Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AP07.20260151
Published: March 25, 2026

A CAMEL-Based Optimization Framework for Risk Reduction and Performance Improvement in Cooperative Banks

Siddhesh Atul Nagle, Debjyoti Bose and Mridul Singh Rajput
National Institute of Technology
Raipur, Chhattisgarh, India
msrajput.me@nitrr.ac.in

Abstract

In India, cooperative banks are extremely relevant to the financial sector especially in promoting local and small-scale economic activities. Nonetheless, numerous such institutions still struggle with persistent issues concerning a decrease in the quality of assets and low levels of profitability. This paper puts forward an optimization-based structure utilizing the conventional CAMEL (Capital Adequacy, Asset Quality, Management Efficiency, Earnings Ability, and Liquidity) framework in a purely diagnostic fashion and examines its application as a decision support tool. This research paper will rely on six years of audited financial information (2019-2024) of an urban cooperative bank to calculate and rank CAMEL indicators according to the provisions of the Reserve Bank of India. The findings of this evaluation show that Net Non-Performing Assets (Net NPA) and Return on Assets (ROA) are persistently weak indicators and therefore require targeted intervention. Goal Programming is used to solve these problems by modifying the NPA generation rate, recovery rate, and provisioning rate to come within realistic operation constraints to reduce Net NPA. Simultaneously, the ROA is optimized with the help of NSGA-II (Non-dominated Sorting Genetic Algorithm II) that optimizes two values, which are income level and asset level. It is implied that Net NPA can be decreased to 1.97% instead of 7.46% and ROA may increase to 0.90% instead of 0.72%, which would lead to a decrease in the total CAMEL score 14 (Moderate Risk) to 10 (Low Risk). All in all, the framework offers a realistic and reproducible method for small cooperative banks in need of increased regulatory compliance and financial sustainability because of systematic optimization.

Keywords
CAMEL Framework, Cooperative Banking, Goal Programming, NSGA-II, Net NPA, ROA, Financial Optimization, Risk Management

1. Introduction
The segment of financial infrastructure in India, which is of particular importance in the rural and semi-urban regions, where the number of commercial banks is comparatively small, is comprised of cooperative banks. These institutions are significant in the mobilization of local savings, provision of credit to small lenders, and the operation of the economy at the community level. Meanwhile, there are still numerous cooperative banks, particularly Tier-2 Urban Cooperative Banks (UCBs), that are still challenged structurally. The increase in the non-performing assets, small profit margins, small capital buffers, and operational restrictions in most instances make these banks unable to maintain high standards regarding the expectations of the regulators.

The CAMEL framework was initially created by the banking regulators in the United States and was subsequently borrowed by the Reserve Bank of India (RBI) providing a standardized approach to assessing the performance of banks in five dimensions, namely Capital Adequacy, Asset Quality, Management Efficiency, Earnings Ability and Liquidity. Practically, CAMEL is mostly applied when regulatory testing is conducted to identify the state of finances

and risk exposure. Nevertheless, it has been used in a largely retrospective form. Although CAMEL scores may be used to establish areas of concern, by itself, the framework does not give much advice on how the weaknesses can be overcome. This restriction is especially applicable at small cooperative banks, which in many cases are not well equipped analytically to translate diagnostic measurements to tangible improvement plans. Figure 1 represents the optimization framework that is used in this study.

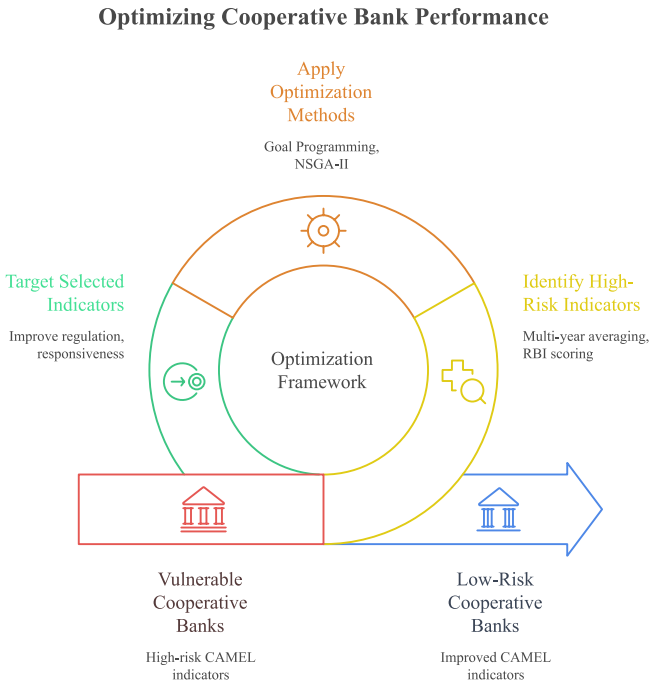

Figure 1. Optimization Framework

The paper aims to fill the gap between the CAMEL-based diagnosis and prescriptive improvement by introducing a framework of optimization that aims at addressing the most vulnerable indicators of CAMEL and deliberates on the possible way of improving these indicators. The given strategy involved the integration of Goal Programming to minimize Net NPA, a problem that mostly depends on requirements of recovery and provisioning with NSGA-II to optimize ROA where the trade-offs between income generation and asset utilization should be balanced. Using these methods on audited financial information on a cooperative bank, the research paper demonstrates how the traditional CAMEL test may be used to go beyond diagnosis to effective decision support.

The paper can be summed up in three sections with its contributions. One, it presents a systematic process of high-risk CAMEL indicators identification based on multi-year averaging and RBI similar scoring limits. Second, it uses two complementary methods of optimization to solve different kinds of performance problems in a banking setting. Third, it provides statistical data that the overall risk rating of the bank may change to Low Risk and selected indicators be targeted with the potentially beneficial effect on regulation evaluation and responsiveness of operations.

2. Problem Formulation

2.1 Applications of CAMEL Framework:

The CAMEL framework has found extensive application in the literature for assessing banking performance across a wide range of institutional and geographical settings. Many studies have used CAMEL as a diagnostic instrument to assess financial health and to help compare banking institutions. As an example, Roman and Şargu (2013) used the CAMELS framework in relation to Romanian commercial banks and showed its relevance in determining the changes in financial stability. The framework has been actively applied to Indian public, private, and nationalized banks, and

Kaur (2010), Dash and Pathak (2011), and Siddiqui (2012) observe that it can be useful in comparative performance analysis.

In addition to India, CAMEL based analysis has also been implemented in other developing economies, which again confirms the strength of the analysis in both regulatory and institutional contexts. Ahmed (2014) has studied the example of Bangladesh and demonstrated that CAMEL measurements can offer valuable information on profitability, asset quality, and capital adequacy on the example of the private commercial banks. Likewise, the applicability of CAMEL as an instrument of banks of any scale to measure their performance was highlighted by Parikh (2018).

The CAMEL framework has also been implemented in studies that examine cooperative banks to a relatively small degree. Fiordelisi and Mare (2013) examined the group of European cooperative banks and developed a connection between the CAMEL-related efficiency indicators and the default probabilities, which demonstrates the applicability of the framework to the institutions that are managed by cooperative ownership arrangements. Overall, literature supports the effectiveness of CAMEL in determining the strengths and weaknesses of the banking performance. Nevertheless, most of the available research are descriptive and retrospective in nature, and they focus more on the performance evaluation than the creation of systematic mechanisms to cope with the mentioned weaknesses.

2.2 Optimization Techniques in Banking

In parallel to the CAMEL-based evaluation studies, there are significant literatures available on optimization methods to enhance the performance of the banking system in various objectives and regulatory limits. Such issues have been tackled with Goal Programming where conflicting goals need to be reconciled as in the case of asset-liability management. The multi-objective optimization models of bank balance sheet control were pioneered by Eatman and Sealey (1979) and Kusy and Ziemba (1986). Giokas and Vassiloglou (1991) also established the suitability of Goal Programming in balancing asset and liability decision-making under operation constraints.

Following works extended Goal Programming into banking. Kosmidou and Zopounidis (2004) used the method in case of the Greek banks to balance the competing financial goals within the regulation, whereas Lee and Kim (2000) used uncertainty in the bank asset-liability optimization models. Viswanathan et al. (2014) used Goal Programming to model asset allocation and liability composition in the Indian banking context, showing it as the appropriate tool in the scenario of regulatory inflexibility and the presence of multiple priorities. In more recent studies, Goal Programming approaches have been applied to financial statement management and optimization of the overall bank performance, respectively, by Halim et al. (2015) and AlArjani and Alam (2021), respectively. All these studies indicate for Goal Programming to be a useful tool in solving decision problems in the banking industry where objectives are prioritized and constraints are binding.

Besides classical methods of optimization, there has been an upsurge in the application of evolutionary algorithms to trade-offs in financial optimization problems. Deb et al. (2002) presented NSGA-II as a quick and effective multi-objective genetic algorithm which has the ability of producing Pareto-optimal solutions. Although NSGA-II has been used in most applications in the context of portfolio optimization, recent literature, including Tuan et al. (2024), has shown that it can be useful in addressing high-dimensional financial decision-making. Though most applications are oriented towards investment and predicting failures, a multi-objective nature of NSGA-II is appropriate in a scenario of internal bank optimization where profitability and risk and considerations need to be trade-offs.

2.3 Regulatory Context and Practical Constraints

A significant factor that is mostly ignored when considering the optimization of banking is that of regulatory restrictions especially when it comes to cooperative banks. In India, the urban cooperative banks are governed by stringent prudential norms established by the Reserve Bank of India such as the rules on the recognition of income, classification of assets, provisioning, and others (Reserve Bank of India, 2020). Moreover, Revised Supervisory Action Framework of UCBs is focused on risk identification early enough and corrective actions because of supervisory assessment (Reserve Bank of India, 2021).

These regulatory specifications introduce binding restrictions on the decision-making of managers and restrict the practicability of aggressive optimization strategies. As a result, optimization structures disregarding regulatory levels can deliver mathematically optimal, but practically infeasible solutions. This shows the necessity of optimization models, which are clearly based on regulatory norms and adapted to the realities of cooperative bank operations.

2.4 Research Gap and Problem Formulation

The analysis of the current literature has shown that there are several gap areas. To begin with, CAMEL-based research does not pay much attention to the translation of diagnostic findings into prescriptive improvement policies, as much as it concentrates on the diagnosis of the banking performance and the comparison of institutions (Kaur, 2010; Roman and Şargu, 2013).

Secondly, there has been a focus of banking optimization research on large commercial banks (and little cooperation banks with different ownership structures, capital limitations, and regulatory frameworks) (Fiordelisi and Mare, 2013).

Thirdly, CAMEL-based risk identification and optimization-based performance improvement are not well-integrated within the same framework.

3. Methods

3.1 CAMEL Scoring Methodology

RBI-consistent scoring thresholds are applied in this study to convert raw CAMEL ratios into standardized risk scores that fall between 1 (Excellent) and 5 (Poor). All CAMEL pillars are based on standard financial ratios: the Capital Adequacy with the Capital to Risk-weighted Assets Ratio (CRAR), Asset Quality using Net NPA to Total Assets and Net NPA to Net Advances, the Management Efficiency using Business per Employee, Earnings Ability using Return on Assets (ROA), and the Liquidity using Liquid Assets to Total Assets. CAMEL scores against every indicator are computed on an annual basis and then add up to form an aggregate score on the five pillars. According to the RBI, total scores of 5-10 are Low risk, 11-15 Moderate risk and 16- 25 High risk. The priority areas are created through average scores of the indicators throughout the six-year period and average scores found to be higher (worse) are labeled as weakest links in need of intervention.

Optimization is restricted to the base year to avoid retrospective distortion of historical performance. Figure 2 represents the overall methodological workflow used in this paper.

3.2 Goal Programming for Net NPA Minimization

Net NPA represents the portion of non-performing loans remaining after accounting for recoveries and provisions. The Goal Programming model formulates Net NPA minimization as follows:

Decision Variables:

x_1 = Percentage of total advances becoming NPAs (NPA generation rate)

x_2 = Recovery rate on gross NPAs (%)

x_3 = Provisioning rate on residual NPAs (%)

Objective Function:

$$\textit{Minimize: Net NPA} = x_1 \times (1 - x_2 - x_3) \times Advances$$

Subject to Constraints:

$$0.06 \leq x_1 \leq 0.10 \quad \text{(NPA generation rate bounds)}$$

$$0.05 \leq x_2 \leq 0.15 \quad \text{(Recovery rate bounds)}$$

$$0.10 \leq x_3 \leq 0.15 \quad \text{(Provisioning rate bounds)}$$

The constraint bounds are defined with reference to RBI prudential norms and observed performance patterns of cooperative banks. The lower bound on x_1 acknowledges that a certain level of NPA generation is unavoidable in routine lending operations. Similarly, the upper bounds on x_2 and x_3 reflect practical limitations on recovery efforts and provisioning capacity, rather than idealized targets with the implicit constraint that recovery and provisioning together cannot exceed total NPAs.

3.3 NSGA-II for ROA Optimization

Return on Assets (ROA) measures how effectively a bank turns its assets into income. Improving ROA poses a multi-objective challenge because boosting income while controlling asset levels often creates trade-offs that do not fit easily into a single goal. NSGA-II addresses this by searching for the solution space to find Pareto-optimal setups that properly balance profitability against asset use. The ROA improvement assumes broadly stable asset levels during the optimization horizon.

Objective:

$$\textit{Maximize: ROA} = \textit{Net Income} / \textit{Total Assets}$$

Decision Variables and Bounds:

$$100 \leq \text{Net Income} \leq 140 \text{ (₹ lakh)}$$
$$14{,}000 \leq \text{Total Assets} \leq 14{,}500 \text{ (₹ lakh)}$$
$$0.80\% \leq \text{ROA} \leq 1.00\% \text{ (target band constraint)}$$

NSGA-II Configuration: Population Size: 100; Generations: 200; Crossover Probability: 0.9; Mutation Probability: 0.1; Elitism: Enabled

The algorithm starts by creating an initial group of potential solutions and checks their quality based on ROA performance. Over 200 rounds of iterations, it applies selection, crossover, and mutation steps to steadily refine those solutions. From the final Pareto front, the best option gets picked as the one delivering the highest workable ROA within the set target range (Figure 2).

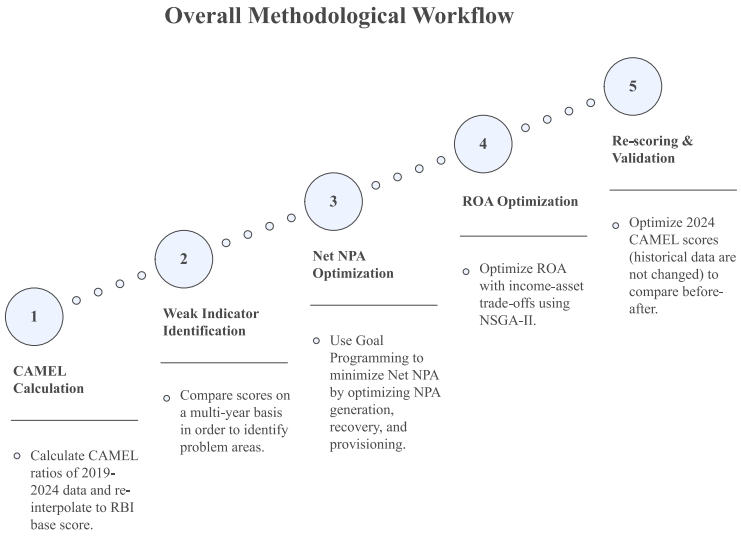

Figure 2. Overall Methodological Workflow

4. Data Collection

The data used are the audited annual financial reports of a Tier-2 Urban Cooperative Bank in Chhattisgarh, India, over the period of six years (2018-19 to 2023-24). It is a locally based bank, which has member-governed structures reflecting common issues of small cooperative banks in India. The dataset incorporates important balance sheet questions, such as share capital, deposits, advances, and working capital, and quality of assets, such as gross NPA, net NPA, and provisioning. The information in income statement includes the total income, expenses, and net income, as

well as the operating information such as the number of employees (it did not change much during the time of 15 employees). Individuals across the board are in lakhs of Indian Rupees (Table 1).

Table 1. Key Financial Data (2019-2024) in ₹ Lakhs

Parameter	2019	2020	2021	2022	2023	2024
Share Capital	323.30	313.19	301.09	289.35	274.65	260.83
Deposits	13,095	13,051	14,085	13,749	12,418	11,124
Advances	3,399	3,934	4,401	4,836	4,695	5,112
Working Capital	14,302	14,145	15,239	15,215	13,931	13,451
Gross NPA	434.22	598.98	516.55	842.86	1,154	1,031
Net NPA	412.22	563.98	450.38	664.11	1,028	1,003

5. Results and Discussion

5.1 Numerical Results

CAMEL Ratio Analysis

The overview of the CAMEL ratios during the study period (six years: 2019-2024) is presented in Table 2. Capital Adequacy, which was measured based on Capital to Risk-weighted Assets Ratio (CRAR) was always much higher than the minimum requirement set by RBI, being 9% with a range of 11.57% to 16.50%. This implies that the bank has sufficient capital buffers over the period in which the study was conducted. It also had a good liquidity performance with the ratio of Liquid Assets to Total Assets being higher than 45% in all the years, which falls in the excellent category.

On the contrary, Asset Quality indicators were persistently weak. The Net NPA to Total Assets was between 2.88% and 7.46 and Net NPA to Advances was between 3.42% and 12.00%. These values continued to stay in the range, which was not comfortable in most of the years, which showed long-time credit stress. Earnings ability also performed poorly because the Return on Assets (ROA) was lower than 1% during the period with a range of 0.08-0.89. The efficiency of the management was moderate, as Business per Employee was about 1,100 lakhs on average. The succeeding scoring and risk identification is based on the CAMEL ratios. The reclassification explained subsequently indicates the scoring-based CAMEL test as implemented in this research that should be viewed in this scope of analysis (Table 2).

Table 2. Computed CAMEL Ratios (2019-2024)

Indicator	2019	2020	2021	2022	2023	2024
CRAR (%)	13.54	12.63	12.10	11.57	12.72	16.50
Net NPA/TA (%)	2.88	3.99	2.96	4.36	7.38	7.46
Net NPA/Adv (%)	4.98	7.60	3.42	6.94	12.00	7.53
Bus./Emp. (₹L)	1,100	1,082	1,232	1,169	1,141	1,082
ROA (%)	0.31	0.31	0.27	0.16	0.08	0.89
Liq. Assets/TA (%)	46.77	49.41	50.24	47.54	64.47	56.07

CAMEL Scores and Risk Identification

Table 3 presents the year-wise CAMEL scores obtained using RBI-aligned scoring thresholds. Total CAMEL scores ranged between 12 and 16 during the study period, placing the bank predominantly in the Moderate Risk category (score range 11-15). The baseline CAMEL score for 2024 was 14.

Asset Quality and Earnings Ability consistently received higher scores compared to other CAMEL pillars, indicating structural weaknesses in these areas. Capital Adequacy and Liquidity showed relatively stronger performance, while Management Efficiency remained moderate (Table 3).

Table 3. Year-wise CAMEL Scores (1=Best, 5=Worst)

CAMEL Pillar	2019	2020	2021	2022	2023	2024
Capital Adequacy	3	2	2	2	2	2
Asset Quality	4	4	4	3	4	4
Management	3	3	4	3	3	3
Earnings	4	3	4	3	4	4
Liquidity	2	1	1	1	1	1
Total Score	16	13	15	12	14	14

5.2 Graphical Results

Figure 3 represents the average CAMEL pillar scores over the six-year period. Asset Quality and Earnings Ability clearly emerge as the weakest pillars, both averaging close to a score of 4. In contrast, Capital Adequacy averaged around 2, Management Efficiency around 3, and Liquidity demonstrated strong performance with an average score close to 1. This graphical analysis guided the selection of Net NPA (Asset Quality) and ROA (Earnings Ability) as priority indicators for optimization.

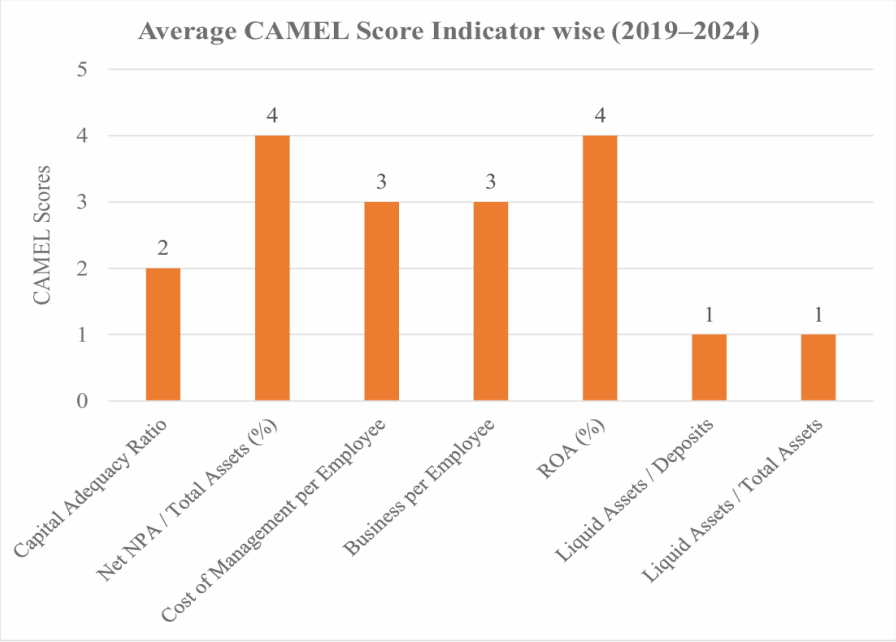

Figure 3. Average CAMEL Pillar Scores (2019-2024)

5.3 Proposed Improvements

Goal Programming Results for Net NPA: The Goal Programming model was solved using Python's SciPy. Optimize module. The optimal configuration achieved was x_1 (NPA generation rate) = 6.5%, x_2 (Recovery rate) = 5%, x_3 (Provisioning rate) = 15%. With Advances of ₹5,112.25 lakh, this yields:

$$Optimized\ Net\ NPA = 6.5\% \times (1 - 0.05 - 0.15) \times 5{,}112.25 = ₹265.58\ lakh$$

This reduces Net NPA to Total Assets from 7.46% to 1.97%, improving the Asset Quality score from 4 (Marginal) to 2 (Good).

NSGA-II Results for ROA: NSGA-II optimization was implemented using the DEAP library in Python. After 200 generations with a population of 100, the algorithm converged to an optimal solution:

Net Income = ₹129.42 lakh, Total Assets = ₹14,300 lakh, yielding:

$$Optimized\ ROA = 129.42 / 14{,}300 \times 100 = 0.90\%$$

This improves ROA from 0.72% to 0.90%, upgrading the Earnings Ability score from 4 (Marginal) to 2 (Good).

5.4 Validation

Actual vs. Optimized Comparison

To validate the effectiveness of the optimization framework, we compare the bank's actual 2024 performance against the optimized scenario. Table 4 presents this comparison across all CAMEL indicators and scores (Table 4).

Table 4. Actual vs. Optimized CAMEL Performance (2024)

CAMEL Indicator	Actual	Optimized	Score Change
CRAR (%)	16.50	16.50	2 → 2 (No change)
Net NPA/TA (%)	7.46	1.97	4 → 2 (Improved)
Net NPA/Adv (%)	7.53	3.10	4 → 2 (Improved)
Business/Emp (₹L)	1,082	1,082	3 → 3 (No change)
ROA (%)	0.72	0.90	4 → 2 (Improved)
Liquid Assets/TA (%)	56.07	56.07	1 → 1 (No change)
Total CAMEL Score	14	10	4-point improvement
Risk Classification	Moderate	Low	Category upgraded

The results show clear gains from the targeted optimization steps. Net NPA to Total Assets dropped by 73.6%, from 7.46% down to 1.97%, while ROA rose roughly 25%, moving from 0.72% to 0.90%. Most significantly, the total CAMEL score improved from 14 to 10, shifting the bank's risk category from Moderate Risk to Low Risk. This upgrade matters practically, since Low Risk banks typically face lighter regulatory oversight and gain more room for management decisions and operations. Figure 4, 5, 6 represents the Net NPA Comparison - Actual vs. Optimized (2024), ROA Comparison - Actual vs. Optimized (2024) and Total CAMEL Score - Actual vs. Optimized (2024) respectively (Figure 4, Figure 5, Figure 6).

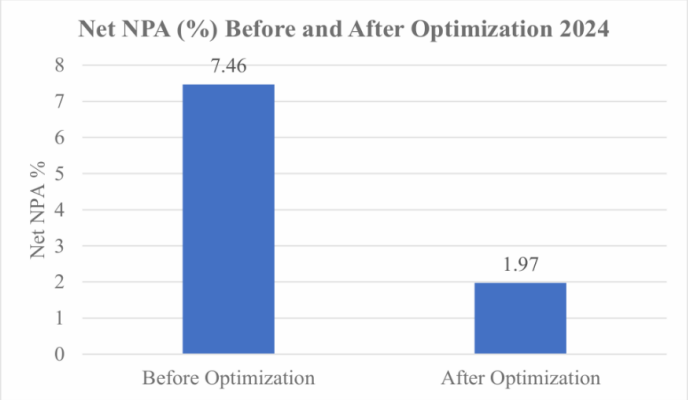

Figure 4. Net NPA Comparison - Actual vs. Optimized (2024)

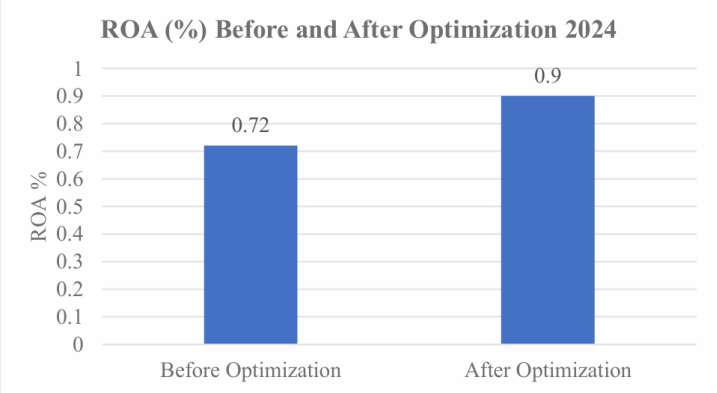

Figure 5. ROA Comparison - Actual vs. Optimized (2024)

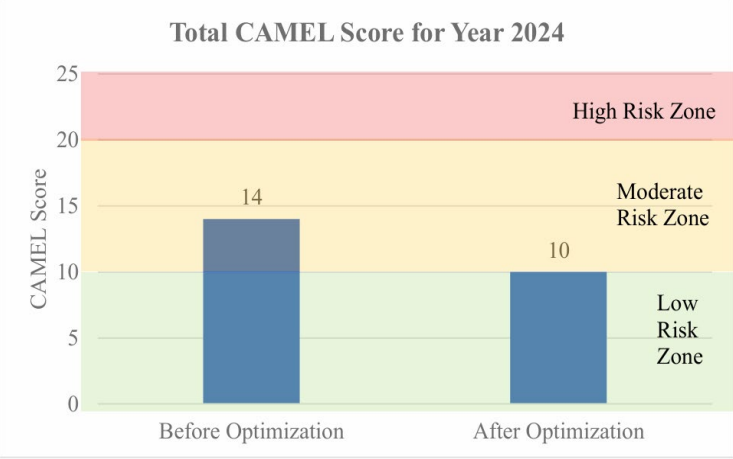

Figure 6. Total CAMEL Score - Actual vs. Optimized (2024)

6. Conclusion

This paper indicates that with specific optimization of a few CAMEL indicators, the crucial change in risk classification of a cooperative bank can be achieved. The paper can demonstrate how optimization can be effectively

integrated into the regulatory assessment framework of cooperative banking institutions by applying the traditional CAMEL framework, rather than by diagnosing the institution as it uses existing data to illustrate how the CAMEL system can be transformed into a prescriptive decision support tool. The Goal Programming was exercised on Net NPA using six years of audited financial data of an urban cooperative bank, and in this case the operational constraints that mostly controlled Net NPA include recovery limits and provisioning rules. Conversely, the balancing of trade-offs between income and asset exploitation was necessary in improvement of ROA, and hence the selection of NSGA-II. This difference underscores the fact that various CAMEL indicators might have to be optimized in diverse ways based on how they are structured.

Optimization is in terms of the base year (2024), and historical data remain constant so that the outcome can be viewed as operational goals moving forward as opposed to the past making an adjustment back. The results suggest that the Net NPA to Total Assets may go down to 1.97 percent compared to 7.46 percent, whereas the ROA can increase to 0.90 percent as compared to 0.72 percent. Collectively, the changes result in a lowering the overall CAMEL score of 14 to 10, moving the bank out of the Moderate Risk to Low Risk. This reclassification is an analytical result, which would reflect the scoring thresholds in line with the scoring standards of RBI, and it does not reflect a formal re-rating of the supervisor.

Although these encouraging outcomes have been achieved, there are a few weaknesses that should be mentioned. To start with, the research centers on one Tier-2 urban cooperated bank located in Chhattisgarh, which might result in the generalization of research results to other cooperated banks that are within different geographical locations or with different regulatory regimes. Second, the optimization model presupposes relatively stable macroeconomic conditions and fails to consider external shocks like economic downturns, changes in regulatory policies, or sector specific crises that may have a strong influence on NPA generation and recovery rates. Third, the bounds placed on the constraint and the goals of both Goal Programming and NSGA-II, though they are based on the RBI norms and the banking tendencies of the past, are based on the past performance trends and might fail to reflect the actual operational conditions in the future. Fourth, the framework deals with two CAMEL pillars Asset Quality and Earnings Ability and excludes Management Efficiency among other qualitative dimensions which the optimization is not contained. Lastly, the analysis is based on quantitative financial performance measures only and it does not quantify qualitative aspects like quality of governance, competence of the management and member participation dynamics, which can play a major role in determining cooperative bank performance.

In practice, the provided framework will provide a systematic and repeatable solution, which will enable small cooperative banks to achieve better regulatory positioning and financial sustainability. The methodology can be applied to other institutional settings by setting up the constraint bounds. In future research, it can be extended to various banks, add stress-testing modules and incorporate a certain qualitative component (e.g., the degree of governance and the engagement of the members in the participants).

Although the suggested optimization structure enhances significant financial indicators, cooperative bank work is also predetermined by qualitative and external conditions, including the structure of governance, the regional economic situation, and borrower behavior. The current quantitative model could not cover these aspects, which can be included in future extensions. Future studies can also involve a comparison between the proposed optimization strategy and other methods of analytic methods such as statistical learning models and artificial intelligence-based models to increase predictive capacity and policy assessment.

References

Ahmed, H., Financial performance evaluation of private commercial banks in Bangladesh: A CAMEL model analysis, *Asian Journal of Finance & Accounting*, vol. 6, no. 1, pp. 43-60, 2014.

AlArjani, A., and Alam, T., Lexicographic goal programming model for bank's performance management, *Journal of Applied Mathematics*, Article 8011578, 2021.

Dash, M., and Pathak, R., CAMEL model analysis of nationalized banks in India, *International Journal of Trade, Economics and Finance*, vol. 2, no. 4, pp. 351-353, 2011.

Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T., A fast and elitist multi-objective genetic algorithm: NSGA-II, *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182-197, 2002.

Eatman, J., and Sealey, C. W., Multi-objective linear programming model for commercial bank balance sheet management, *Journal of Bank Research*, vol. 9, pp. 227-236, 1979.

Fiordelisi, F., and Mare, D. S., Probability of default and efficiency in cooperative banking, *Journal of International Financial Markets, Institutions and Money*, vol. 26, pp. 30-45, 2013.
Giokas, D., and Vassiloglou, M., A goal programming model for bank assets and liabilities management, *European Journal of Operational Research*, vol. 50, no. 1, pp. 48-60, 1991.
Halim, B. A., Karim, H. A., Fahami, N. A., Mahad, N. F., Nordin, S. K. S., and Hassan, N., Bank financial statement management using a goal programming model, *Procedia - Social and Behavioral Sciences*, vol. 211, pp. 498-504, 2015.
Kaur, H. V., Analysis of banks in India - A CAMEL approach, *Global Business Review*, vol. 11, no. 2, pp. 257-280, 2010.
Kosmidou, K., and Zopounidis, C., Goal programming in the asset liability management of banks, *European Journal of Operational Research*, vol. 152, no. 2, pp. 395-405, 2004.
Kusy, M. I., and Ziemba, W. T., A bank asset and liability management model, *Operations Research*, vol. 34, no. 3, pp. 356-376, 1986.
Lee, S. M., and Kim, S. H., A goal programming model for bank asset and liability management under uncertainty, *Computers & Operations Research*, vol. 27, no. 5, pp. 423-440, 2000.
Parikh, H., CAMEL framework as a tool to measure performance of public and private sector banks, *IOSR Journal of Business and Management*, vol. 20, no. 9, pp. 52-60, 2018.
Reserve Bank of India, Master Circular - Prudential Norms on Income Recognition, Asset Classification and Provisioning, 2020.
Reserve Bank of India, Revised Supervisory Action Framework for UCBs, 2021.
Roman, A., and Şargu, A. C., Analyzing the financial soundness of commercial banks using CAMELS framework, *Procedia Economics and Finance*, vol. 6, pp. 703-712, 2013.
Siddiqui, A. A., Towards CAMEL model: A comparative study of public and private sector banks in India, *Journal of Business and Management*, vol. 1, no. 3, pp. 28-34, 2012.
Tuan, L. Q., Lin, C. Y., and Teng, H. W., Machine learning methods for predicting failures of US commercial banks, *Applied Economics Letters*, vol. 31, no. 15, pp. 1353-1359, 2024.
Viswanathan, P. K., Ranganatham, M., and Balasubramanian, G., Modelling asset allocation and liability composition for Indian banks, *Managerial Finance*, vol. 40, no. 7, pp. 700-723, 2014.

Biographies

Siddhesh Atul Nagle is a Master of Technology student in Industrial Engineering and Management at the National Institute of Technology, Raipur, India. His research interests include financial optimization, risk management, and operations research applications in banking.

Debjyoti Bose is a doctoral research scholar in the Department of Mechanical Engineering at the National Institute of Technology, Raipur, India. His research interests include financial performance measurement, optimization models, risk management, and the application of operations research techniques in banking and financial systems.

Mridul Singh Rajput is an Associate Professor in the Department of Mechanical Engineering at the National Institute of Technology, Raipur, India. His research areas include industrial engineering, optimization techniques, and performance management systems.