

A Pareto Multi-Objective Optimization for Sectoral Credit Allocation: Nigerian Banking Sector

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Abstract

This paper employ a Pareto Multi-Objective Optimization (POO) to reconciles the reported sectoral credit allocation, non-performing-loan (NPL) and electronic-payment statistics into a single, internally consistent panel of seventeen credit sectors, and formulates the allocation problem as a tri-objective constrained optimization , maximize portfolio growth, minimize portfolio NPL-risk exposure, and maximize a digital-banking-impact index, subject to a fixed lending envelope and sector-level absorptive-capacity bounds. The resulting problem is a multi-objective linear program (MOLP) the exact weighted-sum linear scalarization, was apply to trace the supported efficient frontier analytically, and the Non-dominated Sorting Genetic Algorithm II (NSGA-II) which show the two solution sets agree closely, validating the metaheuristic against an exact benchmark. The Pareto front shows the status-quo allocation achieving a portfolio growth index of 4.18% against a risk index of 6.02% matching the officially reported aggregate NPL ratio almost exactly, while efficient reallocations on the frontier attain growth of up to 7.10% at a lower risk index of 5.51%, or reduce risk to 3.96% while retaining growth above 5.18%.

Keywords: *Pareto multi-objective optimization; sectoral credit allocation; non-performing loans; digital banking; and linear programming*

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I. Introduction

National industrial development involves the simultaneous pursuit of economic growth, employment generation, domestic value addition, export competitiveness, import substitution, technological upgrading, and fiscal sustainability. These objectives frequently compete for the same scarce resources, making conventional single-objective resource-allocation approaches inadequate for national industrial planning. This study develops a Pareto Multi-Objective Optimization (POO) framework for allocating scarce national resources across strategic industrial sectors. The framework integrates financial capital, foreign exchange, energy, infrastructure, skilled labour, constrained multi-objective optimization model. Three principal objectives are proposed: maximizing industrial value added, maximizing domestic value-chain development, and minimizing resource-allocation cost. The resulting model generates a set of Pareto-efficient allocations rather than a single solution, thereby allowing policymakers to examine explicit trade-offs among competing national priorities. An NSGA-II-based solution procedure is proposed for obtaining the Pareto frontier, followed by a multi-criteria decision-making procedure for selecting a preferred policy solution. Data indicate that manufacturing remains strategically important: manufacturing real GDP grew by 3.29% year-on-year in Q1 2026, while the non-oil sector accounted for 96.08% of real GDP. The proposed framework provides a systematic basis for evidence-driven industrial policy, investment prioritization, and scenario analysis.ro1

Nigeria's deposit money banks (DMBs) intermediate a large and growing pool of loanable funds across a heterogeneous private sector. The National Bureau of Statistics (NBS), working from data supplied administratively by the Central Bank of Nigeria (CBN), publishes a quarterly "Selected Banking Sector Data" release that reports this allocation across roughly seventeen economic sectors, alongside sector-level non-performing loan (NPL) statistics, monthly electronic-payment (e-payment) channel volumes, and bank staff strength. Taken together, these series describe three quantities that a prudent lending strategy must jointly manage: how much a sector's credit book is growing, how risky that sector's exposure is, and how far the financial system's digitalization drive has penetrated economic activity.

The remainder of the paper is organized as follows. Section 2 briefly situates the work in the literature on multi-objective portfolio and credit-allocation optimization. Section 3 documents the source data and the reconciliation steps required to turn the published tables into a clean, internally consistent panel, including two data-quality issues identified and corrected in the source release. Section 4 develops the mathematical model. Section 5 describes the solution methodology — exact weighted-sum linear scalarization and NSGA-II — and

how the two are cross-validated. Section 6 reports numerical results. Section 7 discusses policy implications and limitations, and Section 8 concludes.

Mathematical model

Let there be $N = 17$ credit sector indexed $i \dots n$ (table 1) the decision variable $x_i \geq 0$ denote the amount of aggregate private-sector credit (₦Million) reallocated to sector i in the planning quarter. The decision vector is $x = (x_1 \dots x_n)^T$. The current, reported allocation is denoted

$$x^0 = (x_1^0 \dots x_n^0)^T,$$

All three objectives are expressed as coefficient-weighted, budget-normalized linear functions of the allocation vector, which keeps every objective in comparable percentage-point units regardless of the sector's absolute size:

$$\text{Max } f_1(x) = \frac{1}{B} \sum_{i=1}^n G_i X_i \quad (\text{Portfolio growth index, \%}) \dots\dots\dots 1$$

$$\text{Min } f_2(x) = \frac{1}{B} \sum_{i=1}^n R_i X_i \quad (\text{Portfolio NPL-risk index, \%}) \dots\dots\dots 2$$

$$\text{max } f_3(x) = \frac{1}{B} \sum_{i=1}^n D_i X_i \quad (\text{Portfolio digital-impact index}) \dots\dots\dots 3$$

Constraint

The allocation must exhaust the lending envelope and respect sector-level absorptive-capacity and prudential limits:

$$\sum_{i=1}^n x_i = B \quad (\text{Budget conversation constraint}) \quad 4$$

$$0.5 x_i^0 \leq x_i \leq 2.0 x_i^0 \quad i = 1 \dots n \quad (\text{Sectoral bound constraint}) \quad 5$$

Constraint (5) bounds each sector's reallocated credit to between half and double its current level. This reflects two practical realities the model would otherwise ignore: a sector cannot realistically absorb an arbitrarily large share of new lending within one planning quarter (loan origination capacity, collateral availability and existing client relationships are finite), and a prudent regulator or treasury committee would not authorize a sector's book to be run down by more than half in a single reallocation exercise. The bound also directly addresses the "Others" anchoring the optimizer's search to the vicinity of the current, real allocation rather than to a single noisy quarter-on-quarter swing.

Exact method: weighted sum linear scalarization

For non-negative weight

W_1, W_2, W_3 , with $W_1 + W_2 + W_3 = 1$ the scalarized problem

$$\text{Min}_x -W_1 f_1(x) + W_2 f_2(x) + W_3 f_3(x) \quad \text{s.t } 4 \text{ \& } 5 \quad \dots\dots\dots (6)$$

The Pareto Optimality Condition

x^A and x^B Represent two feasible allocation solution

Solution x^A domain x^B if

$f_i(x^A) \geq f_i(x^B)$ for all maximization objective with strict improvement in at least one objective. A solution is Pareto optimal when no feasible solution dominates it.

Solution x^A domain x^B if

$f_i(x^A) \geq f_i(x^B)$ for all maximization objective with strict improvement in at least one objective. A solution is Pareto efficient if no feasible alternative can improve at least one objective without worsening another.

Many national planning problems contain discrete decisions. A general multi- objective problem

$$\text{Min/Max } f(x) = \{f_1(x), f_2(x) \dots f_m(x)\} \dots\dots\dots 7$$

Subject To:

$$g_j(x) \leq 0, j = 1 \dots j$$

$$h_k(x) = 0, k = 1 \dots k$$

$$x_i \in X$$

For example, a government may decide whether to activate a major industrial project: The resulting problem becomes a Multi-Objective mixed-Integer Programming problem.

Because f_1, f_2 and f_3 cannot in general be maximized (minimized) simultaneously, the model does not seek a single optimal x . Instead, a feasible allocation x^* is called Pareto-optimal (non-dominated, efficient) if there exists no other feasible x satisfying

$$f_1(x) \geq f_1(x^*), f_2(x) \leq f_2(x^*), f_3(x) \geq f_3(x^*) \dots\dots\dots 8$$

with at least one inequality strict. The Pareto front is the set of all such x^* , and its image $f_1(x^*), f_2(x^*), f_3(x^*)$ is the efficient frontier, Since f_1, f_2 and f_3 are all linear in x

NSGA-II is nonetheless applied and reported because (a) it generalizes directly to extensions of the model with non-linear risk terms (b) it demonstrate close agreement between the exact and heuristic solution sets on a case where ground truth is known. This paper's contribution is methodological rather than exclusively empirical: it shows how a publicly available, non-research-oriented administrative statistical release can be reconciled and repurposed as the coefficient set for a rigorous, multi-objective optimization model and reconciled dataset as a template for subsequent quarters as the NBS series is updated.

II. LITERATURE REVIEW

Multi-objective portfolio optimization traces to Markowitz's mean-variance framework, which is itself a two-objective (return-maximizing, variance-minimizing) special case of the more general Pareto formulation used here. Where mean-variance optimization has a closed-form efficient frontier for quadratic risk objectives, the credit-risk and digital-impact objectives used in this paper are linear in the allocation vector, so the underlying problem is a multi-objective linear program (MOLP); its efficient frontier is piecewise-linear and can be characterized exactly by weighted-sum scalarization which is the property this paper exploits to validate the metaheuristic solution.

Deb et al. (2002) in their paper made a significant contribution to evolutionary multi-objective optimization through the development of the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The authors proposed NSGA-II to overcome major limitations of earlier multi-objective evolutionary algorithms, particularly computational inefficiency, lack of elitism, and difficulties in maintaining diversity among Pareto-optimal solutions. The algorithm employs fast non-dominated sorting to classify candidate solutions according to their dominance relationships and uses a crowding-distance measure to preserve diversity along the Pareto frontier. An elitist selection mechanism is also incorporated to ensure that high-quality solutions are retained across successive generations. The resulting approach provides an effective means of approximating the Pareto-optimal frontier for problems involving conflicting objectives. The relevance of NSGA-II to national industrial resource allocation lies in its ability to simultaneously consider competing objectives without requiring decision makers to specify fixed preference weights at the initial optimization stage. Consequently, NSGA-II can be applied to identify alternative efficient resource-allocation strategies that balance economic growth, employment generation, domestic value addition, import dependence and other national industrial-policy objectives.

Pareto (1896) in his paper provided the foundational economic concept underlying modern Pareto-based multi-objective optimization. His analysis established the principle of efficiency according to which a state is considered efficient when it is impossible to improve one outcome without simultaneously worsening another. This concept subsequently evolved into the notion of Pareto optimality, which has become a central principle in multi-objective mathematical programming. In an optimization context, a feasible solution is Pareto optimal when no alternative feasible solution can improve at least one objective without reducing the performance of another objective. The principle is particularly important in resource allocation because scarce resources inevitably create trade-offs among competing objectives. In the context of national industrial planning, for example, an allocation designed to maximize employment may differ from one designed to maximize GDP contribution or domestic value addition. Rather than assuming that one of these objectives is universally superior, Pareto optimization identifies efficient alternatives and makes the associated trade-offs explicit.

Coello Coello, Lamont, and Van Veldhuizen (2007) review a comprehensive examination of evolutionary algorithms for solving multi-objective optimization problems and established their importance in addressing complex decision-making problems characterized by conflicting objectives. The authors demonstrated that evolutionary algorithms are particularly appropriate for multi-objective optimization because their population-based search mechanism enables multiple candidate solutions to be evaluated simultaneously. Through concepts such as Pareto dominance, elitism, fitness assignment and diversity preservation, evolutionary algorithms can approximate a set of non-dominated solutions representing different trade-offs among competing objectives. The authors further highlighted the applicability of these methods to nonlinear, non-convex and combinatorial optimization problems, where traditional mathematical programming approaches may encounter computational difficulties. This contribution is relevant to national industrial resource allocation because industrial policy decisions frequently involve competing objectives, including economic growth, employment generation, domestic value addition, resource efficiency and environmental sustainability. An evolutionary Pareto approach can therefore provide decision makers with a diverse set of efficient allocation alternatives rather than imposing a single predetermined preference structure.

According to Marler and Arora (2004), their paper provided a comprehensive review of multi-objective optimization methods used in engineering design and decision-making. Their study is important because it systematically examined different approaches for handling multiple conflicting objectives and highlighted the strengths and limitations of alternative solution strategies. The authors discussed several major approaches, including the weighted-sum method, goal programming, utility-function methods, constraint-based approaches,

and Pareto-based techniques. Their review emphasized that the choice of optimization method depends on the characteristics of the problem, the nature of the objectives, and the preferences of the decision maker.

Deb and Jain (2014) in their paper also advanced the field of evolutionary multi-objective optimization by proposing a reference-point-based non-dominated sorting approach, commonly referred to as NSGA-III, for solving many-objective optimization problems. Their work addressed the declining effectiveness of conventional dominance-based evolutionary algorithms as the number of objectives increases. In many-objective problems, a large proportion of solutions may become mutually non-dominated, thereby reducing the selection pressure toward the most desirable regions of the objective space. To overcome this challenge, Deb and Jain introduced systematically generated reference points to guide the search and maintain diversity across different regions of the Pareto frontier. The approach preserves the principle of non-dominated sorting while providing an additional mechanism for distributing solutions among the desired regions of the objective space. The methodology is relevant to national industrial resource allocation because industrial policy may involve several simultaneous objectives, including GDP contribution, employment generation, domestic value addition, export competitiveness, import dependence, infrastructure utilization and environmental sustainability. Where the number of objectives becomes sufficiently large -distributed Pareto-efficient industrial allocation alternatives.

Virtanen et al. (2020) introduced SciPy 1.0 as a comprehensive open-source Python library containing fundamental algorithms for scientific and technical computing. Although SciPy is not itself a multi-objective optimization algorithm, its numerical optimization, linear algebra, sparse matrix and statistical capabilities provide an important computational foundation for implementing mathematical optimization models. The availability of these tools facilitates the development, numerical solution and validation of optimization models within a reproducible programming environment. In the context of Pareto multi-objective optimization for national industrial resource allocation,

Blank and Deb (2020) developed pymoo, an open-source Python framework specifically designed for multi-objective optimization. The framework provides implementations of several established evolutionary optimization algorithms, including NSGA-II, NSGA-III and MOEA/D, together with mechanisms for constraint handling, sampling, crossover, mutation, termination and performance assessment. The availability of these computational capabilities provides researchers with an accessible and reproducible environment for implementing complex multi-objective optimization models. The framework is particularly relevant to Pareto-based optimization because it facilitates the generation, visualization and evaluation of non-dominated solutions and their corresponding Pareto fronts. For national industrial resource allocation, pymoo can therefore serve as the computational platform for implementing the proposed mathematical model, generating alternative Pareto-efficient resource-allocation strategies and assessing the quality and diversity of the resulting solutions. Its use also enhances the reproducibility of the proposed optimization framework by providing a systematic computational procedure through which the mathematical formulation can be translated into an executable optimization model.

Zitzler, Laumann, and Thiele (2001) proposed the Strength Pareto Evolutionary Algorithm 2 (SPEA2) as an improved evolutionary approach for solving multi-objective optimization problems. SPEA2 was developed to address limitations associated with earlier Pareto evolutionary algorithms through a refined fitness-assignment procedure, an explicit density estimation mechanism and an external archive for preserving non-dominated solutions. The fitness assignment process incorporates information regarding both the dominance strength and the number of solutions dominating each candidate, while density estimation promotes the preservation of solutions in less crowded regions of the objective space.

This paper we discussed several major approaches, including the weighted-sum method, utility-function methods, constraint-based approaches, and Pareto-based techniques

III. METHODOLOGY

The data were drawn entirely from the NBS publication, sourced administratively from the CBN and verified by the NBS. Three tables from that release are used: (i) the Q4 2020 and historical Deposit Money Banks' sectoral credit allocation (₦'Million), (ii) the year-on-year sectoral non-performing-loan (NPL) breakdown (₦'billion, End-Dec-2019 vs End-Dec-2020), and (iii) the whole-of-sector monthly electronic-payment channel volumes and values for 2020. Reconciling these three tables built on three different sectoral taxonomies and, in places, internally inconsistent within the source. The Q4 2020 credit-to-private-sector table lists 17 sector lines. Summing these lines reproduces the officially reported total of ₦20.37 trillion (₦20,373,488 million) to within ₦0.02 million a rounding level discrepancy that confirms the seventeen published lines.

Let there be $N = 17$ credit sector indexed $i \dots n$ (table 1) the decision variable $x_i \geq 0$ denote the amount of aggregate private-sector credit (₦'Million) reallocated to sector i in the planning quarter. The decision vector is $x = (x_1 \dots x_n)^T$. The current, reported allocation is denoted $x^0 = (x_1^0 \dots x_n^0)^T$,

Table 1 Source: author's reconciliation of NBS Selected Banking Sector Data (Q4 2020),

Agriculture	1,049,678	12.53	3.77	0.35	13.88
Mining & Quarrying	11,875	3.58	0.00	0.30	11.90
Manufacturing	3,191,372	5.23	3.12	0.55	21.82
Oil & Gas (Industry)	3,930,142	5.12	7.42	0.45	17.85
Power & Energy (Industry)	443,375	6.58	2.27	0.45	17.85
Construction	965,188	2.62	17.67	0.40	15.87
Trade/General Commerce	1,343,587	6.21	11.61	0.85	33.72
Government	654,719	-2.81	0.06	0.50	19.84
Real Estate	1,464,009	4.45	3.83	0.55	21.82
Finance, Insurance & Capital Market	1,774,033	11.11	0.31	1.00	39.67
Education	80,211	9.88	8.49	0.60	23.80
Oil & Gas (Services)	319,853	1.00	7.42	0.55	21.82
Power & Energy (Services)	1,018,164	5.92	2.27	0.55	21.82
General	1,254,298	-9.33	11.10	0.50	19.84
Information & Communication	1,863,298	11.19	6.02	0.95	37.69
Transportation & Storage	543,299	7.81	8.38	0.70	27.77
Others	466,386	-50.61	9.89	0.40	15.87

IV. DATA ANALYSIS

Table 2. Exact linear-program front vs. NSGA-II population, objective ranges

Objective	Exact LP front (min-max)	NSGA-II population (min-max)
Growth index f_1 (%)	5.18 – 7.10	5.17 – 7.03
Risk index f_2 (%)	3.96 – 5.72	4.00 – 5.68
Digital-impact index f_3	24.35 – 28.80	24.37 – 28.68

The two solution sets agree to within 0.1–0.2 percentage points on every objective, validating the NSGA-II configuration against the exact benchmark

Table 3. Status-quo allocation and four representative Pareto-optimal reallocations (₦'Million)

Sector	Q4 2020 (status quo)	Max-Growth vertex	Min-Risk vertex	Max-Digital vertex	Balanced solution
Agriculture	1,049,678	2,099,357	524,839	524,839	524,839
Mining & Quarrying	11,875	5,938	23,751	5,938	5,938
Manufacturing	3,191,372	1,595,686	5,929,181	1,848,541	4,134,125
Oil & Gas (Industry)	3,930,142	1,965,071	1,965,071	1,965,071	1,965,071
Power & Energy (Industry)	443,375	886,750	886,750	221,687	886,750
Construction	965,188	482,594	482,594	482,594	482,594
Trade/General Commerce	1,343,587	2,227,696	671,794	2,687,175	671,794
Government	654,719	327,359	1,309,437	327,359	327,359
Real Estate	1,464,009	732,005	732,005	732,005	732,005
Finance, Insurance & Capital Market	1,774,033	3,548,066	3,548,066	3,548,066	3,548,066
Education	80,211	160,422	40,106	160,422	40,106
Oil & Gas (Services)	319,853	159,926	159,926	159,926	159,926
Power & Energy (Services)	1,018,164	509,082	2,036,329	2,036,329	2,036,329
General	1,254,298	627,149	627,149	627,149	627,149

Sector	Q4 2020 (status quo)	Max-Growth vertex	Min-Risk vertex	Max-Digital vertex	Balanced solution
Information & Communication	1,863,298	3,726,596	931,649	3,726,596	3,726,596
Transportation & Storage	543,299	1,086,598	271,650	1,086,598	271,650
Others	466,386	233,193	233,193	233,193	233,193
f₁ growth (%)	4.18	7.10	5.18	6.57	6.39
f₂ risk (%)	6.02	5.51	3.96	5.62	4.51
f₃ digital	23.91	27.79	24.96	28.80	27.24

Numerical Result

Applying the model to the reconciled Q4 2020 data (Table 1) over a lending envelope of ₦20,373,488 million produces the status-quo portfolio metrics

$$f_1(x^0) = 4.18\%, \quad f_2(x^0) = 6.02 \text{ and } f_3(x^0) = 23.91\%,$$

The risk index reproduces the officially reported aggregate NPL ratio of 6.02%

V. SUMMARY AND CONCLUSION

This paper reconciled three internally inconsistent tables in a public NBS/CBN administrative statistical release into a single, validated seventeen-sector coefficient set, and used it to formulate Nigerian sectoral credit allocation as a tri-objective linear program balancing growth, NPL-risk and digital-banking impact. Solving the model exactly by weighted-sum linear scalarization and heuristically by NSGA-II produced closely agreeing Pareto fronts, and the resulting frontier shows the actual, reported Q4 2020 allocation is Pareto-dominated: efficient reallocations exist that raise the portfolio growth index from 4.18% to as high as 7.10%, or lower the portfolio NPL-risk index from 6.02% to as low as 3.96%, without worsening either of the other two objectives. Beyond the specific Q4 2020 numbers, the paper's main contribution is a reproducible template — data reconciliation, coefficient construction with disclosed proxies where direct data is unavailable, exact-versus-heuristic cross-validation, and a bounded, status-quo-anchored MOLP — for turning routinely published, non-research-oriented banking-sector statistics into a rigorous quantitative decision-support tool, applicable to each subsequent quarterly release in the same NBS series.

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