Allowance for Loan and Lease Loss: Organizing Data & Analytics for Success

Beyond Data Aggregation & Compliance Reporting

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Executive Summary

The Allowance for Loan and Lease Losses (ALLL) is one of the most critical line items on a bank's financial statement—and a focus of intense regulatory scrutiny. Examiners seek to ensure that a bank's ALLL methodology is compliant with a number of key regulatory provisions, including:

- Staying abreast of ALLL regulatory changes and their impact on the reserve
- Evaluating impaired loans according to ASC 310-10-35 (FAS 114) and applying the correct impairment analysis
- Applying collateral value, present value of cash flows or Loan pricing methods
- Ensuring appropriate ACS 450-20 (FAS 5) methodology, with accurate loss rates and qualitative factor adjustments for each pool
- Ensuring compliance with IFRS9 loss recognition
- Providing adequate documentation, and satisfying ASU 2010-20 disclosure reporting requirements

The biggest challenge banks face in computing ALLL is gathering data from disparate sources or spreadsheets through manually-intensive, error-prone, and time-consuming processes. All too often, ALLL production demands an excessive effort from bank staff—requiring 80-hour work weeks.

Teradata and Fuzzy Logix can help banks greatly improve the efficiency, accuracy, and regulatory compliance of their methodology. By organizing the bank's ALLL data in a central repository with embedded analytics, they can enhance the quality, consistency, and timeliness of their calculations.

ALLL Defined

Expected Losses = Exposure at Default x Probability of Default x Loss Given Default

The Allowance for Loan and Lease Losses (ALLL) consists of two pieces: calculated components and judgmental components. Many institutions use the ALLL models in business as usual planning as well as DFAST/CCAR/BCAR and BCBS 239 requirements. Additionally IFRS9 compliance places additional requirements for loss recognition.

Scope of Data Required

Original transaction data at the atomic loan level, along with slowly changing data (e.g., payment history and risk ratings) across all portfolios, must be used for regulatory ALLL calculations. They must also be used as the foundation for other regulatory calculations, including BCBS 239 and Comprehensive Capital Analysis and Review (CCAR). Unfortunately, this data is usually distributed across multiple databases and divisions within the bank, making it difficult to integrate for timely calculations. Additionally, reconciliation with the General Ledger is difficult since it provides only aggregated views, and is rarely able to trace back to full data detail at the source.

To build high-quality models, the regulatory burden of data quality and data governance is very high for this foundational regulatory and transactional data. Once the data quality is sufficient, models can be developed that stack upon results from other models. Judgment factors can also be applied with reasonable confidence in the security of capital adequacy, and consequent government approvals.

Scope of Models Required

Given the present portfolio, ALLL models must reflect the expected scenario over the next one-year horizon.

New requirements under the principles-based IFRS9 intensify the requirement for strong internal data for all components of the balance sheet. The loss forecasting will have more complex assessments of cash flows calculations, asset class categorization, balances and loss measurements (including lifetime expected credit losses).

For use in Dodd Frank Annual Stress Testing (DFAST) and CCAR, regulators provide scenarios with multiple key economic variables to reflect the implications of various risk factors on capital security. Bankers calculate the impact of the variables on key metrics, such as starting balances and exposure on revolving credit. ALLL models must perform under multiple scenarios, including multiple baseline and stress scenarios.

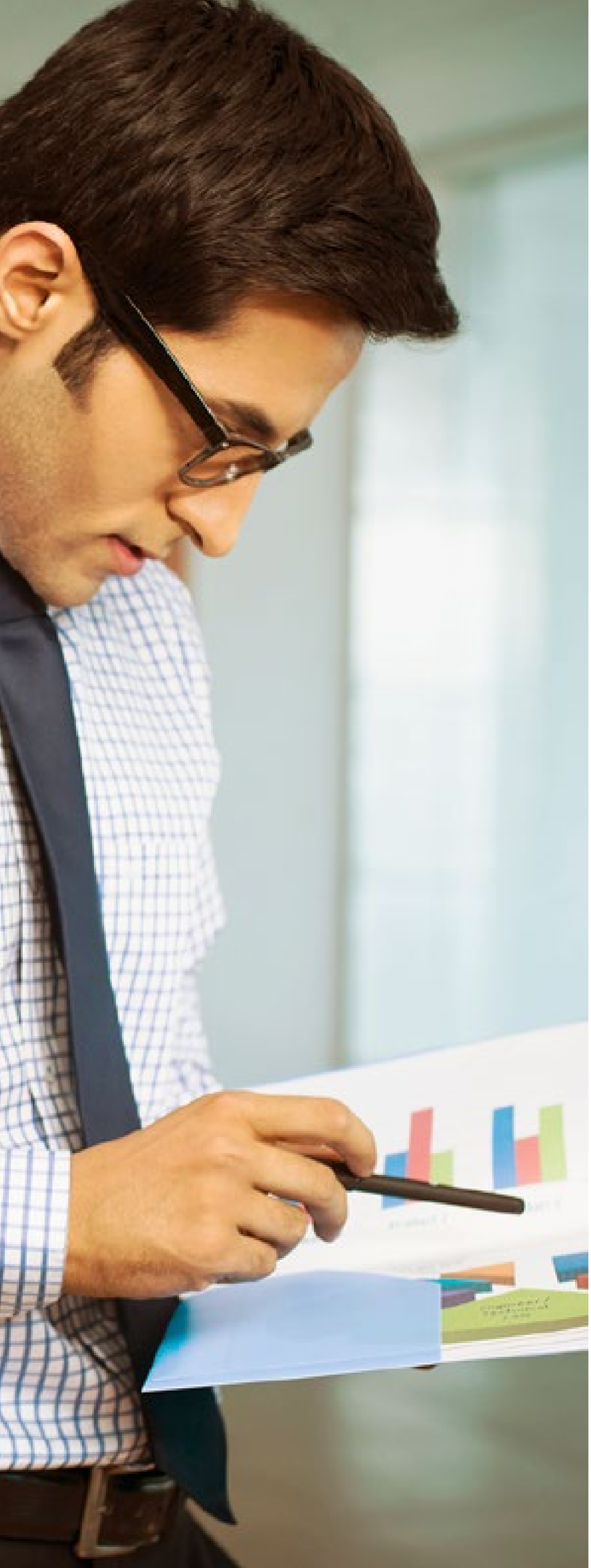
To meet the many new regulatory requirements, ALLL model development requires a long history of reliable data—and the necessary variables for loss estimation and loss drivers that are responsive to economic scenarios.

Additionally, a nimble infrastructure is required for quick updates of loss forecasting to address ad hoc requests from management or regulators, or to quickly reassess loss forecasts due to economic or market shifts. The process may include the following steps:

- Identify model development data requirements and available data sources
- Assess data sources and potential uses in model development
- Model development includes several key steps that are dependent on having sufficient, complete, and accurate data—as well as reliable and efficient model development platforms:
  - Identification of appropriate model segmentation (e.g., along lines of asset classes) that is supported by the historical data, statistical analysis, and business segments
  - Definition and calculation of the outcome to be measured (e.g., lifetime losses) on historical data, and where proxies are required
  - Model methodology selection, such as the type of regression, simulation approaches, use/combination of multiple models, and use of expert judgment
  - Gather reliable candidate variables by classes, such as customer characteristics/performance, portfolio characteristics, and economic, sector or market drivers

Data Aggregation Process and System Constraints

Data—when aggregated and reconciled to the General Ledger, and specific to account level—can be useful for many business purposes. Marketing, regulatory reporting, profiling risk by portfolio, CCAR/DFAS/BCAR, and most other business functions benefit from this reconciled, consistent, and detailed data. This improves regulatory response time, and satisfies Regulator requirements for consistent process and data quality (BCBS 239).



  - Variables selected among classes of variables, including statistical selection procedures and business review (often an iterative process)
  - Model fit / final model design within selected methodology, variable selection, and additional analyses deployed for the model design process
  - Model statistical testing for key model performance requirements
  - Model sensitivity analysis, outcomes analysis / back-testing, and benchmarking of final model
  - Final model documentation of all data attributed, decisions and supporting analysis
- Independent model validation to include conceptual soundness review, data review, statistical testing, sensitivity analysis, outcomes analysis, and benchmarking. For independent validation methodology review and benchmark, models are critical to challenge the model design choices made by the developer
- Model implementation and production, including accurate and efficient data delivery and coding. There are increasing requirements for:
  - Fast implementation of model enhancements and/or updates
  - Movement, merging, and transforming of multiple large sets of data
  - Fast production of results with strong control systems to ensure reliability of results

How it Works Today

The problems with compiling a sufficient, complete, and accurate dataset for model development are fundamental to model development. There are often many distributed datasets with varying data accuracy and completeness of available variables and history.

Organizationally, there may be many locally-maintained databases aggregating the same source data in different manners. Additionally, different groups or divisions may be conducting slightly different calculations of losses—often due to different business uses, different interpretations of the requirements, or different uses of judgment in the final estimates/calculations. These varied local databases and calculations are not easily integrated or reconciled, making the presentation of a final "correct" answer (or a single version of the truth) challenging or even impossible under the current architecture.

Vision for a Streamlined ALLL Process

The ideal state is the integration of data in a dynamic manner from source systems that make it easily accessible for real-time calculations—while supporting enhancements to calculations and models, as needed.

This provides for loss models and forecasting that are based on well-defined business and regulatory requirements; can be quickly adapted, redeveloped, or enhanced to changing requirements or business needs (in efficient, controlled and reliable platforms); can be quickly implemented and aggregated into production systems; and produce reliable results with limited overhead.

Data modeling, forecasting, and reporting need to be nimble with respect to changes in a wide variety of regulatory, business, market, and economic factors, including:

- Lending policies and procedures, including changes in underwriting standards and collection, charge-off, and recovery practices not considered elsewhere in estimating credit losses
- International, national, regional, and local economic and business conditions and developments that effect cash flows and the collectability of a portfolio, including the condition of various market segments
- Nature and volume of a portfolio and in terms of loans and distribution across different segments and asset classes, which can be increasingly complex under IFRS9
- Experience, ability, and depth of lending management and other relevant staff—including their ability to define and refine portfolio strategies and apply expert judgment
- Volume and severity of past due loans, the volume of nonaccrual loans, and the volume and severity of adversely classified or graded loans

The ideal state is the integration of data in a dynamic manner from source systems that make it easily accessible for real-time calculations—while supporting enhancements to calculations and models, as needed.

- Quality of the institution's loan review system, rating philosophy, and ratings migration observed historically and currently
- Value of underlying collateral for collateral-dependent loans, and any changes in rules that impact fair value recognition under different scenarios or unexpected economic or market changes
- Existence and effect of any concentrations of credit, and changes in the level of such concentrations
- Effect of other external factors such as competition, economic, industry, legal and regulatory requirements on the level of estimated credit losses in the institution's existing portfolio

Simulation of results based on multiple and substantially different economic scenarios are often inefficient and

Hypothetical Bank Risk Rating Scheme

Bank Rating	Regulatory Classification	Rating Agency Equivalent	Expected Default Rate (bps)
1	Pass	Aaa	0
2	Pass	Aa	2
3	Pass	A	2
4	Pass	Baa	12
5	Pass	Ba	72
6	Pass	B	304
7	Special Mention	Caa	1335
8	Sub-Standard	Caa	1335
9	Doubtful	Caa	1335
10	Loss	Caa	1335

Figure 1. For illustration purposes only.

prone to error given the often-times many manual steps involved with the process. When economic drivers feed simulations, Fuzzy Logix provides the flexibility to incorporate parameters, starting values, and adjustments that feed Monte Carlo simulations to help refine human judgment with calculated spectrum of possible and likely outcomes.

Proposed Teradata Calibration Tool for Judgmental Portion of ALLL

Discretionary or Judgmental Attributes
1. Changes in lending policies and procedures, including changes in underwriting standards and collection, charge-off, and recovery practices not considered elsewhere in estimating credit losses.
2. Changes in international, national, regional, and local economic and business conditions and developments that affect the collectability of the portfolio, including the condition of various market segments.
3. Changes in the nature and volume of the portfolio and in the terms of loans.
4. Changes in the experience, ability, and depth of lending management and other relevant staff.
5. Changes in the volume and severity of past due loans, the volume of nonaccrual loans and the volume and severity of adversely classified or graded loans.
6. Changes in the quality of the institution's loan review system.
7. Changes in the value of underlying collateral for collateral-dependent loans.
8. The existence and effect of any concentrations of credit, and changes in the level of such concentrations.
9. The effect of other external factors such as competition and legal and regulatory requirements on the level of estimated credit losses in the institution's existing portfolio.

Figure 2

For example, internal ratings are developed based on internally developed models for risk ratings. These risk ratings are correlated to reference model Probability of Default (PD) ratings from agencies such as Moody's, S&P, and Fitch.

Figure 1 illustrates a risk rating scale, how it converts to the corresponding regulatory classification, and how it evolves to Moody's and other ratings through efficient simulations based on multiple scenarios.

For ALLL and loss forecasting, it is imperative to lock down an end-to-end sequence of data feeds and calculations for transparent, consistent, and validated results. This allows banks to include historical and current state information in the required demonstrable processes, while supporting consistent and timely insight to assist in re-calibrating quantitative factors—and verifying qualitative factors with real-time performance metrics.

This also allows banks to support consistent and timely insight to assist in re-calibrating judgmental factors. See Figure 2.

Fuzzy Logix Capabilities

Fuzzy Logix DBLytix® software is a library of analytic functions that are installed and run in the Teradata platform, leveraging the massively parallel processing architecture of Teradata to deliver unsurpassed processing times for analytics. DBlytix is invoked within the SQL environment, making it accessible to the organization's business analysts who are familiar with the world's most popular business querying language.

Embedding analytics with the data in one environment means that time and expense aren't wasted on moving data to specialized computing environments. Data governance and security are simplified, and time isn't spent trying to aggregate modeling components developed in remote environments. Layered modeling tasks like ALLL and CCAR are performed under one roof, meaning that downstream dependencies can run just as soon as upstream results are computed, eliminating the wait time for hand-offs. Models and algorithms can be hard-coded into the Teradata appliance to ensure that querying and analysis are performed in a seamless process—and with guaranteed consistency and accuracy.

More efficient processes mean that multiple scenarios can be explored in the same amount of time it would take to run just one, deepening insights and resulting in improved final answers.

Conclusion

Teradata and Fuzzy Logix offer the tools needed to rationalize the disparate parts of the ALLL process into a streamlined whole, greatly improving consistency, timeliness, and accuracy. By integrating data and analytics into a central repository, banks have an unmatched ability to ensure the quality, transparency, and control of the process—pleasing regulators and making the ALLL process more manageable for everyone involved. Shortened process times give banks greater flexibility to analyze emerging risks, and provide a much needed edge for gaining regulatory approval for annual capital plans.

Together, Teradata and Fuzzy Logix can help with detailed solution development—either onsite or analytics-as-a-service—including data integration, calculation algorithms, and process management. Data movement can be expensive and slow, and introduce error. Teradata and Fuzzy Logix can help your organization with more efficient and consistent data, analytics, and processes for ALLL and related CCAR requirements.

To learn more about how your organization can leverage a sophisticated analytics platform to uncover valuable business insights—and simplify compliance with regulatory demands—visit teradata.com/contact-us.

About the Authors

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Over three decades experience in the financial services industry with emphasis in Enterprise Risk Management, including risk rating process; underwriting and loan review; KPI reporting; credit risk & portfolio monitoring; data integration and decision sciences; regulatory reporting and analytics; allowance for loan loss, CCAR, and Dodd Frank Stress Testing.

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