLN UIP Sulawesi to support the success of Centralized Planning & Investment Optimization and Integrated Financial Management within the framework of Transformation 2.0. The output/results of the model are expected to provide a more accurate forecast foundation to support cash planning decision-making. More specifically, the objectives of this study are: (1) to develop and compare intermittent forecasting models for non-routine investment expenditure disbursement using the TSB (Teunter-Syntetos-Babai), Croston, and ADIDA methods, then determine the best model based on the data characteristics at PLN UIP Sulawesi, and continue by determining the best model based on the accuracy measured with MASE, MAE, and ME through the rolling origin scheme; and (2) to implement hierarchical reconciliation based on Weighted Least Squares (WLS) in an optimal combination framework to ensure consistency and coherence of forecasts across levels of the organization's hierarchy (from the project/contract level to total units) to support vertical-horizontal integration in Centralized Planning by evaluating the effectiveness of reconciliation against hierarchical forecast accuracy using the same metrics.

This research extends intermittent demand forecasting literature beyond spare parts inventory into infrastructure investment cash management an area where IDF methods remain largely unexplored. It also advances hierarchical forecasting theory by testing optimal combination reconciliation in a three-level hierarchy with high intermittency, where previous studies have predominantly focused on regular retail or tourism patterns. Additionally, it provides empirical evidence on the relationship between data characteristics and IDF method performance in the financial domain. This research offers a validated ADIDA + WLS forecasting pipeline for PLN UIP Sulawesi's Monthly Cash Budget preparation, with computational efficiency enabling dynamic monthly re-forecasting. The WLS conservative forecast minimizes idle cash, generating tangible opportunity cost savings consistent with working capital optimization principles. The hierarchical framework ensures forecast coherence across UIP, UPP, and PRK levels, supporting KPI cascading and the Performance Management System. Furthermore, the pre-validated pipeline facilitates PLN's SAP S/4HANA SSoT implementation with auditability aligned to accountability principles, while the PRK-level forecast matrix enables planner review to address administrative zero constraints through hybrid statistical-expert judgment.

METHOD

This research used a quantitative approach with a comparative-experimental applied research design. The quantitative approach was chosen because the object of analysis is numerical time series data, namely the realization of disbursement of funds (disbursement) of PLN UIP Sulawesi's electricity infrastructure project which can be measured, calculated, and compared systematically.

This study does not aim to build a new theory, but rather to apply and evaluate the performance of the Intermittent Demand Forecasting (IDF) method in a new context, namely the financial planning of public sector infrastructure projects in Indonesia. Thus, this research is an applied research that bridges the gap between IDF literature which has been dominated by the context of spare parts inventory and the practical needs of disbursement forecasting within PLN.

Operationally, the third phase (Analysis) consists of three consecutive steps: (1) the application of three Intermittent Demand Forecasting methods, namely Croston, TSB, and ADIDA, then the selection of the best method based on out-of-sample accuracy; (2) reconciliation of the three-level hierarchy (UIP → UPP → Project) of the best method using the Weighted Least Squares (WLS) method with Bottom-Up (BU) and Top-Down (TD) as a comparison; and (3) evaluation of accuracy using a rolling origin scheme with MASE, MAE, and ME metrics.

Research Flow

The research was carried out through a systematic flow starting from problem identification and literature study, followed by data collection and preprocessing, application of analysis methods, to interpretation of results and formulation of managerial implications. The complete research flow is presented as follows:

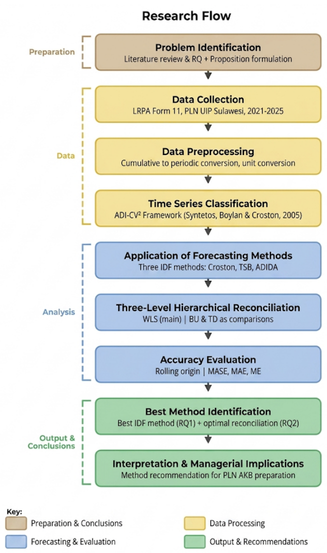

Figure 1. Research Flow
Source: Processed by researcher (2026)

The research flow consists of eight stages organized into four main phases. The first phase (Preparation) includes problem identification and literature studies that produce research question formulations (RQs) and propositions. The second phase (Data) includes the collection of data on the realization of disbursement from the LRPA Form 11 of PLN UIP Sulawesi for the 2021–2025 period, followed by pre-processing of data which includes the conversion of cumulative values to periodic, unit conversion, and time series classification using the ADI-CV^2 framework.

The third phase (Analysis) consists of three consecutive steps: (1) the application of three Intermittent Demand Forecasting methods, namely Croston, TSB, and ADIDA, then the selection of the best method based on out-of-sample accuracy; (2) reconciliation of the three-level hierarchy (UIP → UPP → Project) of the best method using the Weighted Least Squares (WLS) method with Bottom-Up (BU) and Top-Down (TD) as a comparison; and (3) accuracy evaluation using a rolling origin scheme with MASE, MAE, and ME metrics. The fourth phase (Output and Conclusion) includes the interpretation of the results of the evaluation of the two research questions and the formulation of managerial implications in the form of recommendations for the use of the selected method as the basis for the preparation of the Monthly Cash Budget (AKB) PLN UIP Sulawesi.

This study applies a three-stage analytical approach as evidence triangulation. Phase 1 (in-sample validation) used a pilot subset of 29 60-month full active PRKs to validate the methodological pipeline. Phase 2 (rolling origin out-of-sample) used 180 active PRKs for a minimum of 36 months to evaluate the reliability of the method. Phase 3 (production forecast) uses 959 active PRKs for at least 1 year to produce a 2026 forecast as well as hierarchical reconciliation.

Research Objects

The object of the research is PT PLN (Persero) Sulawesi Development Main Unit (UIP), which is PLN's business unit responsible for the development of electricity infrastructure in the Sulawesi region. UIP Sulawesi performs its function as a project manager for the construction and development of transmission networks and substations spread throughout the island of Sulawesi. The subject of the study is PT PLN (Persero) UIP Sulawesi as a provider of data and institutional context. The object of the research is the monthly disbursement realization data per project resulting from PLN UIP Sulawesi's operational activities.

In carrying out its functions, PLN UIP Sulawesi oversees four Project Implementation Units (UPPs) each of which is responsible for a specific administrative area, as presented in Table 1 below.

Table 1. Structure of PLN UIP Sulawesi Project Implementation Unit

No.	Project Implementation Unit (UPP)	Coverage Region
1	UPP North Sulawesi	North Sulawesi Province and Gorontalo Province
2	UPP Central Sulawesi	Central Sulawesi Province
3	UPP South Sulawesi	South Sulawesi Province and West Sulawesi Province
4	UPP Southeast Sulawesi	Southeast Sulawesi Province

Source: Organizational Structure of PLN UIP Sulawesi

The four UPPs are a representation of the middle level (Level 2) in the forecasting hierarchy structure built in this study, with PLN UIP Sulawesi as the highest aggregate level (Level 1) and each project as the lowest level (Level 3).

Data Types and Sources

Data Type

This study uses secondary data, namely data collected by PLN UIP Sulawesi in the context of operational activities and company planning, which is then accessed and reprocessed for the purposes of this research. Primary data in the form of surveys or interviews were not used, because the focus of the research was on the analysis of quantitative time series patterns, not on respondents' perceptions or opinions.

The main data used is the realization of monthly disbursement per project in units of Billion Rupiah (Rp Billion). Disbursement in this context refers to the realization of payment for the progress of work that has been verified through the mechanism of the Handover Minutes (BAST) or equivalent documents in accordance with the provisions of the government goods/services procurement contract.

Data Source

Data was obtained from two categories of sources, namely PLN's internal primary data and the company's official grey literature document, as described in Table 2 below.

Table 2. Research Data Sources

No.	Data Type	Source	Usability in Research
1	Realization of monthly disbursement per project (2021–2025)	PLN UIP Sulawesi financial reporting system	Key data of IDF analysis and hierarchical forecasting
2	RKAP budget per project per year	RKAP PLN UIP Sulawesi Document	Comparative baseline and zero-disbursement context
3	Organizational structure and project mapping to UPP	PLN SK/KepDir Document	Three-level hierarchy construction
4	PLN's SSoT and digital transformation roadmap document	PLN's SSoT internal documents	Justification of managerial relevance and implications

RESULTS AND DISCUSSION

Profile and Characteristics of Disbursement Data

Before conducting Intermittent Demand Forecasting (IDF) analysis and hierarchical reconciliation, the first step was to comprehensively map the profile and characteristics of PLN UIP Sulawesi's disbursement data during the 2021-2025 observation period. This mapping is important as an empirical foundation to ensure that the selection of forecasting methods in Subchapter 4.2 is based on actual data characteristics, not a priori assumptions.

This subchapter is arranged in four interrelated sections. Subchapter 4.1.1 presents the composition of the Work Plan Program (PRK) portfolio and describes the scope of the data analyzed, including the distinction between administrative zero and demand-absence zero that is the basis for data selection. Subchapter 4.1.2 outlines the characteristics of disbursement at the Development Implementation Unit (UPP) level to identify variations in patterns between work areas, as well as to prepare an empirical basis for hierarchical reconciliation. Subchapter 4.1.3 presents the classification of disbursement patterns based on Average Inter-Demand Interval (ADI) and Squared Coefficient of Variation (CV^2) which is the justification for choosing the IDF method. Subchapter 4.1.4 closes with the determination of the selection criteria for PRK which will be analyzed in Subchapter 4.2.

The analysis in this Subchapter uses primary data from the Budget Absorption Realization Report (LRPA) Form 11 of PLN UIP Sulawesi for 2021 to 2025 which has gone through the pre-processing stage as explained in Subchapter 3.4. The monthly disbursement realization data is presented after the transformation of the annual redistribution to deal with the negative value sourced from accounting corrections, so that the total annual disbursement is maintained according to the original data.

Portfolio Composition and Data Coverage

From the mapping results, there are 2,205 PRKs registered in the Mapping_PRK_UPP database, with distribution based on implementing units, namely UPP North Sulawesi (461 PRK), UPP Central Sulawesi (477 PRK), UPP South Sulawesi (685 PRK), and UPP Southeast Sulawesi (582 PRK). This number of PRKs reflects the overall non-routine investment portfolio that has been active for at least one year during the observation period.

The composition of the portfolio observed in each observation year shows significant dynamics, both in terms of the number of active PRKs and the total annual disbursement value.

The number of registered PRKs varies from 629 (in 2023) to 1,039 (in 2021), while the number of active PRKs is relatively more stable in the range of 261 to 359 PRKs per year. The percentage of active PRKs reached its peak in 2022 at 54.3% and the lowest in 2024 at 31.8%. Total annual disbursement shows a pattern that is also volatile, with a peak in 2023 of IDR 4,077.65 billion and a significant decrease in 2025 to IDR 1,836.82 billion. This decline indicates a shift in the intensity of non-routine investment activities at PLN UIP Sulawesi which needs to be further analyzed in the next subchapter.

A prominent phenomenon from the composition of the portfolio is the high proportion of PRKs that do not show disbursement activities in each year of observation. The accumulation of inactive PRKs over five years reached 1,246 PRKs (56.5% of the total 2,205 registered PRKs). This condition is sourced from the administrative mechanism of PLN UIP Sulawesi's investment portfolio, including PRKs whose implementation is delayed due to field constraints such as land acquisition, licensing, or completeness of payment documents, as well as PRKs whose implementation has been completed but has not been cleaned from the system due to linkages with other PRKs in one main work that is still ongoing. This condition is treated as administrative zero which is fundamentally different from demand-absence zero, as discussed in Subchapter 2.1.2.

The distinction between administrative zero and demand-absence zero has important methodological implications. PRKs that are categorized as Inactive during the observation period are excluded from the IDF analysis in Subchapter 4.2, because the absence of disbursement is not a foreseeable demand absence, but a consequence of the portfolio's administrative processes. Thus, the basis of IDF's analysis in this study is focused on PRKs that show at least one positive disbursement during the observation period, namely 959 active PRKs out of a total of 2,205 registered PRKs.

Characteristics of Disbursement per UPP

This study uses a three-level hierarchical structure as the basis for data aggregation, namely the Sulawesi Development Main Unit (UIP) level at the upper level, four Development Implementation Units (UPP) at the middle level, and individual PRK at the basic level. Four UPPs that become unit a

analysis at the intermediate level includes UPP North Sulawesi, UPP Central Sulawesi, UPP South Sulawesi, and UPP Southeast Sulawesi, with each UPP having different work area coverage and portfolio characteristics. The characterization of disbursement at the UPP level is important to be carried out as a basis for understanding the spatial pattern of PLN UIP Sulawesi's investment portfolio, as well as as a preparation for hierarchical reconciliation in Subchapter 4.4.

The dynamics of the distribution of active PRK are different between UPPs. UPP North Sulawesi recorded the highest active by-election in 2021 with 116 by-elections, but experienced a gradual decline to reach 68 by-elections in 2024 before rising back to 91 by-elections in 2025. A different pattern can be seen in the Central Sulawesi UPP which actually increased from 79 PRKs in 2021 to 125 PRKs in 2025, making it the UPP with the most active PRKs in the last observation year. UPP South Sulawesi and UPP Southeast Sulawesi show a relatively more stable pattern with a range of 50-105 active PRKs per year. The difference in dynamics between UPPs indicates that there is a difference in the rhythm of investment project implementation in each work area, which needs to be considered in the disbursement forecasting strategy.

Shows different disbursement patterns between UPPs and between years. UPP North Sulawesi and UPP Central Sulawesi generally dominate the value of disbursement, especially in the 2022-2023 period, with UPP North Sulawesi recording a peak value of IDR 1,825.94 billion in 2023. UPP South Sulawesi recorded the highest disbursement value in 2021 of IDR 1,317.21 billion, but decreased significantly in the following years. UPP Southeast Sulawesi consistently recorded the lowest disbursement value, with a range of IDR 96.45 billion to IDR 471.81 billion per year. The considerable variation in the disbursement value between UPPs reflects the difference in project scale and execution intensity in each work area.

The total disbursement of all Sulawesi UIPs shows a fluctuating pattern with a peak in 2023 of IDR 4,077.65 billion and a significant decrease in 2025 to IDR 1,836.82 billion. This decrease was mostly due to a decrease in disbursement in the North Sulawesi UPP and the Central Sulawesi UPP which previously dominated. This different disbursement pattern between UPPs provides a strong empirical basis for a hierarchical reconciliation approach with Weighted Least Squares (WLS), as large variance between UPPs is a key factor in determining reconciliation weights.

The characteristics of disbursement per UPP observed in this Subchapter provide two important implications. First, the difference in the implementation rhythm between UPPs shows that disbursement forecasting cannot be carried out uniformly, but rather needs to consider the unique characteristics of each UPP. Second, the large variation in disbursement values between UPPs strengthens the justification for using the variance-based hierarchical reconciliation method, since the reconciliation weight proportional to the variance will provide better accuracy than weightless reconciliation (Hyndman et al., 2011; Wickramasuriya et al., 2019).

Classification of Disbursement Patterns Based on ADI and CV^2

Classification of disbursement patterns is a crucial step in choosing the right forecasting method. This study uses the classification framework of Syntetos, Boylan, and Croston (2005) which divides intermittent demand patterns into four categories based on two indicators: Average Inter-Demand Interval (ADI) and Squared Coefficient of Variation (CV^2). ADI measures the average distance between periods with a positive disbursement, while CV^2 measures the variability of the disbursement value relative to the average. The thresholds used were **ADI = 1.32 and CV^2 = 0.49**

The four categories resulting from this classification framework include: Smooth (ADI $\leq$ 1.32 and $CV^2 \leq 0.49$) which show regular disbursement with low variability; (2) Erratic (ADI $\leq$ 1.32 and $CV^2 > 0.49$) which shows regular but variable disbursement; (3) Intermittent (ADI > 1.32 and $CV^2 \leq 0.49$) which showed infrequent disbursement with low variability; and (4) Lumpy (ADI > 1.32 and $CV^2 > 0.49$) which showed infrequent disbursement with high variability. The Inactive category is given to PRK that does not have a positive disbursement in the year of observation, so it cannot be classified.

Table 1. ADI/CV^2 Classification Distribution per Year

Year	Smooth	Erratic	Intermittent	Lumpy	Inactive	Total
2021	1	4	244	110	680	**1.039**
2022	1	20	228	103	296	**648**
2023	4	10	209	62	344	**629**
2024	1	14	161	85	561	**822**
2025	3	14	194	140	671	**1.022**

Source: processed data from LRPA Form 11 PLN UIP Sulawesi 2021-2025

Table 1 shows a very consistent classification pattern over the five years of observation. Of the total active PRKs each year, the Intermittent and Lumpy categories together dominate the distribution with a proportion of 94.4% to 98.6% of the total active PRK. The Smooth category, which shows regular disbursement with low variability, is only identified at 1-4 PRKs per year, while the Erratic category is identified at 4-20 PRKs per year. The consistency of this pattern provides a strong empirical justification for the selection of intermittent demand forecasting methods (Croston, TSB, and ADIDA) as the main forecasting methods in this study, as described in Subchapter 2.1.4.

If Table 1 presents the classification distribution on an annual basis, Figure 4.3 shows the position of all 959 active PRKs in the ADI–CV² field based on a full 60-month series (2021–2025). This full-series approach provides a comprehensive overview of the intermittent character of each PRK, not limited to one year of observation. The distribution shows that almost all PRKs are concentrated in the Intermittent and Lumpy quadrants as many as 957 out of 959 PRKs (99.8%) with only two PRKs classified as Erratic and none of them meeting the Smooth criteria. This very dominant concentration confirms that the disbursement data of PLN UIP Sulawesi is fundamentally intermittent, so the use of the Intermittent Demand Forecasting method (Croston, TSB, and ADIDA) is the right choice for the entire research population.

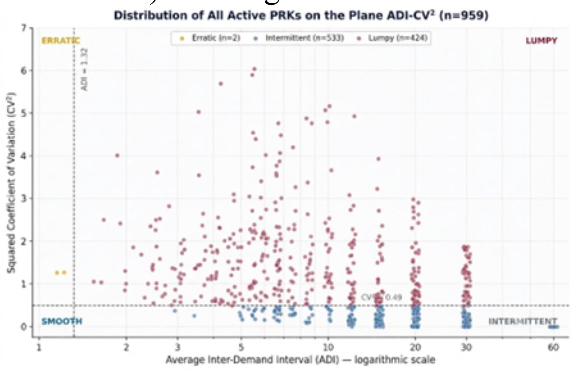

Figure 2. Distribution of All Active PRKs in the ADI-CV² Field (n=959).

Source: processed full series classification of 60 months (2021–2025) per PRK, processed with R.

To see if the classification pattern is consistent between UPPs, aggregation of classification distribution at the UPP level was carried out for five years of observation. By-elections that are active in several years will be recorded in each relevant year. The results are presented in Table 2.

Table 2. Classification Distribution per UPP (Aggregate of 5 Years of Active By-Elections)

UPP	Smooth	Erratic	Intermittent	Lumpy	Total
UPP North Sulawesi	3	17	298	139	**457**
UPP Central Sulawesi	2	21	299	160	**482**
UPP South Sulawesi	3	16	240	115	**374**
UPP Sulawesi	2	8	199	86	**295**

Source: processed data from LRPA Form 11 PLN UIP Sulawesi 2021-2025

Table 2 shows that the pattern of Intermittent and Lumpy dominance is consistent across the four UPPs, with the combined proportion of the two categories reaching 95.4% to 96.6% of the total active PRK per UPP. UPP Central Sulawesi recorded the highest total number of active by-elections over five years (482 by-elections), followed by UPP North

Sulawesi (457 by-elections), UPP South Sulawesi (374 by-elections), and UPP Southeast Sulawesi (295 by-elections). There is no UPP that has the characteristics of a disbursement pattern that deviates from the general pattern, so the intermittent pattern can be considered as a systemic characteristic of the PLN UIP Sulawesi portfolio, not a characteristic of a particular UPP. These findings reinforce the justification for applying the same methodological framework (IDF + hierarchical reconciliation) for all implementing units.

Further analysis was carried out on the stability of the classification of individual PRK between observation years. Of the total 2,205 registered PRKs, as many as 959 PRKs have been active for at least one year during the 2021-2025 period. The distribution of the number of active years for active PRK is presented in Table 3.

Table 3. Distribution of the Number of Active Years of the 2021-2025 By-Election

Number of Active Years	Number of by-elections	Percentage of Active By-Elections
1 year	594	61,9%
2 years	185	19,3%
3 years	105	11,0%
4 years	46	4,8%
5 years	29	3,0%
Total Active By-Elections	**959**	**100,0%**

Source: processed data from LRPA Form 11 PLN UIP Sulawesi 2021-2025

Table 3 shows that most of the active PRKs were only recorded as active in one year of observation, which was 594 PRKs or 61.9% of the total active PRKs. Only 29 PRKs that are active throughout the full five years (3.0%), while PRKs that are active for at least two years reach 365 PRKs (38.1% of active PRK). This pattern reflects the characteristics of PLN's infrastructure investment portfolio, which is dominated by projects with relatively short implementation cycles, so that the same PRK rarely appears in many years in a row.

For PRKs that are active for at least two years (365 PRK), an analysis of the stability of the classification category between years is carried out. The results showed that 170 PRKs (46.6%) had stable categories throughout their active years, while 195 PRKs (53.4%) experienced category changes between years. These findings show that more than half of the active PRKs whose stability can be evaluated show category dynamics between years. Implicitly, the static classification approach (the determination of a single category for the entire period) can cause misallocation of forecasting methods, so that the dynamic classification approach per year applied in this study is more in accordance with the characteristics of the data.

The results of the classification in Subchapter 4.1.3 provide three main implications. First, the dominance of the Intermittent and Lumpy categories consistently between years and between UPPs confirms the relevance of using the IDF method (Croston, TSB, ADIDA) as the main approach to disbursement forecasting at PLN UIP Sulawesi. Second, the characteristics of portfolios dominated by PRKs with short active durations require an adaptive forecasting strategy for new PRKs and PRKs that will be completed. Third, more than half of the PRKs that can be evaluated for stability have experienced changes in classification categories between years. These findings indicate the importance of periodic re-classification in forecasting practices, so that the methods used remain in accordance with the characteristics of the current data.

By-Election Selection Criteria for IDF Analysis

The selection of a subset of PRK that is the basis for the Intermittent Demand Forecasting (IDF) analysis needs to be carried out explicitly and documented so that the research results can be replicated and audited. The establishment of transparent selection criteria is also important to ensure that each PRK that goes into the analysis is truly relevant to the research objectives, as well as to clearly identify the analytical scope and limitations of the research.

The two main criteria used for the selection of PRK in this study include: first, the activeness criterion, i.e. the PRK must show at least one positive disbursement throughout the 2021-2025 observation period; and second, the data duration criterion, which is the number of active years that determines whether the PRK meets the minimum requirements for a particular evaluation technique. These two criteria in stages produce three analytical subsets that will be used in the three-stage analytical approach in Subchapters 4.2, 4.3, and 4.4. The full stages of the PRK selection are presented in Table 4.

Table 4. Funnel By-election selection

Selection Stage	Criteria	Number of by-elections	% of Population
Early Population	Mapping_PRK_UPP	2.205	100,0%
Administrative Zero	Inactive for 5 years	(1.246)	(56,5%)
Full Pilot Subset	Active for 5 full years (60 months)	29	1,3%
Rolling Origin Subset	Minimum 3 years active (≥36 months)	180	8,2%
Active By-Election (IDF Base)	Minimum 1 year active	959	43,5%

Source: processed data from LRPA Form 11 PLN UIP Sulawesi 2021-2025 and Mapping_PRK_UPP

The three subsets of the selection funnel are arranged based on the minimum data requirements demanded by the specific evaluation techniques for each analytical stage, so that they form a layered empirical basis that complements each other.

1. Full Pilot Subset (29 active PRKs 60 months) because the in-sample evaluation of the three IDF methods requires the most complete series of observations so that the method comparison can be carried out without the risk of insufficient data.
2. Subset of Rolling Origin (180 active PRKs for at least 36 months) because the expanding window rolling origin technique requires a minimum of 36 months to form an initial training window (Petropoulos & Kourentzes, 2015), while expanding the representation of portfolio characteristics through a substantially larger sample.
3. A subset of IDF-Based Active PRKs (959 active PRKs for at least one year) because the goal of the 2026 production forecast is maximum operational coverage, so that all active PRKs that have been actively included include short-duration PRKs whose relevance for cash planning is not inferior to full active PRKs.

Thus, the three subsets work in stages and complement each other: the IDF method is first tested on the small subset with the most complete data (Stage 1), then retested on the larger subset to ensure the results remain consistent (Stage 2), then applied to the entire portfolio to produce a forecast 2026 (Stage 3). With this phased approach, the chosen method is statistically tested before being used for the entire operational portfolio.

The first stage in the selection funnel is the exclusion of PRKs that are included in the administrative zero category, namely PRKs that are recorded in the Mapping_PRK_UPP database but do not show any positive disbursement at all during the five years of observation. A total of 1,246 PRKs (56.5% of the population of 2,205 PRK) were identified as administrative zero. This exclusion has been justified in Subchapter 4.1.1 by arguing that the absence of disbursement in the PRK is not a foreseeable demand absence, but a consequence of the administrative mechanism of the investment portfolio. After this stage of exclusion, the IDF's analysis base focused on 959 active PRKs representing 43.5% of the initial population.

The second stage in the selection funnel is the formation of a subset of PRKs that meet the minimum data duration requirements for rolling origin evaluation techniques. Rolling origin is a time-series cross-validation technique that requires a long enough data series to divide the observation period into training sets and test sets repeatedly. In this study, the criteria used were a minimum of three years of activity (equivalent to ≥36 months of observational data), which resulted in a subset of 180 PRKs or 8.2% of the population. The selection of the 36-month threshold is based on the literature recommendations of Petropoulos and Kourentzes (2015) who suggest a minimum of 24-36 observations for reliable forecasting evaluation on intermittent data, with a conservative approach of choosing upper bound to ensure statistical robustness (Hyndman et al., 2018). This subset of rolling origin then becomes the basis for out-of-sample evaluation for the selection of the best IDF method.

This study adopts a three-stage analytical approach to provide strong triangulation of evidence in answering both formulations of research problems. This approach uses three subsets of PRK in stages according to the analytical objectives of each stage. The first phase used a full pilot subset of 29 PRKs that were active for a full five years as a methodological pipeline validation on the richest data conditions, with an in-sample evaluation of Mean Absolute Error (MAE). The second stage used a subset of rolling origin 180 PRK to provide a reliable estimate of out-of-sample forecasting errors through the rolling origin technique with 13 iterations of the expanding window. The third stage uses all 959 active PRKs for the production forecast in 2026, accompanied by the application of three hierarchical reconciliation methods (Bottom-Up, Top-Down, and Weighted Least Squares) whose methodological details have been described in Subchapter 3.6.

The above three-stage analytical approach allows the inclusion of PRKs with a short active duration (1-2 years) into the analysis without compromising the reliability of the evaluation. PRKs that are active for one year as many as 594 PRKs and active PRKs for two years as many as 185 PRKs, as shown in Table 4.6 Subchapter 4.1.3, are still included in Phase 3 (production forecast at 959 PRK) but are not included in Phase 2 (rolling origin) because the duration of the available data does not allow time-series cross-validation. This strategy follows the practice of the intermittent demand forecasting literature which recommends the maximum inclusion of PRK in production to capture portfolio diversity, while maintaining the robustness of evaluation in a subset that qualifies duration (Croston, 1972; Syntetos and Boylan, 2005).

In addition to the two main criteria above, one supporting criterion is applied to ensure the feasibility of hierarchical reconciliation in Phase 3: each of the four UPPs (UPP North Sulawesi, UPP Central Sulawesi, UPP South Sulawesi, and UPP Southeast Sulawesi) must have at least one PRK that is included in the rolling origin subset in order for error evaluationper UPP can be done. Data verification showed that these criteria were met on all four UPPs, so that a three-level hierarchical structure (UIP-UPP-PRK) could be constructed coherently for all stages of analysis.

With the empirical basis of the three-stage analytical approach already described, the next subchapter presents three types of complementary results. Subchapter 4.2 presents Phase 1 results in the form of in-sample performance of three IDF methods (Croston, TSB, and ADIDA) on a subset of pilot 29 PRKs, which provides methodological pipeline validation on overall data conditions. Subchapter 4.3 presents the results of Phase 2 in the form of an out-of-sample evaluation with rolling origin on a subset of 180 PRKs, which is the basis for selecting the best IDF method for Phase 3. Subchapter 4.4 presents the results of Phase 3 in the form of a production forecast for 2026 at 959 active PRKs accompanied by a comparison of three hierarchical reconciliation methods. The consolidation of findings from the three stages and the explicit answers to the two formulations of the research problem are presented in Subchapter 4.5.

The three stages of the study form a series of mutually reinforcing evidence (triangulation), with the scope of PRK progressively expanding from 29 PRKs (Phase 1), 165 PRKs (Phase 2), to 959 PRKs (Phase 3). Figure 2 visualizes the framework.

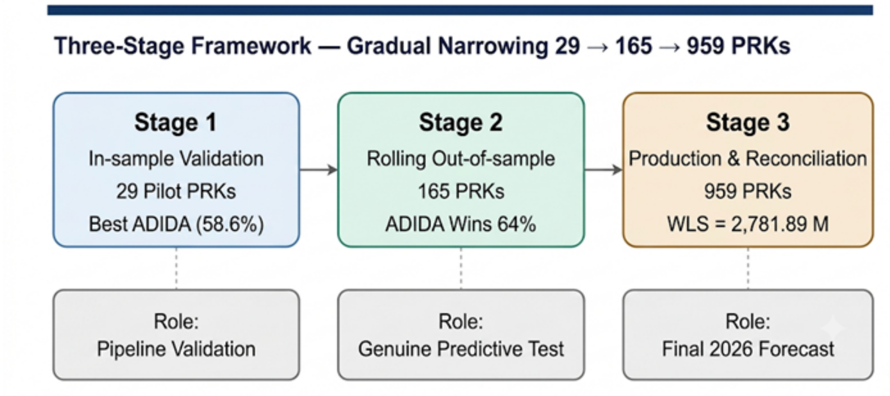

Figure 3. Three-Stage Research Framework

Source: Author's design based on the three-stage analytical approach described in Section 3.6, with PRK selection criteria derived from LRPA Form 11 PLN UIP Sulawesi (2021-2025)

This broad narrowing of scope reflects methodological logic. Phase 1 uses the most stringent subset (29 PRKs with a full 60-month history) to validate the pipeline under ideal conditions; Phase 2 expands to 165 PRKs for realistic out-of-sample predictive testing ; and Phase 3 includes all 959 active PRKs to produce a production forecast for 2026. The roles of the three are different but sequential: pipeline validation, method selection, and production. ADIDA's consistent excellence in all three stages confirms that the findings are not artifacts of a single test method, but rather results that converge across evaluation contexts.

Answer to the First Problem

RQ1: Among the Croston, TSB, and ADIDA methods, which one produces the most accurate forecast for intermittent disbursement at PLN UIP Sulawesi?

Answer: ADIDA with the selection of optimal k per by-election (k ∈ {3, 6, 12}) is the best IDF method for the context of PLN UIP Sulawesi disbursement.

This answer is supported by five mutually reinforcing arguments. First, the statistical dominance is consistent: ADIDA won 58.6% of the PRK in Phase 1 and 64.2% of the PRK by MAE in Stage 2, with a convergent winning pattern on the win rate by MASE (64.8%) indicating that ADIDA's advantage is not artifactal from the selection of certain metrics. Second, the lowest error magnitude : ADIDA's median monthly MAE (IDR 175,432 in Phase 2) is 14% lower than Croston (IDR 203,495) and 8% lower than TSB (IDR 190,749), with an efficiency of 99.03% relative to the Oracle benchmark. Third, the smallest systematic bias: ADIDA's median ME of −Rp 8,328 was 60% lower than Croston's (−Rp 20,567) and 42% lower than TSB's, indicating higher estimation reliability for periodic planning. Fourth, successful full execution: ADIDA managed to provide valid forecasts on all 959 active PRKs in Phase 3 (100%) including the ultra-sparse PRKs that led to Croston's failure in 15 PRKs in Phase 2. Fifth, adaptive flexibility: the different distribution of k_best between the subset of pilots (k=3 dominant 41.4%) and production (k=12 dominant 60.4%) shows that ADIDA clearly adjusts the smoothing strategy to the intermittent character of each PRK, a capability that Croston or TSB do not possess as a single method.

The mechanism that makes ADIDA superior is temporal aggregation which combines short periods into aggregate blocks before exponential smoothing is applied, then proportional disaggregation back to the monthly level for output. This approach, as described by Nikolopoulos et al. (2011), serves as a noise filter while maintaining the main signal in the data with a high level of intermicity. In the context of PLN UIP Sulawesi, which is dominated by Lumpy and Intermittent patterns (94.4% to 98.6% of active PRK as shown in Subchapter 4.1.3), the data character is very much in accordance with ADIDA's working mechanism, so that the empirical advantages observed in this study have a solid theoretical basis.

Although the median MASE TSB (0.8952) is lower than ADIDA (1.0129), the selection of ADIDA as the primary method is based on the win-rate by MASE (64.8% PRK) which illustrates the dominance of the method on a per-PRK basis, rather than an aggregate. The low median MASE of TSB is due to TSB's ability to generate near-zero value forecasts in ultra-sparse PRKs, so the MASE is artificially low even though the absolute value (MAE) is not smaller. ADIDA's consistency of win-rate in both metrics (MAE: 64.2%, MASE: 64.8%) shows a robust advantage over the choice of metrics.

Answer to the Second Problem

RQ2: What is the effectiveness of hierarchical reconciliation (Bottom-Up, Top-Down, and WLS) on the consistency and accuracy of forecast disbursement in the UIP-UPP-PRK hierarchy?

Answer: Hierarchical reconciliation is applied to ADIDA's base forecast through three scenarios: Bottom-Up (BU), Top-Down (TD), and Weighted Least Squares (WLS) all of which ensure coherence between levels but with different distribution characteristics. Among the three, WLS is the most suitable reconciliation scenario for the operational context of PLN UIP Sulawesi, with a total forecast for 2026 of IDR 2,781.89 billion

Before reconciliation, the base forecast at three levels showed an incoherence of Rp 791.43 billion, which is the difference between the total UIP (Rp 3,056.49 billion) and the sum of four UPPs (Rp 2,265.06 billion), while the sum of 959 PRK resulted in Rp 2,968.11 billion. : ADIDA reads different patterns in the series with different aggregation levels. Without reconciliation, organizations cannot use all three estimates simultaneously because they will result in decisions that contradict each other at different levels. Reconciliation is a structural imperative for consistent operational planning across organizational levels.

The selection of WLS as the optimal method is based on three mutually reinforcing arguments. First, the accuracy-based weighting argument: WLS utilizes information from all levels of the hierarchy by giving greater weight to the level with the least error, i.e. the level with the most accurate forecast history (Hyndman et al., 2011). This weight is calculated from the inverse MAE in-sample of each level, namely the smaller the error, the greater the weight, so that the most reliable level has the greatest influence in determining the final result. In the context of PLN, the UPP-level series has the lowest in-sample MAE because the aggregation of hundreds of PRKs produces a smoother series but not over-smoothed like the UIP-level. WLS automatically assigns a dominant weight to the UPP-level, generating a forecast that uses the UPP as the backbone with corrections from PRK (detail) and UIP (macro). Second, the operational argument: WLS forecast of IDR 2,781.89 billion is IDR 183.94 billion lower than the five-year historical average, this conservative output is in line with the goal of minimizing idle cash which is the dominant operational risk at PLN as described in Subchapter 2.3. In a context where cash shortfall is not a material risk due to the RKAP–SKAI-AKB mechanism, a slightly lower than historical forecast reduces the probability of budget over-allocation. Third, a practical argument: WLS can be automated and audited through automatically calculated weights without subjective parameters, thus meeting the auditability needs that are the basic principles of SAP S/4HANA in the implementation of SSoT Wave 3.

Operational Implications and Recommendations for the Management of PLN UIP Sulawesi

The results of this research do not stop at the selection of forecasting and reconciliation methods, but are directed to answer the needs of PLN UIP Sulawesi's cash management in a concrete way. The placement of disbursement forecasting in the corporate cash management function as stated by San José et al. (2008) which places cash forecasting as one of the core functions of the treasury (Subchapter 2.3.1) makes the accuracy and coherence of forecasting not just a statistical technical issue, but a prerequisite for efficient liquidity decision-making. The consolidation of the findings of the following three analytical stages translates into four groups of operational implications and tiered recommendations for management.

Recommendations for the Preparation of the 2026 RKAP Baseline based on WLS

The management of PLN UIP Sulawesi is recommended to use a WLS forecast of IDR 2,781.89 billion as the baseline for the 2026 annual disbursement allocation, with the distribution per UPP: Central Sulawesi IDR 1,009.25 billion (36.3%), North Sulawesi IDR 871.65 billion (31.3%), South Sulawesi IDR 523.63 billion (18.8%), and Southeast Sulawesi IDR 377.35 billion (13.6%). This recommendation is rooted in the principle of capital budgeting (Graham & Harvey, 2001; Subchapter 2.3.2): capital budgeting decisions are the starting point of the entire disbursement chain, so that a more accurate upstream baseline lowers the risk of realization deviations downstream.

WLS's advantage over Bottom-Up (IDR 2,968.11 billion) and Top-Down (IDR 3,056.49 billion) alternatives is strategic for treasury. A more conservative total WLS (about 6–9% lower than BU/TD) means a non-over-committed cash allocation. In the framework of working capital optimization Deloof (2003) and the cash holdings theory of Opler et al. (1999) (Subchapter 2.3.3), the cash allocated in excess but not disbursed becomes idle cash that bears the opportunity cost. WLS thus balances two risks: it is enough to fund real disbursement, but it does not hold back excess liquidity that can be transferred to other units in PLN's corporation.

Recommendations for Operationalization to the Monthly Cash Budget (AKB)

The PRK level forecast matrix (forecast_prk_wls, 959 PRKs × 12 months) is recommended as the initial input for the preparation of the Monthly Cash Budget (AKB) document. However, this study confirms one important principle that is in line with the characteristics of infrastructure project disbursement: the results of statistical models must pass a qualitative review of the UPP planner before being determined. This is because PLN's disbursement pattern is administrative zero, which is a period without disbursement generally due to administrative/field constraints (land acquisition, licensing, completeness of payment documents, dependence on sub-projects), not the absence of real needs. This kind of specific field factor, as implied in the investment phasing structure (Subchapter 2.3.2), is not fully captured by the time-series model and requires a correction of the domain of expertise.

Adaptive Re-forecast and Uncertainty Quantification Recommendations

The ADIDA + WLS pipeline execution speed (approximately 13 seconds for 959 PRKs) allows for monthly re-forecasting whenever the latest realization is available. This adaptive planning capability answers the inherent uncertainty of cash forecasting discussed in Subchapter 2.3.4 where forecasts are not static single numbers, but estimates that must be updated with new information. Management is recommended to set a minimum annual and ideally quarterly re-calibration cycle, in line with the rhythm of the preparation of the RKAP revision.

As a strengthening agenda, the WLS point forecast results can be developed into a P50/P90 prediction interval to support the determination of risk-based cash buffers. Although this probabilistic quantification is beyond the scope of current research, the direction of its development has been prepared by the uncertainty quantification framework in Subchapter 2.3.4, so that management obtains not only point estimates but also relevant ranges for conservative liquidity decisions.

Recommended Integration into the SAP S/4HANA SSoT Ecosystem

The most strategic implication lies in PLN's readiness to welcome the implementation of SAP S/4HANA Single Source of Truth (SSoT) Wave 3 which is scheduled to go live in October 2027 for UIP Sulawesi. As described in Subchapter 2.4.2, the SSoT architecture provides a hierarchical data structure (UIP–UPP–PRK) natively which has been a methodological prerequisite for this study and must be manually reconstructed from the LRPA data. With SSoT, these prerequisites are met automatically, so that the ADIDA–WLS pipeline can be ported from the R environment to the SAP ecosystem via Anaplan as a budget forecasting modeling layer.

Concrete recommendations for management: position WLS output as a statistical baseline that is fed to Anaplan, then adjusted collaboratively by Head Office and UPP planners. This hybrid approach combines the power of statistical forecasting (objectivity, speed, auditability of the WLS weight matrix) with the domain of organizational expertise (field knowledge of administrative constraints). The auditability of WLS, whose weight matrix can be traced back to the empirical roots of the in-sample level, is an important added value in the context of SOEs that demand accountability and traceability of budget decisions.

Table 5. Summary of Tiered Recommendations for Management

Level	Recommendations	Theoretical Basis (Chapter II)
Strategic	Adoption of WLS IDR 2,781.89 Billion as the baseline of the 2026 RKAP	2.3.1 Cash forecasting; 2.3.2 Capital budgeting
Tactical	forecast_prk_wls as input of AKB + UPP review planner	2.3.2 Investment phasing; Administrative Zero
Operational	Monthly/quarterly re-forecasting; develop P50/P90	2.3.4 Quantification uncertainty
Systemic	ADIDA–WLS pipeline port to Anaplan/SAP SSoT (2027)	2.4.2 SSoT architecture as an enabler

Source: Author's synthesis based on research findings and theoretical framework, 2025

Research Limitations and Advanced Research Agenda

The main limitation of this study lies in the use of a single-method approach, namely ADIDA was chosen as a method to forecast the entire PRK portfolio based on the dominance of the win-rate in Phase 1 and Phase 2. This approach is effective and proven to be superior in aggregate, but ADIDA's advantages are dominant, not absolute. In Phase 2, ADIDA won 64.2% of PRK based on MAE and 64.8% based on MASE, which means that there are still about one-third of PRCs where TSB or Croston actually produce higher accuracy. By applying the same method to all PRKs, the potential accuracy in some of these PRKs has not been fully utilized.

This limitation opens up a further research agenda in the form of the development of an adaptive method selection framework based on PRK classification. By assigning a single method to the entire portfolio, the framework maps each PRK to the IDF method that best corresponds to its intermittent pattern, following the Syntetos–Boylan–Croston classification (Smooth, Erratic, Intermittent, and Lumpy) that has been built in Subchapter 4.1.3. Since the stability analysis in Subchapter 4.1.3 shows that 53.4% of PRK changes categories between years, this framework needs to be paired with periodic re-classification so that the methods applied always adapt to the latest data character. This kind of adaptive approach has the potential to improve aggregate accuracy beyond the single-method approach applied in this study, while also making the findings of this study the foundation for such development.

In addition to the methodological limitations above, there are three research agendas that can expand the contribution of these findings. First, replication in other PLN units outside

Sulawesi to test the generalization of findings to the context of investment portfolios with different geographical characteristics. Second, integration with cross-series information such as disbursement correlations between PRKs in the same UPP due to field resource sharing; this dependency modeling has the potential to improve reconciliation accuracy through richer covariance structures. Third, the development of a real-time forecasting dashboard that integrates WLS output into PLN's cash planning system, with the ability to automatically re-forecast when new realizations enter the SAP S/4HANA system. These three agendas together form a roadmap for the transformation of PLN's forecasting disbursement from an experimental approach to integrated operational capabilities.

The consolidation of the findings and the answers to the two problem formulations that have been presented in this subchapter closes Chapter IV of the research. A comprehensive conclusion of the research contribution, along with strategic suggestions for the utilization of the findings by PLN UIP Sulawesi and the agenda for further research, is presented in Chapter V.

CONCLUSION

This study aims to answer two main problems, namely determining the best method to predict the intermittent disbursement of Non-Routine Investment Budget Expenditure at PLN UIP Sulawesi and choosing a hierarchical reconciliation approach that is in accordance with the organizational structure. The study uses a TSB-Croston–ADIDA approach based on hierarchical reconciliation through three stages of analysis, namely in-sample validation in 29 pilot PRKs for the period January 2021-December 2025, out-of-sample evaluation with expanding window rolling origin in 180 active PRKs, and production forecast in 2026 in 959 active PRKs. The results of the study show that ADIDA is the most effective Intermittent Demand Forecasting (IDF) method compared to Croston and TSB. In the validation stage, ADIDA won 58.6% of the pilot PRK with a median MAE of IDR 721,539, while in the out-of-sample evaluation, ADIDA dominated with a win rate of 64.2% based on MAE and 64.8% based on MASE. ADIDA's advantage is due to its temporal aggregation capabilities that reduce noise and maintain key patterns in data with high intermittency rates. Furthermore, the Weighted Least Squares (WLS) approach was chosen as the best hierarchical reconciliation method because it was able to produce coherent forecasts between levels by considering the level of accuracy of each hierarchy. WLS generated a total forecast disbursement in 2026 of IDR 2,781.89 billion, which was distributed to the four UPPs proportionally. This research makes a methodological contribution through the integration of IDF method selection, hierarchical reconciliation, and multi-stage forecasting evaluation in one systematic pipeline. Practically, the resulting model can support PLN UIP Sulawesi's cash planning and the integration of the SAP S/4HANA Single Source of Truth (SSoT) system to improve the accuracy of investment cash flow management.

REFERENCES

Croston, J. D. (1972). Forecasting and stock control for intermittent demands. *Operational Research Quarterly, 23*(3), 289–303. https://doi.org/10.2307/3007885

Deloof, M. (2003). Does working capital management affect profitability of Belgian firms? *Journal of Business Finance & Accounting, 30*(3–4), 573–588. https://doi.org/10.1111/1468-5957.00008

Graham, J. R., & Harvey, C. R. (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics, 60*(2–3), 187–243. https://doi.org/10.1016/S0304-405X(01)00044-7

Hollyman, R. A. (2024). *Forecasting in hierarchical systems: Improving accuracy, enhancing scalability and managing risk.*

Hyndman, R. J., Ahmed, R. A., Athanasopoulos, G., & Shang, H. L. (2011). Optimal combination forecasts for hierarchical time series. *Computational Statistics & Data Analysis, 55*(9), 2579–2589. https://doi.org/10.1016/j.csda.2011.03.006

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and practice* (2nd ed.). OTexts. https://otexts.com/fpp2/

Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting, 22*(4), 679–688. https://doi.org/10.1016/j.ijforecast.2006.03.001

Hyndman, R. J., Lee, A. J., & Wang, E. (2016). Fast computation of reconciled forecasts for hierarchical and grouped time series. *Computational Statistics & Data Analysis, 97*, 16–32. https://doi.org/10.1016/j.csda.2015.11.007

Kourentzes, N. (2014). On intermittent demand model optimisation and selection. *International Journal of Production Economics, 156*, 180–190. https://doi.org/10.1016/j.ijpe.2014.06.007

Kumar, S. (2025). Integrating top-down and bottom-up forecasting in supply chain intelligence. *Journal of Engineering and Computer Sciences, 4*(8), 206–213.

Nikolopoulos, K. (2021). We need to talk about intermittent demand forecasting. *European Journal of Operational Research, 291*(2), 549–559. https://doi.org/10.1016/j.ejor.2019.12.046

Nikolopoulos, K., Syntetos, A. A., Boylan, J. E., Petropoulos, F., & Assimakopoulos, V. (2011). An aggregate–disaggregate intermittent demand approach (ADIDA) to forecasting: An empirical proposition and analysis. *Journal of the Operational Research Society, 62*(3), 544–554. https://doi.org/10.1057/jors.2010.32

Opler, T., Pinkowitz, L., Stulz, R., & Williamson, R. (1999). The determinants and implications of corporate cash holdings. *Journal of Financial Economics, 52*(1), 3–46. https://doi.org/10.1016/S0304-405X(99)00003-3

Petropoulos, F., & Kourentzes, N. (2015). Forecast combinations for intermittent demand. *Journal of the Operational Research Society, 66*(6), 914–924. https://doi.org/10.1057/jors.2014.62

PLN. (2025a). *Decree of the Board of Directors of PT PLN (Persero) No. 0332.K/DIR/2025 concerning the establishment of a Single Source of Truth Team*. PT PLN (Persero).

PLN. (2025b). *Guidelines for the implementation of Single Source of Truth (SSoT) based on SAP S/4HANA*. PT PLN (Persero).

PLN. (2025c). *Senior leader socialization material: Roadmap for the implementation of SSoT Wave 1–3*. PT PLN (Persero).

San José, L., Iturralde, T., & Maseda, A. (2008). *Treasury management vs. cash management: A particular study with Spanish firms* (Working Paper Series). University of the Basque Country (UPV/EHU).

Syntetos, A. A., Boylan, J. E., & Croston, J. D. (2005). On the categorization of demand patterns. *Journal of the Operational Research Society, 56*(5), 495–503. https://doi.org/10.1057/palgrave.jors.2601841

Teunter, R. H., Syntetos, A. A., & Babai, M. Z. (2011). Intermittent demand: Linking forecasting to inventory obsolescence. *European Journal of Operational Research, 214*(3), 606–615. https://doi.org/10.1016/j.ejor.2011.05.018

Vespoli, S., De Martino, M., Grassi, A., & Guizzi, G. (2026). An auction-based mechanism for decentralised backlog management in Industry 4.0 semi-heterarchical architectures. *International Journal of Production Research, 64*(4), 1436–1460.

Wickramasuriya, S. L., Athanasopoulos, G., & Hyndman, R. J. (2019). Optimal forecast reconciliation for hierarchical and grouped time series through trace minimization. *Journal of the American Statistical Association, 114*(526), 804–819. https://doi.org/10.1080/01621459.2018.1448825