Application of Linear Programming for Optimal Net Revenue on Bank Loan

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Abstract

The primary aim of this study is to optimize the Bank's net return on loans granted to its customers. The Bank is confronted with the task of efficiently allocating funds among five distinct types of loans: Home loans, Personal loans, Car loans, Business loans, Credit Card loan, Flex i-loan and Organization loans, all of which have the potential to yield substantial net returns. Utilizing linear programming techniques, this research employs a solution approach to maximize the net return of loans disbursed by the Bank. The findings reveal an optimal allocation strategy: Home loans should receive no allocation (₦60,000000), Business Loans should be allocated ₦0 million, Personal Loans should be allocated ₦0 million, Car loans should be allocated ₦0 million, Credit Card should be allocated ₦150,000000 million and Organization loans should receive no allocation (₦90,000000). These allocations are determined from a total available loan pool of ₦300,000000 million. The calculated annual rate of return stands at 12.9%, which is slightly lower than the highest net interest rate of 58.6% observed for Personal loans(x_3). Another noteworthy observation pertains to the constraint that car and organization loans combined must account for at least 45% of the total loans (constraint 2). This requirement compels the solution to assign ₦60,000000 million to Home loans, even though they yield a lower net rate of 12.9%. It is evident that translating these insights into concerted efforts could undoubtedly enhance the Bank's profitability in terms of net return.

Keywords: Linear programming, loan portfolio, optimal allocation, Constraint, Profit

Introduction

The future of banking is being shaped by rapid advancements in financial technology and the growing influence of the Internet, both of which continue to transform the landscape of financial inter-mediation. This paper extends theoretical discussions by offering an analytical framework through which these dynamics can be scrutinized, with a particular emphasis on the evolving patterns that inform scholarly debate and industry practice. Central to this discussion is a renewed examination of the nature of financial inter-mediation and the mechanisms of financial transactions. (Isa & Rashid, 2018). Ketzenberg, *et al* (2015) made it known that One of the most significant developments in contemporary banking is the increasing importance of asset–liability management (ALM). Whereas banks once focused primarily on the allocation of assets, the simultaneous management of both assets and liabilities has now become critical. ALM seeks to achieve an optimal balance between the deployment of funds into income-generating assets and the management of obligations, thereby enhancing profitability while mitigating risk. In this study, mathematical models are employed to demonstrate how banks can optimize the allocation of funds in pursuit of these objectives.

A portfolio, in this context, represents an investment structure held either by individuals or institutions, and may be managed directly by investors or delegated to professional managers. Portfolios typically consist of a mix of financial assets, such as equities, bonds, and cash, selected in accordance with an investor's risk tolerance, investment horizon, and financial goals. Papahristodoulou, *et 'al* (2004). define an "optimal" portfolio as the most favorable choice among available alternatives, one that balances the investor's pursuit of returns with their aversion to risk. The optimization of portfolios remains a cornerstone of finance and investment theory, with significant implications for investors and financial managers who must allocate resources across multiple asset categories. In addressing such allocation problems, linear programming (LP) offers a powerful methodological tool. LP is designed to optimize the use of scarce resources among competing alternatives, provided that the relationships between decision variables remain linear. The method focuses on identifying the most advantageous solution, whether maximization or minimization, of an objective function subject to a set of constraints. This property makes LP particularly suitable for financial applications, including portfolio and loan optimization, where the efficient allocation of limited capital is central to decision-making. Linear programming (LP) has emerged as a fundamental methodological framework for addressing complex allocation problems across numerous disciplines. Meng and Yang Meng, (2000) provide a comprehensive examination of LP's theoretical foundations and practical applications, particularly emphasizing its pivotal role in aggregate production planning optimization. Within the financial domain, seminal contributions by Markowitz. Konno, & Yamazaki, 1991 established modern portfolio theory, which formalized the fundamental risk-return trade-off as the cornerstone of quantitative investment management. This foundational work was subsequently extended by Konno and Yamazaki, who reformulated the Markowitz framework as a single-period optimization model designed to maximize expected portfolio returns under uncertainty. William, (1964). Building upon these theoretical foundations, Sharpe William, 1971). developed the Capital Asset Pricing Model (CAPM), which provided an empirically tractable framework for expected return estimation while significantly reducing the computational complexity inherent in the original Markowitz formulation. Sharpe's subsequent work, Ogryczak,(2000). Further advanced portfolio optimization methodologies by introducing techniques that substantially reduced both data requirements and computational burden, thereby enhancing the practical applicability of quantitative portfolio management.

Subsequent research has expanded LP applications to increasingly specialized financial contexts. Ogryczak (1999) Demonstrated the efficacy of the simplex algorithm in solving complex asset allocation problems, contributing novel insights into cross-asset expected return estimation methodologies. Similarly, Marcus, (2011) Investigated portfolio management through benchmark tracking optimization, with particular emphasis on volatility minimization subject to equity market constraints. Olayinka (2015). Provided theoretical elaboration on market efficiency, establishing that security prices incorporate all available information necessary for accurate valuation. The application domain of LP has extended beyond traditional capital markets to encompass entrepreneurial and operational decision-making contexts. Oladejo *et 'al*. (2017). Applied LP optimization to profit maximization in the food service industry, demonstrating how product portfolio selection and cost optimization could be achieved in inflationary economic environments. Complementary, Yutin *et' al* (2023) illustrated the application of optimization techniques to cost minimization and operational efficiency enhancement in bakery production through AMPL software implementation. More recently, (Isa,, & Rashid, 2018). Developed a sophisticated loan recommendation framework for peer-to-peer lending platforms, utilizing a comprehensive data set comprising over 1.8 million

Lending Club loans spanning 2007-2020 and employing logistic regression for default probability forecasting.

Material and Method

Formulation of The Linear Programming Model

The following general LP model was considered:

Optimize: $f(x)$

Subject to the following constraints:

$$\left.\begin{array}{l} g_i(x) \leq b_i \text{ For } 1 \leq i \leq p \\ g_i(x) = b_i \text{ For } p+1 \leq i \leq k \\ g_i(x) \geq b_i \text{ For } k+1 \leq i \leq n \end{array}\right\} \quad (1)$$

Additionally, $x \geq 0$ for all decision variables x_i

Where; $f(x)$ is the objective function of a vector variable.

$x=(x_1,x_2,x_3...x_n)^T$ represents the measure of effectiveness of a decision $g_i(x)(1 \leq i \leq m)$ is the constraint function of x. The variable $x_j=(j=1,2,3,...,n)$ is the activity level associated with the decision-making problem. The term $b_i(1 \leq i \leq m)$ represents the upper or lower limit of the i^{th} constraint functions. Constraint $x \geq 0$ restricts the decision variables $x_j=(j=1,2,3,...,n)$ to non-negative real numbers. Since the objective and constraint functions are linear, they are precisely defined in the form

$$f(x)=c_1x_1+c_2x_2+...+c_nx_n=\sum_{j=1}^{n} c_jx_j \quad (2)$$

$$g_i(x)=a_{i1}x_1+...+a_{in}x_n=\sum_{j=1}^{n} a_{ij}x_j \quad (3)$$

From (2) and (3), we then write the linear programming

As:

$$Z=\sum_{j=1}^{n} c_jx_j \quad (4)$$

Subject to:
$$\left.\begin{array}{c}\sum_{j=1}^{n} a_{ij}x_j \; For\ 1 \le i \le p\\ \sum_{j=1}^{m} a_{ij}x_j \; For\ p+1 \le i \le k\\ \sum_{j=1}^{n} a_{ij}x_j \; For\ k+1 \le i \le n\\ x_j > 0 1 \le j \le n\end{array}\right\} \quad (5)$$

where, $a_{i,j}$ and c_j are called technological and cost coefficients, respectively. b_i is the main parameters of the models

Equations (4) and (5) can be expressed in the forms of the

Matrix:

$$Maximize\ Z = CTx \quad (6)$$

Subject to the following constraints:

1. $A_x \le b_2$ (8)

2. $x \ge 0$ (9)

Where C is a column vector represented as $C = [c_1, c, \cdots, c_n]^T$.

Where, K is a feasible set standard LP while K = $\{x \in R^n : Ax = b, x \ge 0\}$ If $x \in K$ or if x satisfies $Ax = b$ and $x \ge 0$, then x is a feasible solution. Let $C^T x$ be the objective function of a LP to be optimized. $x \in K$ is an optimal solution if for all $y \in K$, $C^T x > C^T y$. Let x be a basic solution of $Ax = b$. If $x \ge 0$, then it is called a basic feasible solution (BFS). An artificial variable $A_i \ge 0$ is a dummy variable added for the specific purpose of generating an initial basic feasible solution. It has no economic meaning.

Method of solution

Model Assumption:

1. A subtle assumption in the preceding formulation is that all loans are issued at approximately the same time. This allows us to ignore differences in the time value of the funds allocated to the different loans.

2. That the bank would want to loan out all ₦200 million.

Data Collection

The data was collected in January 2025 from Access Bank in Ado Local Government Area, Ogun State. It includes details on loan categories and types, capital availability, expected returns, risk and regulatory constraints, historical and market data, objective function parameters and decision variables of bank loan data, budget constraint, risk constraint and proportional allocation constraint.

3.3.4 Decision Variables

Let:

x_1= Amount allocated to Home Loans

x_2=Amount allocated to Business Loan

x_3= Amount allocated to Personal Loan

x_4= Amount allocated to Car Loans

x_5=Amount allocated to Credit Card Loans

x_6=Amount allocated to Flex i Loans

x_7= Amount allocated to Organization Loans

Table Model Data

Types of Loan	Interest Rate	Bad – debt ratio
Home	0.170 (17%)	0.10
Business	0.160 (16%)	0.08
Personal	0.150(15%)	0.07
Car	0.140 (14%)	0.08
Credit Card	0.130 (13%)	0.03
Flexi	0.125 (12.5%)	0.05
Organization	0.100 (10%)	0.02

Source: First Bank Plc (2022).

Table 3.1 shows the different loan types with corresponding interest rates and bad- debt ratios. It provides a comparative summary of various loan types offered by a financial institution along with two key metrics:

Interest Rate: This represents the expected return on the loan, i.e., the income the bank expects to earn as a percentage of the loaned amount.

Bad-Debt Ratio: This indicates the proportion of the loan expected to go unpaid (i.e., defaulted). It's a measure of risk or creditworthiness for each loan type.

Home Loans offer the highest interest rate (17%), but they also come with the highest risk (10% bad-debt ratio). This reflects the large loan size and long tenure typically associated with home loans. Organization Loans offer the lowest interest rate (10%) but also come with the lowest risk (2% bad-debt ratio), suggesting they are more secure and predictable.

Credit Card Loans are notable for their low bad-debt ratio (3%), despite being unsecured. The relatively high interest rate (13%) makes them attractive from a return-to-risk perspective. Business and Car Loans share similar bad-debt ratios (8%), but the business loan offers a slightly better return. For each loan type, we compute the following:

Net Return = Interest Rate − Bad-Debt Ratio

Table 3.2: Net Return Calculation for Each Loan Type

Loan Type	Interest Rate	Bad-Debt Ratio	Net Return
Home	0.170	0.10	0.070
Business	0.160	0.08	0.080
Personal	0.150	0.07	0.080
Car	0.140	0.08	0.060
Credit Card	0.130	0.03	0.100
Flexi	0.125	0.05	0.075
Organization	0.100	0.02	0.080

Table 3.2 shows the net return calculation for each loan type. The objective function formula is written mathematically as:

Maximize $Y=\sum_{i=1}^{7}\left(InterestRate\text{-}Bad\text{-}DebtRatio\right)x_i$ (10)

Maximize: $Y = (0.170 - 0.10)x_1 + (0.160 - 0.08)x_2 + (0.150 - 0.07)x_3 +$

$(0.140 - 0.08)x_4 + (0.130 - 0.03)x_5 + (0.125 - 0.05)x_6 + (0.100 - 0.02)x_7$ (11)

By simplifying equation 3.19, the objective function, therefore, is:

Maximize: $Y = 0.070x_1+0.080x_2+0.080x_3+0.060x_4+0.100x_5+0.075x_6+0.080x_7$ (12)

$x_1, x_2 ... x_7$ are the amounts allocated to each loan type

Subject to:

$x_1+x_2+x_3+x_4+x_5+x_6+x_7 \leq 300,000,000$ (18)

$0.3x_1+0.3x_2-0.7x_3-0.7x_4+0.3x_5+0.3x_6-0.7x_7 \leq 0$ (13)

$-0.6x_1+0.4x_2+0.4x_3+0.4x_4+0.4x_7 \leq 0$ (14)

$0.04x_1+0.02x_2+0.01x_3+0.02x_4-0.03x_5-0.01x_6-0.04x_7 \leq 0$ (15)

Where,

$$\left.\begin{array}{l} x_1 \geq 0 \\ x_2 \geq 0 \\ x_3 \geq 0 \\ x_4 \geq 0 \\ x_5 \geq 0 \\ x_6 \geq 0 \\ x_7 \geq 0 \end{array}\right\} \text{are non – negative constraint}$$

(22)

The decision variables$(x_1, x_2, x_3, x_4, x_5, x_6, x_7)$ are the unknown variables. The following is our objective function and its constraints

Maximize $Y = 0.070x_1+0.080x_2+0.080x_3+0.060x_4+0.100x_5+0.075x_6+0.080x_7$ (16)

Subject to:

Budget Constraint= $x_1+x_2+x_3+x_4+x_5+x_5+x_7 \leq 300,000,000$ (17)

Proportional Allocation Constraint= $0.3x_1+0.3x_2-0.7x_4+0.3x_5+0.3x_6-0.7x_7 \leq 0$ (18)

Risk Constraint= $0.04x_1+0.02x_2+0.01x_3+0.02x_4-0.03x_5-0.01x_6-0.04x_7 \leq 0$ (19)

Results and Discussion

In this study, we presented the results of the model objective function and constraints for optimal net return in Bank. We used the linear programming method of solution to solve the model. The table below shows the breakdown of the allocation and its potential implication

Table 4.1: Loan Allocation Results

Loan Type	Allocation (₦)	Allocation (%)
Home (X1)	60,000,000	20.0%
Credit Card (X5)	150,000,000	50.0%
Organization (X7)	90,000,000	30.0%
Total	300,000,000	100%

Table 4.1 shows the results of the loan allocation. The results of the linear programming model revealed an optimal allocation of ₦300 million across three loan categories: Home Loans, Credit Card Loans, and Organization Loans. Specifically, ₦60 million (20%) was allocated to Home Loans, ₦150 million (50%) to Credit Card Loans, and ₦90 million (30%) to Organization Loans. This allocation maximizes the bank's objective, likely net returns, while adhering to risk constraints, proportional limits, and total budget restrictions. The exclusion of Business, Personal, Car, and Flex i Loans from the allocation indicates that these loan products either offered lower return-to risk ratios or violated one or more model constraints. Credit Card Loans (X_5) received the highest allocation (₦150 million), accounting for 50% of the total. This suggests that credit card loans may offer the highest return

relative to risk or are otherwise highly favorable based on the model's objective function. Organization Loans (X_7) received ₦90 million (30%). These could rep resent stable, low-risk institutional borrowers that align with risk mitigation constraints. Home Loans (X_1) received ₦60 million (20%), indicating moderate profitability or a role in fulfilling regulatory or strategic portfolio balance requirements. Other loan categories, Business, Personal, Car, and Flex i Loans, were allocated ₦0 because they either offer lower returns, exceed risk tolerance, or were constrained by proportional or policy rules in the LP model.

Strategic Implications

The strategic implications of this loan allocation includes: capital efficiency, risk control, regulatory compliance and dynamic adjustment.

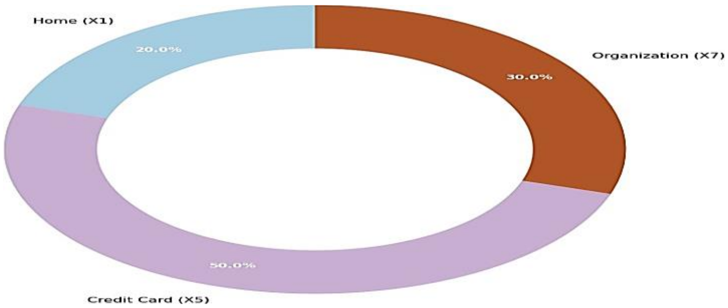


Figure 4.1: Optimal Loan Allocation (Pie Chart)

Figure 4.1: shows the pie chart of the optimal loan allocation for three loan categories. It visually represents how the total loan budget is allocated across three loan categories: Home (X_1), Credit Card (X_5), and Organization (X_7). It is observed that Credit Card, Organization and Home Loans have an allocation of 50%, 30% and 20% of the total loan budget respectively.

Table 4.2 shows the summary of the optimal loan allocation per type. The optimal loan allocation model has recommended distributing the available ₦300 million across just three loan types: Credit Card Loans, Organization Loans, and Home Loans. Here's a breakdown of each allocation:

Credit Card Loans (X_5): ₦150 million (50%)

Table 4.2: Optimal Loan Allocation per Type

Loan Type	Allocation (₦)	Percentage of Total
Home (X1)	60,000,000	20.0%
Business (X2)	0	0.0%
Personal (X3)	0	0.0%
Car (X4)	0	0.0%
Credit Card (X5)	150,000,000	50.0%
Flexi (X6)	0	0.0%
Organization (X7)	90,000,000	30.0%
Total	300,000,000	100.0%

This loan type received the highest allocation among all others. It likely offers higher returns or has favorable risk-return characteristics. It also indicates strong strategic importance or profitability for the bank.

Organization Loans (X_7): ₦90 million (30%)

This loan type received the second highest allocation. It suggests that organization loans may be relatively safe or profitable and are tied to reliable repayment or corporate relationships. Home Loans

(X_1): ₦60 million (20%). Homes often offer collateral, reducing default risk, and this moderate allocation implies a balanced approach between return and security.

Business, Personal, Car, and Flexi Loans: ₦0

These types received no allocation in the optimal solution. This may be due to higher risk, lower return on investment, or failure to meet certain constraint threshold like risk tolerance. It also indicates they may not be cost-effective under the given optimization criteria.

Strategic Implications. The bank should prioritize funding credit card, organization, and home loans, while recognizing that the zero allocation to other loan categories does not imply their irrelevance, but instead reflects a need to reassess their risk pro files, interest rates, or lending terms. This distribution, shaped by current market conditions and model assumptions, should be periodically reviewed to ensure continued alignment with strategic goal

Figure 4.2: Optimal Loan Allocation Per Loan Type

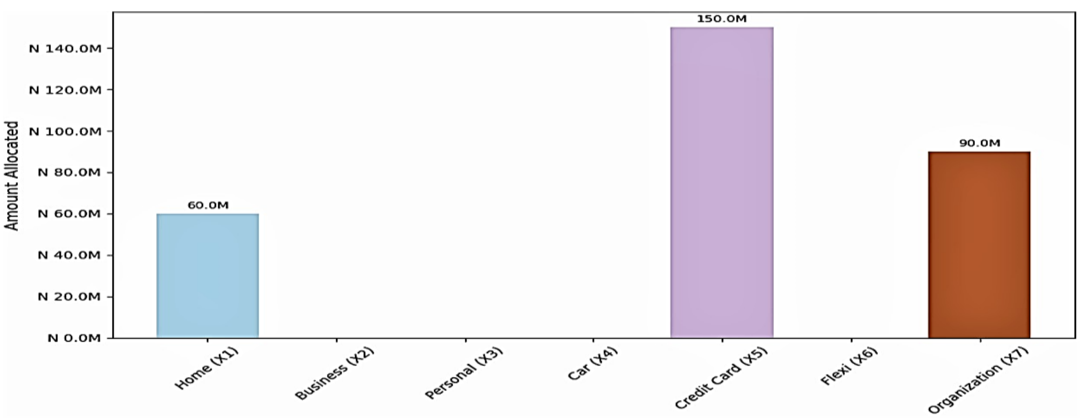


Figure 4.2: is a bar chart which shows the optimal allocation per loan type. It shows how funds are distributed across various loan categories. The x-axis lists seven loan categories, each labeled with a variable code (X_1 to X_7), and the y-axis represents the amount allocated in millions of Naira (₦).

Table 4.3: Net Return Contribution per Loan Type

Loan Type	Allocation (₦)	Return Rate (%)	Net Return (₦)	Contribution (%)
Home (X1)	60,000,000	5.3	3,180,000	12.9%
Credit Card (X5)	150,000,000	9.61	14,415,000	58.6%
Organization (X7)	90,000,000	7.8	7,020,000	28.5%
Total	300,000,000	22.71	24,615,000	100%

Table 4.3: shows the net return rate per loan type. It illustrates how the majority of net returns are driven by Credit Card and Organization Loans, which together contribute over 87% of total returns.

Despite a lower return rate, Home Loans play a supporting role in the portfolio. In this case, the total investment is ₦300,000,000, and the total net return from the optimal allocation is ₦24,615,000.

Below is the breakdown:

Credit Card Loans (X_5)

Allocated Amount = ₦150,000,000

Return Rate = 9.61% (0.0961)

Net Return Contribution = ₦150,000,000 × 0.0961 = ₦14,415,000 Credit Card Loans contribute the highest net return to the portfolio. This high profitability justifies the largest allocation (50%) of the total capital. It reflects the strong return-to-risk profile of this loan type in the model.

Organization Loans (X_7)

Allocated Amount = ₦90,000,000

Return Rate = 7.8% (0.078)

Net Return Contribution = ₦90,000,000 × 0.078 = ₦7,020,000

Home Loans (X_1)

Allocated Amount = ₦60,000,000

Return Rate = 5.3% (0.053)

Net Return Contribution = ₦60,000,000 × 0.053 = ₦3,180,000

Home Loans provide a modest return but are still included due to their relatively low risk and possible collateral value. They may also be necessary to meet certain proportional or regulatory requirements. The optimal loan allocation is primarily driven by credit card and organization loans, which deliver the highest returns. Home Loans are included possibly for diversification or strategic reasons despite lower profitability. Other loan types are excluded due to lower efficiency or constraint violations.

Figure 4.3: Net Return Contribution Per Loan Type

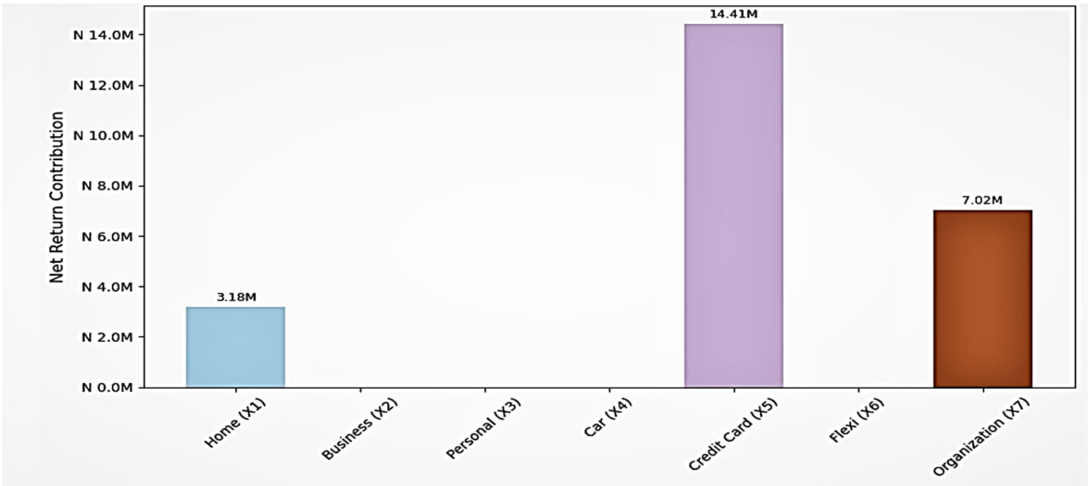


Figure 4.3 is a bar chart which shows the net return contribution of each loan type and is calculated by multiplying the allocated amount for each loan type with its respective return rate (profit coefficient). This value represents how much each loan type contributes to the overall return from the total allocation.

Analysis of the Overall Portfolio Bad Debt Rate (Figure 4.4)

Y-Axis (Bad Debt Rate %): Measures the percentage of the loan portfolio that is expected to default.

Left Bar – Actual Portfolio Rate:

Value = 4.10%

Represents the current average bad debt rate of the loan portfolio.

It is below the maximum allowed threshold, indicating a healthy level of credit risk.

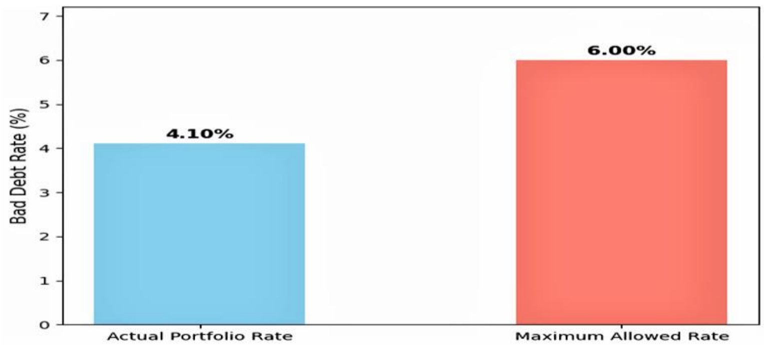
Right Bar – Maximum Allowed Rate:

Value = 6.00%

Represents the upper limit of acceptable risk, often set by internal policies or regulatory bodies.

The comparison between overall portfolio bad rate and limit is necessary for the following reasons: risk control, regulatory compliance and strategic balance.

Figure 4.4: Overall Portfolio Bad Debt Rate



The actual bad debt rate of 4.10% is within the allowable maximum of 6.00%. This implies the loan portfolio is well within acceptable risk limits. In optimization terms, this constraint is not binding, meaning the solution is not currently limited by this condition. The bank could, if beneficial, accept a slightly higher risk level while still remaining compliant. Figure 4.4 is a bar chart that compares the actual portfolio bad debt rate (4.10%) with the maximum allowable limit (6.00%). The significantly lower actual rate demonstrates effective risk management within the loan allocation strategy, ensuring compliance with the predefined risk threshold while maintaining portfolio health.

Constraint Analysis (Figure 4.5)

Constraint B: Personal + Car + Organisation %

Y-axis = Percentage of Total Loans (%)

X-axis label = Actual %

Actual Value = 30.00%

Required Minimum = ≥ 30% (indicated by a red dashed line). This means the allocation to personal, car, and organizational loans makes up exactly 30% of total loans, which meets the minimum required threshold which states that Personal, Car and Organization loans should be equal to at least 30% of all loans. This means the constraint is satisfied but binding—any reduction in these allocations would violate the constraint.

Constraint C: Home % of Subset

Y-axis = Percentage of Subset (%)

X-axis label = Actual %

Actual Value = 40.00%

Required Minimum = ≥ 40% (red dashed line)

This means the percentage of home loans within a specified subset (e.g., housing-related or secured loans) is exactly 40%, again meeting the required minimum which states that Home loans should be equal to 40% of Business, Personal, Car, Organization and Home loans. Like Constraint B, it is satisfied and binding, showing that the optimizer has allocated just enough to fulfill the rule.

Constraint D: Overall Bad Debt %

Y-axis = Bad Debt Rate (%)

X-axis label = Actual %

Actual Value = 4.10%

Maximum Allowed = ≤ 6.00% (red dashed line)

This means the portfolio's overall bad debt rate is 4.10%, which is be low the allowable limit of 6.0% since dad debts should not exceed 6% of all loans. This constraint is satisfied and not binding, meaning there is still room to include slightly riskier loans if it would increase returns, without violating the constraint.

Figure 4.5: Key Constraints Satisfaction

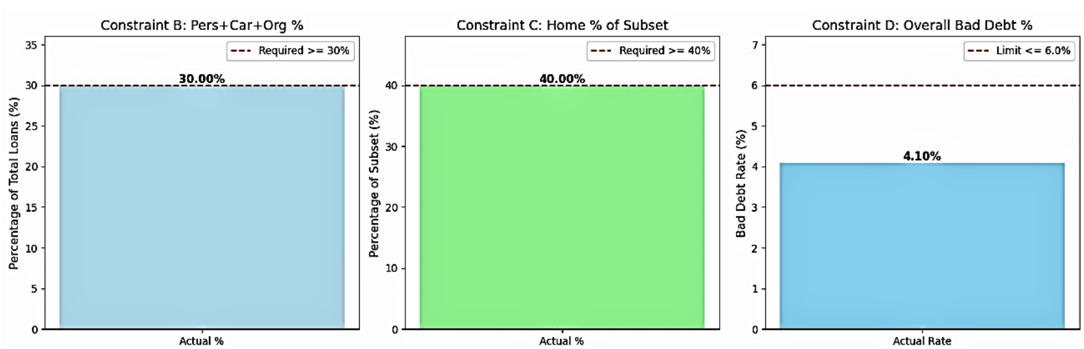


Figure 4.5: above shows the satisfaction for three key constraints: Proportional Al- location (Constraint B), Minimum Proportional Allocation (Constraint C) and Risk Constraints (Constraint D) respectively. Loan Types and Their Net Return Rates (Figure 4.6)

Home Loan (X_1) = 5.30%
Business Loan (X_2) = 6.72%
Personal Loan (X_3) = 6.95%
Car Loan (X_4) = 4.88%
Credit Card Loan (X_5) = 9.61% (highest return)
Flexi Loan (X_6) = 6.88%
Organization Loan (X_7) = 7.80%

Conclusions

This study applied linear programming techniques to the optimization of bank loan portfolios with the specific objective of maximization net revenue. By incorporating realistic budgetary, proportional, and risk-related constraints, the model demonstrated how computational optimization can guide strategic lending decisions in a commercial banking context. The empirical application, based on data from a Nigerian bank, revealed an optimal allocation of ₦300 million across three loan types, Credit Card, Organization, and Home Loans, which collectively achieved a net return of ₦24.6 million, equivalent to a portfolio return rate of 12.9 per cent. From a theoretical perspective, the research extends the application of linear programming beyond traditional cost minimization or risk reduction frameworks by explicitly modelling net revenue as the optimization objective. This contribution situates the study within the broader literature on operational research in finance, highlighting the importance of integrated frameworks that balance profitability, risk, and regulatory compliance.

In terms of managerial implications, the findings provide actionable guidance for bank executives and portfolio managers. The dominance of Credit Card Loans in the optimal allocation underscores the potential of unsecured retail lending when default rates are relatively low. Organization Loans reinforce the value of institutional clients in stabilizing revenues, while the inclusion of Home Loans demonstrates the role of diversification and regulatory proportionality in shaping portfolio design. Together, these insights suggest that optimization tools can help banks improve capital efficiency, strengthen risk management, and enhance compliance with supervisory requirements.

The study also acknowledges several limitations. The model is static and assumes simultaneous loan disbursement, thereby excluding the time value of money and dynamic changes in loan performance. It also relies on historical data, which may not fully capture future volatility in credit risk or shifts in borrower behavior. Furthermore, the analysis is confined to a single bank in Nigeria, which may limit venerability across institutions or markets. Future research could address these limitations by incorporating dynamic optimization models that account for multi-period lending horizons and stochastic elements of loan performance. Comparative studies across banks or regions could further test the robustness of the model, while the integration of machine learning techniques alongside LP could offer enhanced predictive power for default risk and loan profitability. By pursuing these avenues, subsequent work can build on the present findings to deepen both academic understanding and practical application of optimization in banking.

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