Optimizing Financial Ratios with AI: A Dynamic Control Framework for Credit Institutions

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ABSTRACT

This study presents a new approach to the internal control in credit institutions by proposing a closed-loop framework that replaces static financial ratio thresholds with dynamic, adaptive boundaries. Compared to conventional Machine Learning (ML), which only emphasizes forecasting, the proposed approach integrates multivariable regression with multi-objective optimization to convert predictions into a real-time control mechanism. The methodology includes a composite objective function that minimizes deviations from optimal financial ratios while penalizing allocations with high predictive uncertainty. The novelty of the study lies in the dynamic normative boundary, a time-dependent reference that synthesizes historical benchmarks, model-derived optima, and market signals. A comprehensive ratio framework based on asset structure was implemented, and its applications were demonstrated through a case study of Aregak Co. (Armenia). The results identify a capital surplus of 483% above the optimum and demonstrate the framework's capacity to uncover strategic pathways for enhancing Return on Equity (ROE) by up to 14%, all within explicit risk constraints. This study establishes a viable architecture for transforming internal control from a periodic compliance exercise into a continuous process of strategic optimization.

Keywords-artificial intelligence; internal control; credit institution; financial ratio optimization

I. INTRODUCTION

The application of Artificial Intelligence (AI) in financial analysis has become a focus of research, with ML and deep learning models outperforming traditional analytical approaches [1, 2]. Research demonstrates that the role of AI has evolved from merely accelerating routine computations to generating predictive, contextualized, and decision-relevant insights [3-5]. A particularly active research direction involves using AI to enhance the accuracy and timeliness of financial reporting and diagnostics. It has been shown that ensemble and hybrid neural architectures outperform conventional statistical techniques in critical areas, such as credit-risk forecasting and non-performing loan prediction [6-8], underscoring that AI offers not only speed but also substantially improved reliability.

This transformation is particularly important for credit institutions, where accurate credit-risk evaluation and consistent internal control are essential for regulatory compliance. It has been demonstrated that hybrid ML-based credit scoring models can achieve higher predictive accuracy and lower error rates than traditional scoring approaches when applied to real-world credit datasets [9]. In parallel, AI- and ML-driven credit assessment frameworks increasingly incorporate alternative data sources to enhance borrower evaluation, improve confidence in automated decisions, and support financial inclusion, while simultaneously raising the need for transparent and ethical governance structures [10]. Moreover, contemporary credit-risk assessment frameworks emphasize the integration of traditional financial indicators, advanced statistical methods, and ML tools within unified evaluation architectures, enabling continuous risk reassessment and improved portfolio-level monitoring compared to purely periodic or expert-based verification practices [11].

Instead of relying solely on manual checks or scheduled audits, AI systems enable real-time, monitoring of transactional and risk-related indicators, thereby enhancing the consistency of internal control and improving the robustness of supervisory reporting [12]. In addition, advanced anomaly-detection algorithms, including intrusion-detection mechanisms, are developed for cybersecurity and IoT systems, and adapted for financial compliance monitoring, enabling faster identification of suspicious behavior, non-compliance, or potential fraud [13, 14]. This indicates a significant improvement over legacy cycle-based audit approaches which have historically dominated internal control practices.

In addition to AI-centered developments, contemporary internal control frameworks are shaped by supervisory standards such as Basel III/IV capital requirements, internal control guidelines, and risk-management expectations established by financial regulators [15, 16]. These standards emphasize dynamic capital planning, forward-looking risk assessment, and continuous monitoring of ratio trajectories. Incorporating these regulatory principles into the proposed architecture strengthens the alignment between AI-driven optimization and supervisory compliance.

Authors in [17] found that a credit institution's asset structure holds significant explanatory power for predicting key financial variables, including profit, income, capital, and liabilities, using multivariate regression. While that work successfully validated the forecasting module, its outputs remained numerical estimates. These predictions were not translated into actionable control boundaries; thus, the model served as a predictor but not as a driver of strategic alignment.

Accordingly, this study proposes an operational closed-loop internal control framework, in which an AI-based forecasting model becomes a dynamic control instrument. The key contribution of this study lies in (i) the formalization of a dynamic normative boundary operator, (ii) embedding it inside a multi-objective ratio optimization structure, and (iii) demonstrating its viability on a real credit institution dataset.

II. METHODOLOGY

ML-based forecasting and multi-objective ratio optimization are integrated into a unified architecture that converts predictive outputs into dynamic control boundaries. The methodology builds upon the regression engine developed in [17].

A. Forecasting Model

The base model [17] employs multiple linear regression, in which key financial outcomes (profit, income, capital, and liabilities) are predicted based on the institution's asset structure components. The statistical evaluation of the base model demonstrated a strong fit, with the coefficient of determination (R^2) ranging from 0.81 to 0.93 across different target variables and a Root Mean Square Error (RMSE) ranging from 2.8% to 6.4%. While this ensures high interpretability and computational efficiency, the model's core assumptions (linearity and homoscedastic errors) represent its primary limitation, particularly in the case of non-linear market dynamics or structural portfolio shifts. These specific limitations served as motivation for the improvements presented in this study. These improvements include the integration of time-weighted estimation, multi-objective optimization, and the novel dynamic normative boundary operator.

Let $X = (x_1, x_2, \dots . x_p)$ denote the asset structure vector. Forecasted financial variables (profit, income, capital, or liabilities) are represented as $Y(X)$, indicating their functional dependence on the asset composition. The predictive model is expressed through the multivariable linear regression [18]:

$$Y(X) = \beta_0 + \sum_{i=1}^{p} \beta_\mathrm{i} \, x_i + \epsilon, \tag{1}$$

where β_0 is the intercept term, β_i are the regression coefficients quantifying the marginal contribution of the asset component x_i to the financial variable $Y(X)$, and ϵ is the error term, assumed to be independent and identically distributed with zero mean and constant variance.

Parameter estimation is performed by minimizing the residual sum of squares:

$$RSS = \sum_{t=1}^{n} \omega_t \left(y_t - \beta_0 - \sum_{i=1}^{p} \beta_i \, x_{i,t}\right)^2 \tag{2}$$

where y_t is the observed target variable at period t, $x_{i,t}$ is the i^{th} asset component, and ω_t is a time decay weight that increases the effective contribution of recent observations.

B. Multi-Objective Optimization Problem

Forecasts from (1) become input parameters for a multi-objective optimization problem where the objective simultaneously penalizes deviations of financial ratios from their optimal levels and penalizes portfolio states with high prediction uncertainty. The composite optimization target is defined as:

$$\min_X F(X) = \sum_{k=1}^{K} \omega_k \left(\frac{\theta_k(X) - \theta_k^{opt}}{\theta_k^{opt}}\right)^2 + \gamma Tr(\Sigma(X)) \tag{3}$$

where $\theta_k(X)$ is ratio k evaluated at the asset structure X, θ_k^{opt} is the model-derived optimal ratio value, ω_k is the ratio weight reflecting strategic preference, γ is the regularization parameter controlling uncertainty penalty intensity, and $Tr(\sum(X))$ represents the forecast uncertainty penalty.

The first term in (3) minimizes relative deviations from optimal ratio targets, while the second term penalizes asset allocations with high aggregate prediction uncertainty, ensuring that solutions remain within statistically reliable regions.

The optimization is subject to a system of regulatory and institutional constraints, formalized as:

- Credit risk: Portfolio default probability not exceeding 0.03.
- Liquidity risk: Liquidity coverage ratio not falling below 100%.
- Concentration risk: Herfindahl-Hirschman index not exceeding 0.35.

These regulatory-compliant constraints ensure that the optimized asset allocation maintains prudent risk levels while pursuing profitability targets, creating a balanced approach to financial optimization, which aligns with both institutional risk appetite and regulatory requirements. The resulting constrained optimization problem was solved using a quasi-Newton method with a backtracking line search. A numerical convergence tolerance of 10–6 was utilized for the gradient norm. To mitigate the risk of converging to local minima, the optimization routine was initiated from multiple starting points within the feasible domain, consistently yielding the same solution, which reinforces confidence in the result.

While multi-objective problems are often analyzed via Pareto fronts, the operational need of a financial institution for a single, consistent, and auditable supervisory target necessitates scalarization with fixed strategic weights. The implications of this choice are partially addressed through a sensitivity analysis of the strategic weights ω_k.

C. Dynamic Normative Boundary Formation

Internal control is not based on static normative limits. Instead, normative targets become time-dependent values constructed as weighted combinations of historical benchmarks, model optimal values, and market signals. The dynamic normative reference for a ratio θ is expressed as:

$$\theta^{norm}(t) = \alpha(t)\theta^{hist} + \big(1-\alpha(t)\big)\theta^{opt} + \beta\Delta_m(t) \quad (4)$$

where θ^{hist} is the historical benchmark value of the ratio, typically defined as a rolling window average or an exponential moving average of its past observations, $\alpha(t) \in [0,1]$ is a volatility-dependent weighting coefficient between historical and optimal values, β is the market-signal coefficient, and $\Delta_m(t)$ is an adjustment derived from market conditions such as interest rate movements or credit spreads.

The weighting coefficient $\alpha(t)$ was calibrated as an inverse function of short-term volatility of the corresponding ratio, such that more volatile ratios place greater emphasis on historical benchmarks, while stable ratios rely more heavily on model-derived optima. In experimental configurations, $\alpha(t)$ ranged between 0.42 and 0.68. The market-signal coefficient β is set to zero in the current operational version; however, back testing indicated that values between 0.05 and 0.15 produce stable behavior once sufficiently frequent market data streams are incorporated.

Although the market-adjustment term is inactive in the present implementation, the intended set of market indicators includes credit spreads, the central bank policy rate, the interbank refinancing rate, and the yield curve slope. These indicators are designed to be updated every month, with a one-period lag imposed to prevent look-ahead bias in supervisory decision-making.

In the complete architecture, all three terms of (4) are conceptually present; however, in the present implementation, the market-dependent adjustment term was set equal to zero. This corresponds to a reduced operational form of (4), where the normative reference was computed solely from historical benchmarks and model-derived optimal values. Thus, the theoretical model is three-component, while the current implementation is two-component.

Equations (1-4), therefore, form a closed loop. The forecasting block maps asset composition to financial variables. The optimization block determines the structurally efficient ratio configuration. The dynamic normative boundary formation transforms the optimized ratio targets into supervisory reference thresholds that evolve through time. The system can then operate as a dynamic internal control mechanism, because observed ratio trajectories are continuously evaluated relative to $\theta^{norm}(t)$, but not relative to fixed constants.

Figure 1 illustrates the closed-loop architecture integrating forecasting, optimization, and dynamic normative boundary formation mechanisms.

The schematic shows the forward information flow from the asset structure vector through the forecasting block, then into the multi-objective optimization module, and finally into the dynamic normative boundary formation layer. The resulting time-dependent supervisory targets are subsequently fed back to the internal control monitoring block, establishing a closed-loop configuration rather than a static threshold system. In addition to the main forward flow, the schematic of the framework also shows the exogenous inputs that feed each block.

Historical financial datasets, specifically, the aggregated balance sheet and income statement time-series for the Armenian banking sector published by the Central Bank of Armenia [19], are used for the forecasting engine to estimate the regression coefficients. Strategic ratio weights ω_k, regularization parameter γ, and regulatory portfolio constraints are provided to the multi-objective optimization module. Historical benchmarks and market signals enter the dynamic normative boundary formation block to construct time-dependent supervisory reference thresholds. These explicit input flows highlight that parameterization is not implicit, but instead an integral part of the control loop configuration.

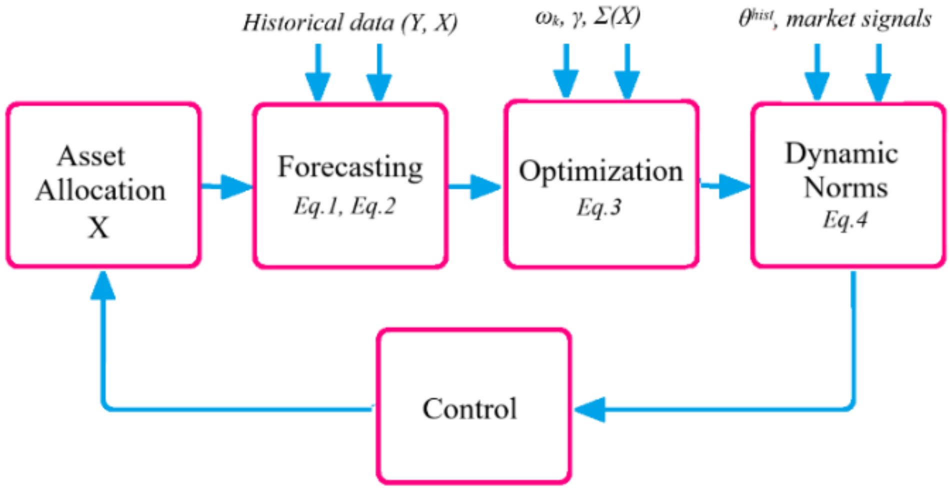

Fig. 1. Schematic of the proposed dynamic control framework.

III. FINANCIAL RATIO FRAMEWORK AND IMPLEMENTATION RESULTS

A. Comprehensive Ratio Framework

The complete ratio framework integrates twelve financial ratios in a unified optimization structure that is fully compatible with (3). Each ratio is an explicit function of the asset structure vector X and the forecast outputs of (1). Profitability is represented through Return on Assets (ROA) and ROE:

$$ROA(X) = \frac{Profit(X)}{Assets(X)}, ROE(X) = \frac{Profit(X)}{Capital(X)}$$

which captures asset utilization efficiency and the value creation density for equity. Ratios, such as Profit to Earning Assets and Profit to Income, reflect operational extraction efficiency from income-generating assets and net operating margin quality. These profitability functions directly influence the first summation term of (3) through their squared deviation from θ_k^{opt}, and their relative importance is expressed by weight ω_k.

Table I presents typical values of ω_k derived from the empirical analysis of credit institutions' strategic priorities and expert assessment of financial stability frameworks using the analytic hierarchy process based on the standard Saaty and Vargas scale [20]. The weighting scheme reflects the relative importance assigned to each ratio category in achieving balanced financial performance, with profitability receiving the highest priority due to its direct impact on institutional sustainability and growth.

The capital structure resilience is quantified using complementary leverage ratios that measure balance sheet composition and financial cushion. The core metrics are defined as:

$$\theta_{L1}(X) = \frac{Assets(X)}{Total\ Capital(X)}, \theta_{L2}(X) = \frac{Total\ Capital(X)}{Liabilities(X)}$$

which together define the degree to which capital absorbs balance sheet exposure.

This constraint block ensures optimization stability by eliminating solutions that achieve profitability targets through excessive financial leverage. The dynamic nature of these ratios is incorporated through (4), where their normative targets $\theta^{norm}(t)$ evolve based on historical patterns, model-derived optima, and current market conditions, particularly credit spread fluctuations and regulatory requirement changes.

TABLE I. STRATEGIC WEIGHTS FOR FINANCIAL RATIO CATEGORIES

Category	Strategic weight	Rationale
Profitability	0.35	Based on regulatory focus on sustainable earnings and survey data from bank strategic plans
Leverage and stability	0.30	Derived from capital adequacy requirements and financial stability indicators
Asset efficiency	0.25	Calculated from industry benchmarks for asset utilization in emerging markets
Risk adjustment	0.10	Determined from historical loss data and stress testing scenarios

Asset efficiency metrics serve as critical connectors between portfolio composition and operational performance, quantifying how effectively the institution deploys its resources to generate income. Ratios, such as Earnings Assets to Total Assets, measure the productive allocation of the portfolio, while Credit Investments to Assets assesses business concentration and sectoral exposure. These metrics directly reflect the quality of asset structure decisions and their impact on revenue generation capacity.

Since all financial variables, both numerators and denominators, are derived from the predictive model outputs in (1), any modification to the asset allocation vector X, produces coordinated, simultaneous changes across all ratio categories. The framework, thus, operates not as a simple collection of independent indicators, but as an integrated state-dependent mapping:

$$X \to \{\theta_{profit}(X), \theta_{leverage}(X), \theta_{efficiency}(X)\}.$$

This integrated approach ensures that the optimization identifies the asset structure X, which minimizes the composite objective function in (3), achieving balanced improvement across all financial dimensions without creating suboptimal trade-offs or unintended imbalances between profitability, stability, and efficiency goals.

B. Case Study

To validate the practical applicability of the proposed framework, an in-depth case study of Aregak Co. (Yerevan, Armenia) [21] was conducted. Aregak Co. is a universal credit institution with a strategic focus on lending to small and medium-sized enterprises and financing "green" [22] and agricultural projects [23]. This focus on development lending and higher-risk segments often necessitates a conservative capital structure to ensure stability, providing a highly relevant context for testing the proposed optimization framework. The diagnostic analysis compares the institution's actual financial ratios with both sector benchmarks and the model-derived optima, revealing specific pathways for strategic improvement.

The comprehensive results of this analysis are presented in Table II. In this study, "Norm" refers to the sector benchmark levels, calculated as arithmetic means across a representative sample of 12 major peer institutions within the Armenian credit market, covering over 85% of the market share. Data were aggregated for the period 2012-2024 from publicly available annual financial statements. These normative values serve as external reference points and are used solely for interpretive comparison, whereas the optimization target values originate from the model-derived optima.

The data presented in Table II reveal three critical aspects of the company's financial condition.

Profitability optimization cluster analysis shows that the company demonstrates strong profitability performance, which significantly exceeds sector normative benchmarks while remaining below model-optimized targets. The institution's ROA of 11% substantially outperforms the sector normative value of 4.03%, though it remains below the model-optimized target of 15%. The ROE of 13% shows a similar pattern, which is strong against the sector normative 7.65% but with significant potential toward the model-proposed 27%. This indicates efficient current operations but substantial upside through strategic optimization, as defined by the proposed multi-objective framework in (3), with the profitability cluster carrying a combined strategic weight of 0.35 in the optimization objective.

Leverage and stability matrix assessment reveals that the institution exhibits exceptionally conservative financial structure, with capital adequacy ratios that dramatically exceed both sector norms and optimization targets. The assets to total capital ratio of 1.164 indicates minimal leverage utilization compared to the sector normative 1.90 and model proposal of 1.81. The extraordinary total capital to liabilities ratio of 611% versus the normative 111% demonstrates significant underutilization of debt financing capacity, suggesting an opportunity for strategic leverage increase within the dynamic boundary constraints established in (4). This conservative stance directly impacts profitability metrics, as excessive capital dilutes ROE despite adequate operational performance.

TABLE II. COMPREHENSIVE RATIO ANALYSIS

Category	Ratio	Actual	Model	Norm	Gap
Profitability	ROA	11%	15%	4.03%	+4%
	ROE	13%	27%	7.65%	+14%
	Profit to earning assets	12%	15%	5.97%	+3%
	Profit to income	49%	67%	34.5%	+18%
Leverage	Assets to total capital	1.164%	1.81%	1.90%	+0.646%
	Total capital to liabilities	611%	128%	111%	-483%
	Total capital to assets	86%	56%	52.7%	-30%
	Liabilities to assets	14%	44%	47.3%	+30%
Efficiency	Earning assets to assets	94%	97%	92.7%	+3%
	Credit investments to assets	84%	56%	57.8%	-28%
	Financial leasing to assets	0%	15%	16.3%	+15%
	Fixed assets to assets	1%	1%	1.04%	0%

The analysis identifies the institution's primary strategic challenge as excessive financial conservatism constraining profitability, directly addressable through the optimization of the proposed framework. The practical implementation requires establishing a responsive control mechanism that operates within the boundaries defined by (4). For the case study institution, this translates to a phased asset reallocation strategy governed by the adaptive control algorithm [24]:

$$X_{t+1} = X_t + \gamma(\theta_{norm} - \theta_t)\nabla_X \mathrm{F(X)}$$

where X_{t+1} represents the target asset allocation for the next period, X_t is the current allocation, γ is the adjustment rate parameter calibrated to institutional risk tolerance, θ_{norm} is the dynamic normative boundary from (4), θ_t is the current ratio value, and $\nabla_X \mathrm{F(X)}$ is the gradient of the objective function from (3).

The institution's capital levels were found to be 483% above the model-optimized target, indicating a significant opportunity cost. Model simulations suggest that a strategic redeployment of this excess capital could potentially enhance ROE by up to 14 percentage points, while the dynamic boundary mechanisms ensure that financial stability is maintained within predefined constraints.

A targeted sensitivity analysis was performed to evaluate the robustness of the optimization outcomes with respect to the exogenously set strategic weights ω_k and the uncertainty-penalty parameter γ. Each parameter was perturbed within a ±20% interval—consistent with standard supervisory robustness tests—and the optimization problem was resolved for each configuration. Across all perturbations, the ordering and directional tendencies of the proposed ratios remained unchanged, indicating that the solution is structurally stable. Variations in γ within the range 0.05-0.25 influenced only the intensity of uncertainty penalization but did not alter the qualitative structure of the optimal asset allocation. These results confirm that the model yields robust supervisory signals under plausible parameter variations.

To further assess the general applicability of the proposed framework beyond the primary case study, the full forecasting and optimization pipeline was also applied to a second major credit institution operating in the Armenian market. The model identified a similar structural conservatism in the capital structure and provided optimization signals that were qualitatively consistent in direction and magnitude. This replication of core findings across two distinct institutions strengthens the evidence for the robustness and general applicability of the proposed dynamic control framework. The optimization framework can accommodate strategically important but lower-profit activities by modifying strategic ratio weights, adding dedicated policy-driven constraints, or adjusting target values θ_k^{opt}. This ensures that priority projects aligned with national or institutional mandates can be incorporated into the optimization task without compromising supervisory rigor.

The monitoring infrastructure enables real-time surveillance of financial ratio deviations, with automated alert protocols triggering predefined response mechanisms when dynamic normative boundaries are breached. This ensures continuous risk control throughout the optimization cycle, validating the practical utility of the AI-driven framework for enhancing internal control systems while maintaining financial stability.

The implementation demonstrates how credit institutions can systematically transition from conservative positions to optimized capital structures without compromising risk management objectives.

IV. CONCLUSION

This study presented an Artificial Intelligence (AI)-driven dynamic control framework designed to transform the internal control systems of credit institutions into adaptive, optimization-oriented architectures. Unlike conventional static approaches, the proposed model integrates Machine Learning (ML) forecasting with multi-objective ratio optimization and introduces a dynamic normative boundary that continuously adjusts supervisory thresholds based on historical data and model-derived optima. This integration enables a closed-loop configuration where predictive analytics directly inform real-time financial control and decision-making.

Experimental validation through the case study of Aregak Co. (Armenia) demonstrated the framework's practical applicability and strategic value. The results indicated a capital surplus of 483% above the optimal level, implying a substantial opportunity to enhance Return on Equity (ROE) by up to 14% through controlled reallocation of assets, while maintaining compliance with credit, liquidity, and concentration risk constraints.

The proposed architecture provides a systematic foundation for adaptive financial governance, where internal control parameters evolve in response to institutional performance and market dynamics. Future research will focus on extending this approach toward real-time supervisory applications, incorporating market signal integration, and developing regulatory learning modules to further enhance financial system resilience and efficiency.

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