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Optimizing Life Insurance Solvency and Profitability in Morocco Using a Hybrid Generative and Genetic Algorithm Frameworks

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Abstract

Life insurance companies in Morocco face a structural tension between maximizing profitability and maintaining regulatory solvency under volatile macroeconomic and demographic conditions. This study proposes a hybrid framework combining a multivariate generative scenario engine with a real-coded multi-objective Genetic Algorithm (GA) to optimize Asset-Liability Management decisions. The GA simultaneously optimizes three objectives: Profitability Rate (f_1), Solvency Ratio (f_2), and Claims-to-Premiums Ratio (f_3), across four decision variables, namely Life Premiums, Death Cover, Investment Income, and Life Provisions, calibrated on official Moroccan data from ACAPS, HCP, and the Casablanca Stock Exchange over the period 2012 to 2024. Results demonstrate average improvements of 20% to 40% in both profitability and solvency relative to historical baselines. Sensitivity analysis identifies GDP and market capitalization as the dominant drivers of profitability, while life expectancy and mathematical provisions constitute the primary determinants of long-term solvency. Stress tests confirm that optimized allocations maintain regulatory compliance under recession scenarios through the horizon 2030. The proposed framework provides insurance executives and regulators with a quantitative decision-support tool for navigating the profitability-solvency trade-off under dynamic macroeconomic conditions.

Keywords: Asset-Liability Management; Multi-objective Genetic Algorithm; Life Insurance Optimization; Solvency and Profitability; Generative Scenario Simulation.

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1 Introduction

Over the past two decades, the life insurance industry in emerging economies has undergone profound structural transformation, driven by the confluence of regulatory modernization, demographic evolution, and deepening financial market integration. Within the Kingdom of Morocco, this transformation has been particularly pronounced: the national insurance sector has emerged as one of the most sophisticated financial ecosystems on the African continent, functioning simultaneously as a dominant institutional investor, a cornerstone of long-term domestic savings mobilization, and a systemic pillar of capital market development.

Yet, despite this sustained trajectory of expansion, Moroccan life insurers operate within an increasingly volatile and structurally complex macroeconomic environment. Asset-Liability Management (ALM) in this context demands continuous navigation of compounding systemic pressures, including persistent inflationary dynamics, cyclical gross domestic product (GDP) fluctuations, and the inherent volatility of domestic capital markets, while simultaneously accommodating accelerating demographic transitions characterized by secular improvements in life expectancy at birth and the gradual redistribution of mortality risk across multi-cohort policyholder portfolios. These converging forces fundamentally reshape the

actuarial risk architecture and long-term liability commitments underpinning the life insurance balance sheet.

Within this intricate financial landscape, insurance corporations are compelled to sustain a structurally precarious equilibrium between two fundamentally antagonistic corporate imperatives. On one side, competitive market dynamics and fiduciary obligations toward equity stakeholders exert continuous pressure to maximize investment returns and underwriting profitability. On the other side, prudential regulatory frameworks impose stringent capital adequacy requirements and minimum solvency thresholds, mandating that insurers maintain sufficient reserves to honor long-term policyholder commitments and preserve systemic financial stability under adverse macroeconomic conditions. The tension between these competing imperatives defines the central optimization challenge confronting contemporary life insurance management.

Theoretical Foundations and Methodological Limitations of ALM

The theoretical foundations of modern ALM trace back to the portfolio efficiency principles established by [1] and subsequently extended by [2]. Applied to life insurance asset management, these frameworks support the allocation of technical reserves across asset classes to maximize risk-adjusted returns. However, the application of mean-variance optimization to insurance reserve portfolios is severely constrained by regulatory investment limits, liquidity requirements, and liability-matching imperatives, introducing non-convexities incompatible with classical quadratic programming solvers [3].

On the liability side, classical quantitative approaches to ALM originate from the foundational immunization and duration-matching principles of [4], who demonstrated that a life insurance fund could shield its net worth from interest rate fluctuations by matching the duration of its assets to that of its liabilities. This pioneering framework assumes a deterministic and stationary environment and provides no mechanism for handling non-linear, stochastic interactions. Subsequent theoretical advances extended the immunization paradigm toward multi-period stochastic programming formulations. [5] developed integrated asset-liability optimization models that simultaneously simulate joint distributions of multi-asset returns and insurance liability cash flows across multiple time periods, while [6] incorporated scenario-based optimization with guarantee constraints.

Despite representing a substantial methodological advance, these stochastic programming models share a common limitation: they rely on gradient-based or linear programming solvers that presuppose linearity, stationarity, convexity, and differentiability. This structural assumption renders them fundamentally ill-equipped to handle the non-convex, discontinuous, and high-dimensional optimization landscapes generated by the interaction of underwriting decisions, investment allocation constraints, and regulatory solvency requirements [3].

The Profitability-Solvency Conflict and Longevity Risks

The maximization of profitability and solvency has traditionally been approached through independent streams in the academic literature. On the underwriting side, [7] established a framework for measuring technical profitability, demonstrating that premium volume growth, while improving absolute profitability, simultaneously amplifies claims exposure. This creates a fundamental tension between revenue expansion and risk control. On the solvency dimension, [8] provided a comprehensive comparative analysis of risk-based capital frameworks, demonstrating that the solvency ratio constitutes the primary quantitative indicator of an insurer's capacity to honor long-term policyholder commitments.

Furthermore, [9] identified longevity risk, measured through increasing life expectancy and declining mortality rates, as the dominant structural driver of long-term solvency deterioration. Secular improvements in policyholder longevity amplify the present value of future obligations, placing persistent downward pressure on solvency margins that cannot be offset by investment return optimization alone. This necessitates dynamic actuarial provisioning strategies that continuously update the liability valuation basis, motivating the inclusion of mathematical provisions as a controllable decision variable rather than a fixed actuarial output.

The simultaneous optimization of profitability and solvency represents a significantly underexplored area. [10] examined this trade-off through an econometric framework, demonstrating that insurers systematically sacrifice short-term solvency margins in pursuit of market share growth, recovering capital adequacy only after a multi-year lag as premium reserves mature into investment returns. This dynamic trade-off structure confirms the multi-period, path-dependent nature of the problem and underscores the inadequacy of static single-period frameworks. To the best of our knowledge, no prior study has

formulated and solved the joint profitability-solvency optimization problem for life insurance as a formal multi-objective program with explicit Pareto frontier identification [11].

Evolutionary Optimization and the Moroccan Empirical Context

Genetic Algorithms (GAs), as population-based meta-heuristic optimization methods formalized by [12] and extended to continuous search spaces by [13] and [14], offer a powerful alternative for exploring non-convex, discontinuous, and high-dimensional solution spaces without requiring gradient information. The introduction of multi-objective evolutionary frameworks, particularly by [11] and [15], provided the theoretical foundation for identifying full Pareto-optimal solution sets rather than compressing multiple competing objectives into a single arbitrary weighted function.

In practice, the application of Genetic Algorithms in the insurance domain has been concentrated almost exclusively in non-life insurance contexts. In the Moroccan market, [16] applied a genetic algorithm framework to optimize the technical surplus of Takaful operators, while [17] deployed GAs to optimize reinsurance treaty structures for general insurance operators under solvency constraints. In parallel, [18] applied mathematical modeling to address non-linear climate-related risks in Moroccan crop insurance pricing, and [19] deployed statistical learning models to forecast automobile insurance claims patterns. More broadly, [20] validated the application of deep learning and hybrid optimization architectures for macro-financial risk modeling in the Moroccan financial sector.

Critically, a systematic review of the existing literature reveals a near-total absence of Genetic Algorithm applications specifically targeting life insurance Asset-Liability Management, and in particular the joint multi-objective optimization of profitability, solvency, and claims efficiency within a unified Pareto framework. This gap is especially pronounced in the African and North African insurance context, where the specific combination of rapid demographic transitions, volatile macroeconomic conditions, and evolving prudential regulatory frameworks creates an optimization environment substantially different from developed markets.

To visually contextualize these gaps, Table 1 provides a taxonomy of traditional optimization methodologies and their limitations, while Table 2 synthesizes the positioning of this study against the existing Moroccan empirical literature.

Table 1: Taxonomy of Optimization Methodologies in Insurance ALM and Their Limitations.

Methodological Approach		Key Contributions	Limitations in Life Insurance ALM Context
Deterministic	Immunization [4]	Pioneered duration matching for asset and liability cash flows in life insurance.	Ineffective under non-linear macroeconomic shocks; no mechanism for multi-objective trade-off management.
Stochastic	Programming [5, 6]	Multi-period scenario simulation for joint asset-liability optimization.	Assumes convexity and normality; high computational burden; cannot handle discontinuous insurance liability dynamics.
Econometric	Profitability-Solvency Analysis [8–10]	Empirical identification of profitability and solvency determinants in life insurance markets.	Descriptive rather than prescriptive; provides no optimization framework for decision variable allocation.
Multi-objective Evolutionary	Algorithms [11, 15]	Theoretical foundations for Pareto-optimal multi-objective search in non-convex spaces.	No direct application to life insurance ALM; requires domain-specific adaptation for actuarial constraint integration.
GA Applications in Non-life Insurance	[16, 17]	Applied GA to Takaful and reinsurance optimization in the Moroccan market.	Segment-specific; no integrated multi-objective life insurance ALM framework; no generative scenario engine.

Table 2: Positioning of This Study Against Existing Moroccan Insurance Literature.

Focus Area	Key Empirical Findings	Identified Literature Gap
ALM and Solvency Frameworks	Analyzed transition toward Solvency II-inspired frameworks in Morocco.	Retrospective compliance focus; no forward-looking multi-objective optimization.
Takaful and Reinsurance Optimization [16, 17]	Applied GA to technical surplus and treaty optimization under solvency constraints.	Restricted to non-life and Islamic insurance; no joint profitability-solvency Pareto framework.
Agricultural and Auto Insurance Modeling [18, 19]	ML and mathematical models for claims forecasting and climate risk pricing.	Single-objective; no ALM integration; not applicable to life insurance balance sheet optimization.
Macro-financial Risk Modeling [20]	Validated hybrid AI-actuarial approaches for Moroccan financial risk.	No life insurance-specific ALM optimization; no Pareto frontier identification.
This Study	Hybrid generative-GA framework for joint optimization of profitability, solvency, and claims efficiency in Moroccan life insurance.	First integrated multi-objective ALM optimization framework for Moroccan life insurance; bridges generative simulation with evolutionary meta-heuristics.

Proposed Framework and Research Objectives

To overcome these methodological limitations and bridge the identified literature gaps, this study advances a novel, data-driven hybrid optimization framework that integrates a generative macroeconomic scenario simulation engine with a multi-objective real-coded Genetic Algorithm (GA). Rather than treating asset allocation and liability underwriting as operationally independent decision domains, the proposed architecture models their dynamic interaction as a continuous, closed-loop optimization process. The generative engine produces statistically coherent synthetic financial and actuarial trajectories, preserving empirical cross-correlations and tail-risk structures across macroeconomic and demographic state variables, while the multi-objective GA systematically navigates the high-dimensional decision space to identify Pareto-non-dominated allocation strategies that simultaneously advance competing corporate objectives [11, 15].

The empirical foundation of this study rests on a longitudinal dataset spanning 2012 to 2024, constructed from primary official sources: insurance sector indicators compiled by the *Autorité de Contrôle des Assurances et de la Prévoyance Sociale* (ACAPS), macroeconomic aggregates provided by the *Haut-Commissariat au Plan* (HCP), and capital market data sourced from the Casablanca Stock Exchange. To operationalize this model, these indicators are macro-aggregated at the national level, reflecting the consolidated structural performance of the Moroccan life insurance sector rather than an individual commercial entity. By mapping the explicit sensitivities of key decision variables, encompassing premium allocation structures, death coverage ratios, mathematical reserve levels, and investment income streams, against exogenous macroeconomic and demographic shocks, this research delivers a granular, context-specific assessment of ALM optimization in the Moroccan life insurance sector. In doing so, it contributes an actionable decision-support platform through which insurance executives and prudential regulators can jointly explore the Pareto frontier at which corporate financial performance and regulatory solvency compliance converge.

To rigorously evaluate the structural trade-offs inherent to the Moroccan life insurance market and validate the analytical capability of the proposed hybrid framework, the study advances four empirically testable research hypotheses:

- H₁:** A fundamental structural tension exists between an insurer’s short-term Profitability Rate (f_1) and its regulatory Solvency Ratio (f_2): aggressive portfolio allocations toward high-volume life premium underwriting temporarily compress capital adequacy margins prior to the investment maturation of accumulated premium reserves.
- H₂:** Macroeconomic growth indicators, specifically GDP growth rates and MASI equity index performance, exert a dominant and asymmetric influence on the Profitability Rate (f_1) relative to

demographic parameters, establishing financial market dynamics as the primary exogenous lever in the optimization architecture.

- H₃:** Long-term structural demographic shifts, operationalized through secular improvements in Life Expectancy and evolving multi-cohort Mortality Rates, exert a disproportionately greater sensitivity on the long-term Solvency Ratio (f_2) than inflationary fluctuations captured by the Consumer Price Index (CPI), necessitating dynamic and prospective actuarial provisioning strategies.
- H₄:** The hybrid generative-GA framework yields Pareto-optimal asset-liability allocations that materially outperform historical baseline strategies, sustaining superior capital protection profiles under simulated macroeconomic contraction scenarios while preserving competitive profitability under expansionary conditions.

The remainder of this paper is organized as follows. Section 2 outlines the quantitative methodology, detailing the hybrid generative scenario framework and the multi-objective optimization formulation. Section 3 reports and critically discusses the empirical results, including sensitivity analyses and stress test outcomes. Finally, Section 4 provides concluding remarks, operational recommendations, and avenues for future research.

2 Methodology

Figure 1 illustrates the proposed hybrid decision-support architecture integrating data-driven learning, generative scenario modeling, and multi-objective evolutionary optimization.

The process begins with a comprehensive data pipeline involving collection, cleaning, normalization, and stationarity adjustment of insurance, macroeconomic, and financial variables. This step ensures that the dataset is structurally consistent and suitable for both predictive modeling and optimization.

In parallel, a generative scenario engine constructs stochastic macroeconomic and demographic environments based on variables such as GDP, CPI, mortality rate, MASI performance, and life expectancy. These scenarios represent plausible states of the economic system and introduce uncertainty directly into the optimization process.

The core of the framework is the Multi-Objective Genetic Algorithm, which operates on normalized financial decision variables. Unlike traditional optimization methods, the GA evaluates each candidate solution not under a single deterministic environment but across multiple generated scenarios. This is achieved through a scenario-based fitness aggregation function, ensuring that the optimization process explicitly accounts for uncertainty and systemic variability.

Once the algorithm converges, it produces a Pareto-optimal set of solutions $\mathcal{P}^*$ representing efficient trade-offs between profitability, solvency, and claims efficiency. These solutions are not considered final decisions but serve as optimal strategic candidates under uncertainty.

A second analytical layer is then applied through post-optimization stress testing. In this stage, extreme but plausible macroeconomic shocks are introduced to evaluate the robustness and stability of the Pareto solutions. This step allows identification of solutions that remain stable under adverse economic conditions.

Finally, an interpretability layer based on SHAP values and permutation importance is applied to explain the contribution of each financial and macroeconomic variable to the model outputs. This enhances transparency and supports regulatory and managerial understanding of the optimization results.

Overall, the framework integrates optimization, uncertainty modeling, and explainability into a unified structure, enabling robust, interpretable, and economically consistent decision support for life insurance portfolio management.

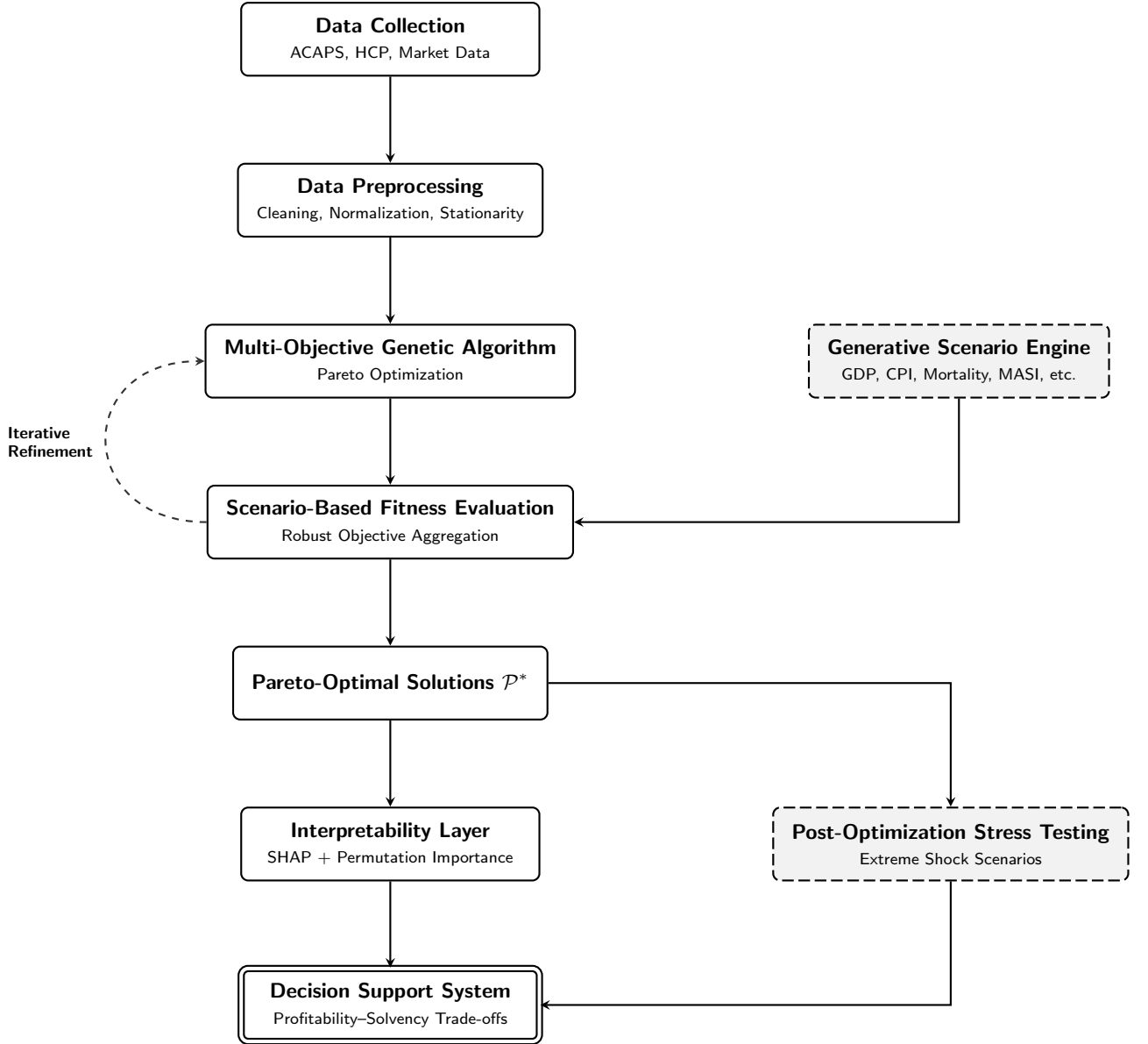


Figure 1: Hybrid Generative-Genetic Optimization Framework for Life Insurance Decision-Making

2.1 Data Collection and Dataset Description

2.1.1 Data Sources

The first step in our methodology is to construct a reliable and coherent dataset covering insurance, macroeconomic, financial, and demographic dimensions. These data are essential for implementing a hybrid generative-predictive model and for optimization using genetic algorithms. The dataset spans the period 2012–2024 and is sourced from official and recognized institutions to ensure reliability and representativeness of the Moroccan market.

Data related to life insurance companies were collected from the *Autorité de Contrôle des Assurances et de la Prévoyance Sociale (ACAPS)* [21]. Collected variables include life premiums, life claim payments, death benefits, technical provisions, solvency ratio, number of life contracts, and bancassurance share. These data are crucial for understanding the technical and financial performance of life insurance companies.

Macroeconomic and demographic data were obtained from the *Haut-Commissariat au Plan (HCP)* [22], including Gross Domestic Product (GDP), Consumer Price Index (CPI), mortality rate, and life expectancy. These variables allow the integration of socio-economic dimensions into the analysis and help identify exogenous factors affecting insurers' financial results.

Financial market data were obtained from the *Casablanca Stock Exchange*, including the MASI Index and market capitalization relative to GDP [23]. These variables capture the impact of market performance on insurers' investment income.

Once collected, the data were prepared and harmonized to ensure quality and consistency. Temporal alignment was performed so that all variables correspond to the same years (2012–2024). Missing values were treated using linear interpolation for continuous variables or mean imputation for discrete variables. Some variables, such as GDP, life premiums, and provisions, were normalized or logarithmically transformed to reduce scale differences and facilitate model training. After these steps, the dataset is ready for descriptive analysis, predictive modeling, and optimization using genetic algorithms.¹

2.1.2 Variables Used in the Study

Table 3: Variables used in the study

Variable	Description
Year	Observation period
Life.Premiums (million MAD)	Life insurance premiums collected
Life.Claims (million MAD)	Life insurance claims expenses
Death.Coverage (million MAD)	Death cover insurance premiums
Technical.Result.Life (million MAD)	Technical result of life insurance operations
Profitability.Rate	Insurers' profitability ratio
Solvency.Ratio	Insurers' solvency ratio
Life.Provisions (million MAD)	Life insurance technical provisions
Investment.Income.Life (million MAD)	Investment income from life insurance
CPI	Consumer Price Index
GDP	Gross Domestic Product
Mortality.Rate	Mortality rate
Bancassurance.Life	Life insurance bancassurance and capitalization
Life.Expectancy	Life expectancy at birth
MASI.Performance	Moroccan stock index (MASI) performance
MarketCap.GDP	Market capitalization to GDP ratio

As shown in Table 3, the study considers a set of variables covering the main aspects of the Moroccan life insurance sector. Life insurance operational variables include premiums collected, claims expenses, death coverage, technical results, profitability rates, solvency ratios, technical provisions, and investment income, which collectively describe insurers' financial performance and risk exposure. Macroeconomic indicators such as CPI and GDP capture inflationary trends and economic growth. Demographic and market variables, including mortality rate, life expectancy, MASI performance, and MarketCap/GDP, provide additional context on population health and market conditions. Overall, these variables enable a comprehensive analysis of the life insurance sector, capturing both internal financial dynamics and external economic influences.

¹Dataset available on Kaggle: <https://www.kaggle.com/drasmaafaris/dataset123>

2.2 Exploratory Data Analysis

2.2.1 Descriptive Statistics

Table 4: Descriptive statistics of technical and macro-financial indicators

Variable	count	mean	std	min	25%	50%	75%	max	range
Year	13	2018.0	3.894	2012	2015	2018	2021	2024	12
Life_Premiums	13	17623.1	6773.7	8600	10600	18200	22900	27100	18500
Life_Claims	13	22126.8	28140.6	6183	6476.2	12156	26500	111000	104817
Death_Cover	13	2514.8	952.2	885.9	2581	2842.5	3213.2	3440.5	2554.6
Technical_Result_Life	13	1350.3	1662.7	688	759.7	912.5	991	6859.9	6171.9
Profitability_Rate	13	0.095	0.008	0.073	0.094	0.096	0.099	0.107	0.034
Solvency_Ratio	13	3.979	0.590	3.103	3.693	4.070	4.147	5.220	2.117
Life_Provisions	13	84610.7	27277.8	50530.8	61702.9	81689.2	104178	132375	81844.2
Investment_Income_Life	13	2606.6	690.7	1919.2	2122.6	2492.2	2702	4200	2280.8
CPI	13	0.019	0.021	0.0004	0.007	0.014	0.019	0.066	0.066
GDP	13	0.028	0.035	-0.072	0.027	0.031	0.041	0.082	0.153
Mortality_Rate	13	5.761	0.341	5.2	5.63	5.67	5.77	6.48	1.28
Bancassurance_Life	13	0.547	1.401	0.004	0.117	0.184	0.2	5.2	5.196
Life_Expectancy	13	74.979	1.993	71.67	73.61	75.5	76.7	77.2	5.53
MASI_Performance	13	0.033	0.150	-0.198	-0.073	0.056	0.128	0.305	0.502
MarketCap_GDP	13	0.511	0.040	0.445	0.485	0.513	0.535	0.582	0.137

Table 4 presents the descriptive statistics of technical and macro-financial indicators for Moroccan life insurance companies over 2012–2024. Technical indicators include *Life_Premiums*, *Life_Claims*, *Death_Cover*, *Technical_Result_Life*, *Profitability_Rate*, *Solvency_Ratio*, *Life_Provisions*, *Investment_Income_Life*, while macro-financial and demographic indicators include *CPI*, *GDP*, *Mortality_Rate*, *Bancassurance_Life*, *Life_Expectancy*, *MASI_Performance*, *MarketCap_GDP*. These statistics provide insights into central tendencies, dispersion, and range, highlighting the growth trends and variability across both technical and macro-financial dimensions.

The technical life insurance indicators show substantial growth over 2012–2024. *Life_Premiums* and *Life_Claims* exhibit strong upward trends, with premiums averaging 17,623 MAD and claims demonstrating high variability (standard deviation $\approx 28,140$), reflecting the diverse risk exposure and market expansion. *Death_Cover* and *Technical_Result_Life* display moderate increases, suggesting stable product performance. The *Profitability_Rate* remains relatively constant at 0.095, while the *Solvency_Ratio* indicates adequate capital adequacy. *Life_Provisions* and *Investment_Income_Life* steadily rise, highlighting the accumulation of reserves and investment growth critical to the financial stability of life insurers.

Macro-financial indicators show moderate fluctuations during the period. GDP and CPI display small variations, with GDP ranging from -7.2% to 8.2%, indicating periods of contraction and expansion. *Mortality_Rate* is relatively stable, while *Bancassurance_Life* exhibits high variability due to its low baseline and occasional spikes. Life expectancy steadily increases from 71.67 to 77.2 years. Market indicators (*MASI_Performance* and *MarketCap_GDP*) suggest moderate market performance and capitalization trends. These findings highlight the heterogeneity across technical and macro-financial variables, which is important to consider before implementing genetic algorithm optimization.

2.2.2 Correlation Analysis

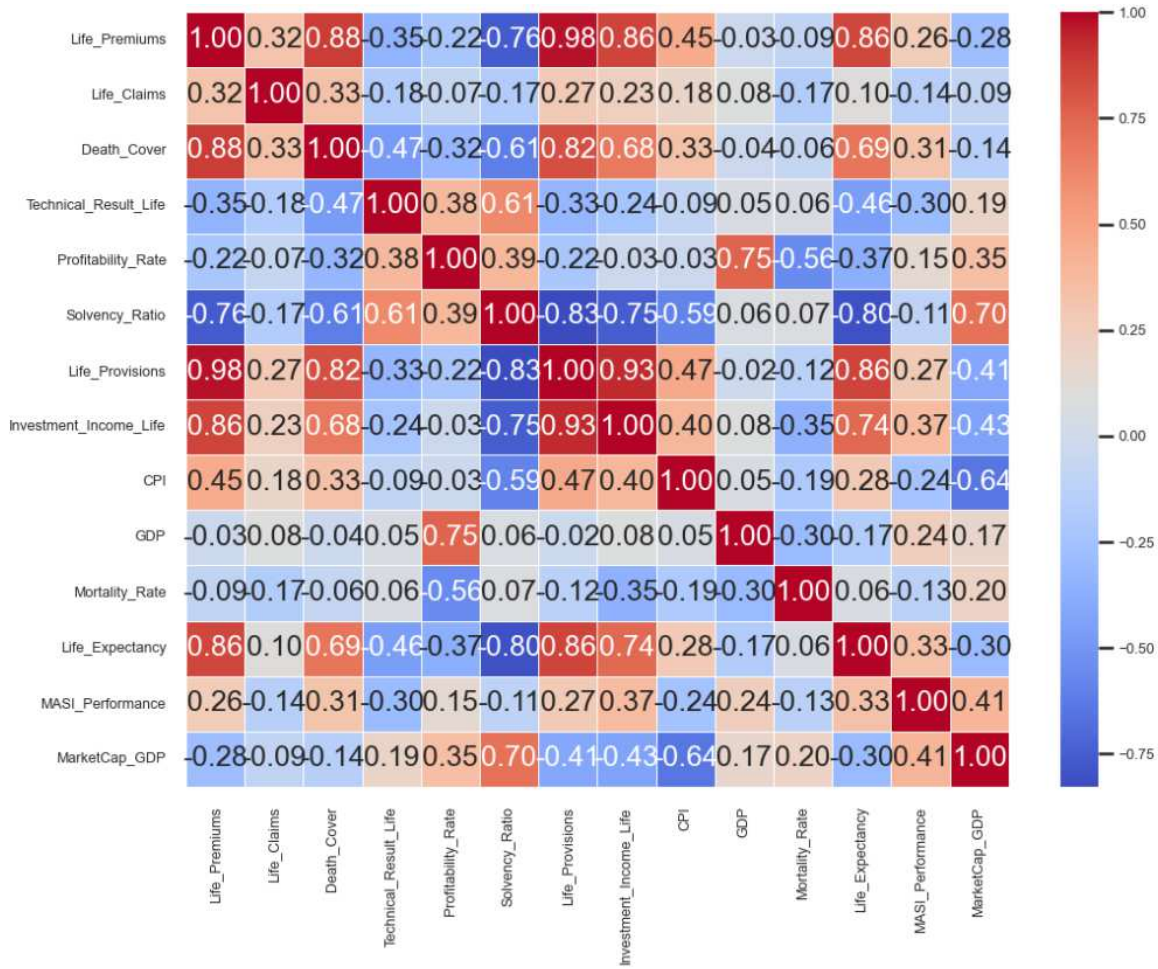


Figure 2: Correlation Matrix

The correlation matrix (Figure 2) provide a visual overview of how the variables co-move. A strong positive correlation exists between Life Premiums and Life Provisions (0.98), indicating that as the business volume increases, the reserves set aside for future payouts grow almost identically. Similarly, Life Premiums are strongly correlated with Life Expectancy (0.86), reflecting the accumulation of liabilities as policyholders live longer. Investment Income is highly correlated with Life Provisions (0.93), demonstrating the efficiency of the insurers' investment engine: more assets under management translate into higher returns.

Conversely, the analysis also highlights an efficiency-solvency trade-off. The Solvency Ratio shows a strong negative correlation with Life Provisions (-0.83) and Life Premiums (-0.76), suggesting that rapid growth in liabilities and business volume can temporarily reduce solvency margins until capital adjusts. Profitability Rate is negatively correlated with Mortality Rate (-0.56), which is consistent with the expected higher payouts reducing net profitability. Macroeconomic variables also play a key role: GDP exhibits a strong positive correlation with Profitability Rate (0.75), reflecting the sector's sensitivity to economic cycles, while CPI and MarketCap/GDP show an inverse relationship (-0.64), capturing the effect of inflation on market valuations. Interestingly, Life Claims display relatively weak correlations with other variables, indicating stochastic behavior that is less predictable in relation to business volume.

2.2.3 Temporal Trends

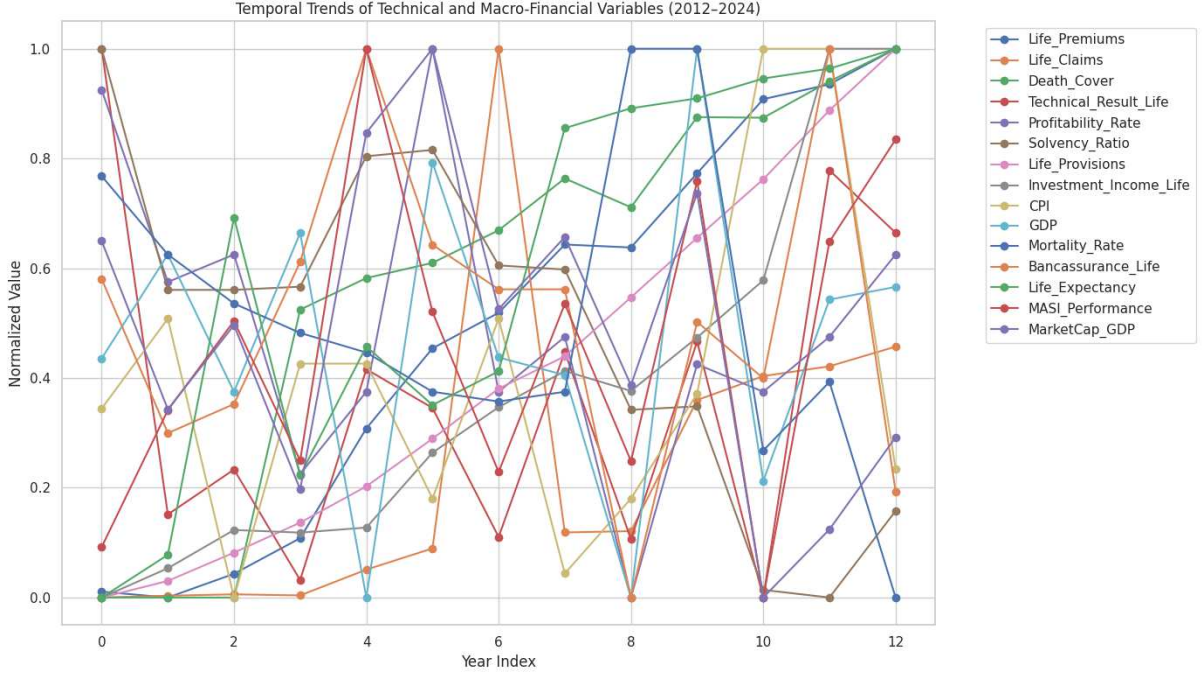


Figure 3: Temporal Trends

The temporal analysis (Figure 3) reveals long-term growth patterns and volatility in the dataset. Life Provisions and Life Expectancy show stable upward trends, reflecting increasing liabilities as policyholders live longer. The Bancassurance Life variable demonstrates notable growth toward 2024, highlighting the increasing importance of bank-mediated distribution channels.

On the other hand, variables such as MASI Performance and MarketCap/GDP display pronounced volatility, characteristic of equity market behavior. The Profitability Rate exhibits cyclical peaks in alignment with investment income, but is susceptible to sudden "V-shaped" drops, notably around Years 8 and 10, corresponding to global economic disruptions. The Solvency Ratio shows high initial values but fluctuates in response to Life Claims spikes, suggesting an inverse relationship during stress periods. GDP and CPI movements further influence the sector, with GDP recovery toward the end of the period aligning with a rise in Life Premiums.

2.2.4 Stationarity Analysis

Stationarity testing using the Augmented Dickey-Fuller (ADF) test [24] ensures the compatibility of the dataset with predictive models and optimization algorithms. Before differencing, most series were non-stationary, except Life Claims and MASI Performance. After first-order differencing, variables including Life Premiums, Death Cover, Profitability Rate, Solvency Ratio, CPI, and GDP became stationary, confirming that differencing successfully removed trends and stabilized the series for modeling purposes.

Table 5: ADF Test Results for Insurance and Macro-financial Variables

Variable	ADF Statistic	p-value	Stationary?
<i>Before Differencing</i>			
Year	0.5175	0.9854	No
Life_Premiums	-1.8028	0.3791	No
Life_Claims	-3.4239	0.0102	Yes
Death_Cover	-2.0348	0.2715	No
Technical_Result_Life	2.4499	0.9990	No
Profitability_Rate	0.0605	0.9633	No
Solvency_Ratio	-2.3309	0.1622	No
Life_Provisions	2.0210	0.9987	No
Investment_Income_Life	2.0893	0.9988	No
CPI	-1.3648	0.5990	No
GDP	-2.2191	0.1994	No
Mortality_Rate	-1.5188	0.5242	No
Life_Expectancy	-0.1724	0.9417	No
MAISI_Performance	-4.4407	0.0003	Yes
MarketCap_GDP	-2.6635	0.0806	No
<i>After First-Order Differencing</i>			
Year	-2.7680e-16	0.9585	No
Life_Premiums	-3.3260	0.0138	Yes
Life_Claims	-5.1161	1.30e-05	Yes
Death_Cover	-11.8735	6.42e-22	Yes
Technical_Result_Life	2.3980	0.9990	No
Profitability_Rate	-5.3293	4.76e-06	Yes
Solvency_Ratio	-4.5974	0.0001	Yes
Life_Provisions	-1.8185	0.3713	No
Investment_Income_Life	-0.0024	0.9583	No
CPI	-86.0770	0.0000	Yes
GDP	-8.7922	2.23e-14	Yes
Mortality_Rate	1.0441	0.9947	No
Life_Expectancy	-1.6621	0.4507	No
MAISI_Performance	-2.2527	0.1877	No
MarketCap_GDP	-2.7415	0.0671	No

2.3 Data Preprocessing

2.3.1 Data Cleaning and Normalization Framework

To prepare the dataset for optimization within the hybrid architecture, a rigorous data preprocessing workflow is required. Raw macro financial and insurance datasets frequently exhibit missing observations, structural outliers, and scale variances that can destabilize the fitness landscape of genetic algorithms and bias generative models [25]. The data preparation workflow is systematically partitioned into three consecutive phases executed within a single unified pipeline: missing value mitigation, robust outlier handling, and feature scaling.

First, missing data points are addressed based on the statistical nature of each indicator. Continuous macroeconomic and technical insurance variables undergo linear interpolation to preserve the underlying temporal trends, with any remaining isolated gaps filled using the series mean [26]. For categorical or discrete series, missing entries are imputed using the empirical mode to maintain distribution integrity.

Second, to protect the optimization process from anomalous volatility shocks while retaining historical information, an outlier winsorization procedure is implemented. The framework computes the Interquartile Range (IQR) for each variable, establishing lower and upper boundaries via the standard statistical threshold [27]:

$$\text{Lower Bound} = Q_1 - 1.5 \times IQR \quad (1)$$

$$\text{Upper Bound} = Q_3 + 1.5 \times IQR \quad (2)$$

Values lying outside this academic range are capped and brought to the nearest acceptable boundary rather than eliminated, ensuring that sample size and chronological continuity over the 2012 to 2024 window remain fully intact.

Third, because genetic algorithms are highly sensitive to magnitude differences among decision variables and predictors, a global Min Max normalization is applied. Transforming all continuous features into a uniform range of $[0, 1]$ prevents variables with large absolute values, such as Life Claims or GDP in millions of MAD, from dominant scaling distortions during fitness evaluation and selection phases [12].

The complete stepwise operational sequence for this data engineering phase is formally specified in Algorithm 1. This integrated procedure uncovers the clean structure, temporal dynamics, and relationships of the life insurance and macro financial dataset spanning 2012 to 2024, successfully conditioning the fitness landscape for predictive modeling and evolutionary optimization.

Algorithm 1: Data Cleaning and Normalization for Genetic Algorithms

Input: Raw dataset D with variables $V = \{v_1, v_2, \dots, v_n\}$ covering technical and macro financial indicators.

Output: Cleaned and normalized dataset D' suitable for genetic algorithm optimization.

```

1 foreach variable  $v_i \in V$  do
2   if  $v_i$  is continuous then
3     Interpolate missing values using linear interpolation;
4     Replace any remaining missing values with mean;
5   else
6     Replace missing values with mode;
7   Compute  $Q_1$  and  $Q_3$  of  $v_i$ ;
8   Compute  $IQR = Q_3 - Q_1$ ;
9   Set lower bound =  $Q_1 - 1.5 \cdot IQR$ ;
10  Set upper bound =  $Q_3 + 1.5 \cdot IQR$ ;
11  if value < lower bound then
12    replace with lower bound
13  if value > upper bound then
14    replace with upper bound
15 foreach variable  $v_i \in V$  do
16   Apply Min-Max normalization:

```

$$v'_i = \frac{v_i - \min(v_i)}{\max(v_i) - \min(v_i)}$$

```

17 return  $D'$ 

```

2.4 Multi-objective Optimization Framework

The management of life insurance companies is inherently characterized by the simultaneous pursuit of multiple, structurally conflicting objectives. Insurers are required to enhance profitability and shareholder value through the expansion of premium income and the optimization of investment returns, while ensuring compliance with regulatory solvency requirements that guarantee the fulfillment of long-term policyholder obligations. At the same time, they must effectively manage exposure to insurance claims, which represent the primary liability component of their balance sheets. These objectives are intrinsically interdependent, as improvements in one dimension often induce deterioration in another.

This structural tension naturally motivates a multi-objective optimization formulation, in which competing objectives are optimized concurrently rather than reduced to a single scalar function. The resulting solution is characterized by a Pareto-optimal frontier that captures the trade-offs between conflicting criteria [15, 28]. Unlike single-objective frameworks, this approach preserves the full spectrum of admissible compromises, thereby providing decision-makers with a structured set of efficient allocation strategies, each reflecting a distinct balance between profitability, solvency, and risk exposure [7, 8].

2.4.1 Decision Variables

The decision space is defined by four normalized control variables $\mathbf{x} = [x_1, x_2, x_3, x_4]^\top \in [0, 1]^4$. The variable x_1 represents life premium allocation, serving as the primary revenue driver. The variable x_2 corresponds to death cover exposure, reflecting underwriting risk. The variable x_3 captures investment income derived from assets backing technical reserves. The variable x_4 denotes life provisions, which represent long-term liabilities associated with policyholder obligations.

These variables jointly determine the insurer's financial structure by balancing revenue generation, risk exposure, investment performance, and liability coverage. Their joint optimization enables exploration of feasible strategic configurations under regulatory and market constraints.

2.4.2 Optimization Objectives

Objective 1: Profitability Maximization (f_1). Profitability is a fundamental indicator of financial performance in life insurance, reflecting the insurer's ability to generate net income from underwriting activities and investment operations. It is driven by premium inflows, returns on assets backing technical reserves, and operational efficiency. Sustained profitability supports capital accumulation, business growth, and competitive positioning in the insurance market [10].

The first objective is defined as:

$$\max \quad f_1(\mathbf{x}, \mathbf{v}^{(s)}) = \frac{x_3 \cdot \alpha(\text{MASI}^{(s)}, \text{GDP}^{(s)}) + x_1 - \text{Life_Claims}^{(s)} - x_2}{x_1} \quad (3)$$

where $\alpha(\cdot)$ represents a macroeconomic amplification function capturing the effect of financial market performance and economic growth on investment returns, while $\text{Life_Claims}^{(s)}$ is modeled as a stochastic exogenous variable conditioned on scenario $\mathbf{v}^{(s)}$.

Objective 2: Solvency Ratio Maximization (f_2). Solvency is a core regulatory constraint in insurance, measuring the insurer's capacity to meet future obligations through the ratio of eligible own funds to required solvency capital. Maintaining an adequate solvency position is essential to ensure financial stability, protect policyholders, and comply with prudential regulations, including those enforced by ACAPS in Morocco [9].

The second objective is formulated as:

$$\max \quad f_2(\mathbf{x}, \mathbf{v}^{(s)}) = \frac{\text{Eligible_Own_Funds}^{(s)}}{x_4 \cdot \beta(\text{Life_Expectancy}^{(s)}, \text{Mortality}^{(s)}) + x_2} \quad (4)$$

where $\beta(\cdot)$ captures demographic risk effects, increasing technical provisions in response to rising life expectancy and declining mortality rates.

Objective 3: Claims-to-Premiums Efficiency (f_3). Claims constitute the dominant liability in life insurance portfolios and directly affect technical profitability and capital adequacy. Since claim occurrences are exogenous and driven by demographic and stochastic factors, direct minimization of claims is neither realistic nor operationally meaningful. Instead, efficiency is assessed through the claims-to-premiums ratio, which reflects the insurer's ability to absorb claims through adequate premium structuring [7].

The third objective is defined as:

$$\min \quad f_3(\mathbf{x}, \mathbf{v}^{(s)}) = \frac{\text{Life_Claims}^{(s)}}{x_1} \quad (5)$$

Trade-offs Between Objectives. The three objectives are inherently conflicting. Increasing premium volume enhances profitability and improves claims absorption efficiency, yet simultaneously expands future liability exposure, thereby increasing required provisions and exerting pressure on solvency. Conversely, strengthening solvency buffers may reduce investable resources, limiting investment income and profitability. These interdependencies define a non-convex Pareto frontier, which is approximated using evolutionary optimization methods [28].

2.4.3 Exogenous Macroeconomic Variables

The objective functions are conditioned by an exogenous scenario vector $\mathbf{v}^{(s)}$, defined as:

$$\mathbf{v}^{(s)} = [\text{GDP}, \text{CPI}, \text{MASI}, \text{MarketCap_GDP}, \text{Life_Expectancy}, \text{Mortality_Rate}]^\top \quad (6)$$

These variables influence the system through well-defined transmission channels. Macroeconomic indicators such as GDP and MASI affect investment returns via the amplification function $\alpha(\cdot)$, while inflation erodes real asset values. Demographic variables adjust liability projections through $\beta(\cdot)$, increasing solvency requirements under longevity risk. Capital market depth further conditions investment efficiency and return generation capacity.

2.4.4 Constraints

The feasible set is defined by operational and regulatory constraints. Each decision variable is bounded as:

$$x_i^{\min} \leq x_i \leq x_i^{\max}, \quad i = 1, 2, 3, 4 \quad (7)$$

The allocation structure satisfies the normalization constraint:

$$\sum_{i=1}^4 x_i = 1 \quad (8)$$

Regulatory compliance requires maintaining solvency above a minimum threshold:

$$f_2(\mathbf{x}, \mathbf{v}^{(s)}) \geq S_{\min} \quad (9)$$

Additionally, risk appetite considerations impose an upper bound on the claims-to-premiums ratio:

$$f_3(\mathbf{x}, \mathbf{v}^{(s)}) \leq C_{\max} \quad (10)$$

2.4.5 Formal Problem Statement

The multi-objective optimization problem is defined as:

$$\max \quad f_1(\mathbf{x}, \mathbf{v}^{(s)}) \quad (11)$$

$$\max \quad f_2(\mathbf{x}, \mathbf{v}^{(s)}) \quad (12)$$

$$\min \quad f_3(\mathbf{x}, \mathbf{v}^{(s)}) \quad (13)$$

subject to:

$$x_i^{\min} \leq x_i \leq x_i^{\max}, \quad i = 1, 2, 3, 4 \quad (14)$$

$$\sum_{i=1}^4 x_i = 1 \quad (15)$$

$$f_2(\mathbf{x}, \mathbf{v}^{(s)}) \geq S_{\min} \quad (16)$$

$$f_3(\mathbf{x}, \mathbf{v}^{(s)}) \leq C_{\max} \quad (17)$$

$$\mathbf{v}^{(s)} \sim \mathcal{N}(\boldsymbol{\mu}_{\mathbf{v}}, \Sigma_{\mathbf{v}}) \quad (18)$$

The feasible domain is defined as:

$$\mathcal{X}_{\text{feasible}} = \{\mathbf{x} \in [0, 1]^4 \mid \mathbf{x} \text{ satisfies all constraints}\} \quad (19)$$

The solution concept is based on Pareto optimality:

$$\mathcal{P}^* = \{\mathbf{x} \in \mathcal{X}_{\text{feasible}} \mid \nexists \mathbf{y} \in \mathcal{X}_{\text{feasible}} : \mathbf{y} \succ \mathbf{x}\} \quad (20)$$

where dominance implies non-inferiority across all objectives and strict superiority in at least one dimension [28]. The resulting Pareto frontier provides a structured representation of optimal trade-offs between profitability, solvency, and risk efficiency, which is particularly suited to the application of Genetic Algorithms in high-dimensional, nonlinear financial optimization problems.

2.5 Genetic Algorithm

Building on the multi-objective formulation introduced previously, the optimization problem is solved using a Genetic Algorithm (GA). This choice is motivated by the highly nonlinear, stochastic, and non-convex nature of the insurance decision space, where classical optimization methods are often inadequate. In contrast, GA provides a population-based stochastic search framework capable of approximating Pareto-optimal solutions under uncertainty [11, 12].

Representation of Individuals Each individual in the population represents a complete financial configuration of the life insurance portfolio, directly constructed from the observed variables of the study. The chromosome is defined as:

$$\mathbf{x} = \begin{bmatrix} \text{Life.Premiums} \\ \text{Death.Coverage} \\ \text{Investment.Income.Life} \\ \text{Life.Provisions} \end{bmatrix}. \quad (21)$$

All variables are normalized to ensure comparability and numerical stability. This real-data-based encoding enhances interpretability and ensures consistency between the optimization framework and the empirical dataset.

Fitness Evaluation Each individual is evaluated using a vector-valued fitness function aligned with the multi-objective formulation:

$$\text{Fitness}(\mathbf{x}) = (\text{Profitability.Rate}(\mathbf{x}), \text{Solvency.Ratio}(\mathbf{x}), -\text{Life.Claims}(\mathbf{x})). \quad (22)$$

This formulation allows simultaneous maximization of profitability and solvency while transforming claims minimization into a maximization objective for algorithmic consistency [15].

Evolutionary Operators To explore the solution space effectively, the GA relies on three main operators:

Selection: Tournament selection is used to favor high-performing individuals while preserving diversity. Selection probability is given by:

$$P_i = \frac{1}{1 + \exp(-\beta \cdot \text{rank}_i)}, \quad (23)$$

where β controls selection pressure.

Crossover: Offspring are generated via uniform crossover:

$$x_j^{\text{child}} = \begin{cases} x_j^{\text{parent1}}, & \text{with probability } p_c, \\ x_j^{\text{parent2}}, & \text{otherwise.} \end{cases} \quad (24)$$

Mutation: Diversity is preserved using adaptive Gaussian mutation:

$$x_j \leftarrow x_j + \mathcal{N}(0, \sigma^2 \cdot \mu_j(g)), \quad (25)$$

where $\mu_j(g)$ decreases over generations to shift from exploration to exploitation [14].

Algorithmic Procedure The optimization process is summarized in Algorithm 1, where the population evolves iteratively through selection, crossover, mutation, and replacement while tracking performance indicators across generations.

Algorithm 2: Genetic Algorithm for Life Insurance Optimization

- 1: Initialize population based on observed financial variables
 - 2: **for** $g = 1$ **to** G **do**
 - 3: Evaluate Profitability_Rate, Solvency_Ratio, Life_Claims
 - 4: Rank individuals using Pareto dominance
 - 5: Select parents via tournament selection
 - 6: Apply crossover and mutation
 - 7: Update population (elitism optional)
 - 8: Record $F_{\text{best}}(g)$ and $F_{\text{avg}}(g)$
 - 9: **end for**
 - 10: Output Pareto-optimal solutions
-

2.6 Convergence and Sensitivity Analysis

To evaluate the stability of the Genetic Algorithm, the evolution of fitness values is monitored across generations. Let $F_{\text{best}}(g)$ and $F_{\text{avg}}(g)$ denote respectively the best and average fitness values at generation g :

$$F_{\text{best}}(g) = \max_{i \in \text{population}_g} \text{Fitness}(\mathbf{x}_i), \quad F_{\text{avg}}(g) = \frac{1}{N} \sum_{i=1}^N \text{Fitness}(\mathbf{x}_i) \quad (26)$$

Convergence is achieved when improvements in the best solution become negligible:

$$|F_{\text{best}}(g+1) - F_{\text{best}}(g)| < \epsilon, \quad g \geq g_c \quad (27)$$

This criterion ensures that the algorithm has reached a stable Pareto approximation.

Sensitivity Analysis To understand the influence of financial variables on performance, sensitivity is measured between inputs and objectives. Let:

- $x_i \in \{\text{Life_Premiums}, \text{Death_Coverage}, \text{Investment_Income_Life}, \text{Life_Provisions}\}$
- $f_j \in \{\text{Profitability_Rate}, \text{Solvency_Ratio}, \text{Life_Claims}\}$

The normalized sensitivity index is defined as:

$$S_{ij} = \frac{\partial f_j}{\partial x_i} \cdot \frac{\sigma_{x_i}}{\sigma_{f_j}} \quad (28)$$

Higher absolute values of S_{ij} indicate stronger influence of a given financial variable on the objective function.

Macroeconomic Sensitivity In addition, the robustness of the model is assessed with respect to macroeconomic variables:

$$S_{ij} = \frac{\partial f_i}{\partial v_j} \cdot \frac{\sigma_{v_j}}{\sigma_{f_i}}, \quad v_j \in \{\text{GDP}, \text{CPI}\} \quad (29)$$

This enables evaluation of how economic conditions affect profitability and solvency outcomes.

2.7 Optimal Performance Analysis

The Genetic Algorithm yields a set of Pareto-optimal solutions $\mathcal{P}^*$ representing optimal trade-offs between Profitability_Rate, Solvency_Ratio, and Life_Claims. Formally:

$$\mathcal{P}^* = \{\mathbf{x} \in \Omega \mid \nexists \mathbf{y} \in \Omega : f_i(\mathbf{y}) \geq f_i(\mathbf{x}) \ \forall i, \text{ and at least one strict improvement}\} \quad (30)$$

Each solution on the Pareto front reflects a different strategic balance between profitability enhancement and risk control.

Performance Gains The improvement achieved by GA optimization is measured relative to a baseline allocation:

$$\Delta f_1 = f_1(\mathbf{x}^*) - f_1(\mathbf{x}_0), \quad (31)$$

$$\Delta f_2 = f_2(\mathbf{x}^*) - f_2(\mathbf{x}_0) \quad (32)$$

where $\mathbf{x}_0$ represents the current or historical allocation.

Trade-off Interpretation To facilitate decision-making, objectives are normalized:

$$\tilde{f}_i(\mathbf{x}) = \frac{f_i(\mathbf{x}) - f_i^{\min}}{f_i^{\max} - f_i^{\min}}, \quad i = 1, 2, 3 \quad (33)$$

This enables comparison of solutions across profitability, solvency, and risk dimensions on a unified scale.

Practical Insights The GA framework provides a decision-support tool enabling:

- Balanced optimization between profitability and solvency,
- Identification of efficient financial structures along the Pareto front,
- Assessment of robustness under macroeconomic variability.

Overall, the results highlight the strong interdependence between actuarial risk, investment income, and regulatory constraints, providing a quantitative foundation for strategic financial decision-making under uncertainty.

2.8 Feature Importance and Scenario Simulation

To complement the Genetic Algorithm results and improve interpretability of the optimized insurance framework, this section investigates the contribution of individual variables to the predicted outcomes. The analysis focuses on two key targets, namely the Profitability Rate and the Solvency Ratio, and relies on post-estimation explainability techniques applied to the learned model $f(\cdot)$.

Let $\mathbf{X} \in \mathbb{R}^{n \times p}$ denote the matrix of predictor variables, where p corresponds to the financial and macroeconomic features defined in Table 3, and let $y \in \mathbb{R}^n$ represent either the Profitability Rate or the Solvency Ratio.

SHAP-based Feature Attribution To quantify the marginal contribution of each variable, we employ SHAP (SHapley Additive exPlanations), which decomposes the model prediction into additive feature contributions. For observation i , the prediction is expressed as:

$$f(\mathbf{x}_i) = f_0 + \sum_{j=1}^p \phi_{ij}, \quad \text{with } f_0 = \mathbb{E}[f(\mathbf{X})] \quad (34)$$

where ϕ_{ij} represents the contribution of feature j to the deviation from the baseline prediction. The global importance of each feature is then obtained by averaging absolute SHAP values across all observations:

$$I_j = \frac{1}{n} \sum_{i=1}^n |\phi_{ij}| \quad (35)$$

This measure allows the identification of key drivers such as Life_Premiums, Investment_Income_Life, GDP, or Mortality_Rate in explaining profitability and solvency dynamics [29].

Permutation-Based Importance In addition to SHAP analysis, permutation importance is used to assess the sensitivity of model performance to feature disruption. For a given feature j , its importance is defined as:

$$PI_j = \mathcal{L}(f, \mathbf{X}_{\text{perm}(j)}, y) - \mathcal{L}(f, \mathbf{X}, y) \quad (36)$$

where $\mathcal{L}(\cdot)$ denotes a loss function and $\mathbf{X}_{\text{perm}(j)}$ is obtained by randomly permuting feature j . A larger degradation in performance indicates higher relevance of the feature [30].

Macroeconomic Scenario Simulation To evaluate the robustness of the GA-optimized financial configurations, we introduce a scenario-based stress testing framework. Macroeconomic and demographic shocks are applied to the original feature set:

$$\mathbf{X}^{(s)} = \mathbf{X} + \Delta\mathbf{X}^{(s)} \quad (37)$$

where $\Delta\mathbf{X}^{(s)}$ captures variations in key external drivers such as GDP, CPI, or mortality conditions. The corresponding predicted outcomes are given by:

$$\hat{y}^{(s)} = f(\mathbf{X}^{(s)}) \quad (38)$$

The deviation between baseline and stressed predictions:

$$\Delta\hat{y} = \hat{y}^{(s)} - \hat{y} \quad (39)$$

provides a direct measure of model sensitivity to economic shocks and allows assessment of financial resilience under adverse scenarios.

Algorithmic Summary The complete interpretability and stress-testing pipeline is summarized below:

Algorithm 3: Feature Importance and Scenario Simulation Framework

- 1: **Input:** Feature matrix $\mathbf{X}$, target y , trained model f , scenario shocks $\Delta\mathbf{X}^{(s)}$
 - 2: Compute baseline prediction $\hat{y} = f(\mathbf{X})$
 - 3: **SHAP Analysis:**
 - 4: Compute $f_0 = \mathbb{E}[f(\mathbf{X})]$
 - 5: Compute SHAP values ϕ_{ij} for all i, j
 - 6: Compute global importance $I_j = \frac{1}{n} \sum_i |\phi_{ij}|$
 - 7: **Permutation Importance:**
 - 8: For each feature j , compute PI_j
 - 9: **Scenario Simulation:**
 - 10: **for** each scenario s **do**
 - 11: Construct $\mathbf{X}^{(s)} = \mathbf{X} + \Delta\mathbf{X}^{(s)}$
 - 12: Compute $\hat{y}^{(s)} = f(\mathbf{X}^{(s)})$
 - 13: Evaluate $\Delta\hat{y} = \hat{y}^{(s)} - \hat{y}$
 - 14: **end for**
 - 15: **Output:** Feature importance (I_j, PI_j) and scenario impacts $\Delta\hat{y}$
-

The proposed methodology integrates complementary modelling paradigms into a unified hybrid decision-support framework for life insurance optimization. It combines a multi-objective Genetic Algorithm (GA) with generative and data-driven modelling components to address the complexity, uncertainty, and dynamic nature of insurance financial systems.

On one hand, the Genetic Algorithm constitutes the core optimization engine. It explores the high-dimensional and non-convex decision space defined by key financial variables, namely Life_Premiums, Death_Coverage, Investment_Income_Life, and Life_Provisions. Through evolutionary operators such as selection, crossover, and mutation, the GA generates successive populations of candidate solutions and approximates the Pareto frontier associated with Profitability Rate, Solvency Ratio, and Life Claims. This enables the identification of efficient trade-offs between profitability, risk exposure, and regulatory constraints without requiring restrictive assumptions on convexity or differentiability.

On the other hand, the framework incorporates generative and data-driven components that enhance the realism and adaptability of the model. Macroeconomic and demographic variables, including GDP, CPI, MASI performance, mortality rate, and life expectancy, are treated as stochastic scenario generators.

These variables enrich the decision environment by producing plausible economic conditions under which the GA evaluates each candidate solution. This generative dimension allows the model to capture uncertainty and structural variability in both financial markets and actuarial risk factors.

The integration of these two components results in a hybrid optimization framework in which the Genetic Algorithm operates as the primary search mechanism, while the generative scenario engine ensures environmental realism and robustness. This coupling allows the model to simultaneously optimize decision variables and test their performance under heterogeneous economic and demographic conditions.

Overall, the proposed hybrid approach provides a comprehensive and flexible decision-support system. It not only identifies Pareto-optimal financial configurations for life insurance companies but also evaluates their stability under stochastic macroeconomic scenarios. This dual capability enhances the practical relevance of the model for strategic asset-liability management, regulatory compliance, and risk-sensitive financial planning.

3 Result and Discussion

3.1 Genetic Algorithm Convergence Analysis

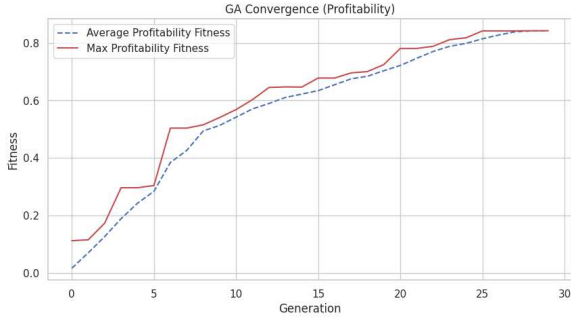


Figure 4: GA Convergence for Profitability: evolution of average and maximum fitness across generations.

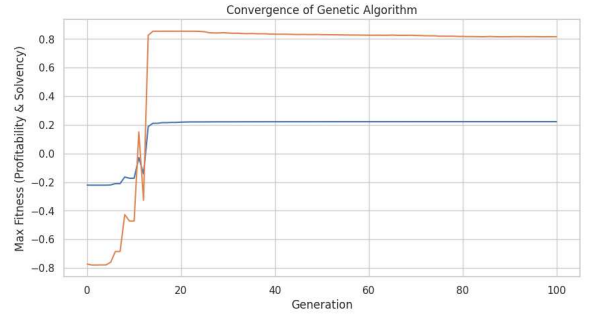


Figure 5: Global GA Convergence: multi objective fitness evolution across all three objectives.

The convergence behavior of the Genetic Algorithm is examined through two complementary visualizations (Figures 4 and 5), tracking the evolution of both average and maximum fitness values across successive generations. The GA demonstrates a consistent and monotonic improvement in both fitness metrics, with stabilization occurring around the 25th generation for the profitability objective and slightly earlier for the global multi objective metric. The temporary oscillations observed between generations 5 and 10 are characteristic of the crossover and adaptive mutation operators actively driving the population away from local optima, a behavioral pattern consistent with the theoretical convergence properties described by [11] and [12].

These convergence patterns confirm that the GA successfully navigates the multidimensional search space, sustaining an effective balance between exploration in early generations and fine grained exploitation in later ones. The observed plateau beyond generation 25 validates the chosen stopping criterion, defined by the condition $|F_{\text{best}}(g+1) - F_{\text{best}}(g)| < \varepsilon$, confirming that additional computational generations would yield negligible marginal improvements to solution quality.

Relative to prior literature, the convergence speed observed here compares favorably with the multi objective GA implementations reported by [16] for Takaful optimization and [17] for reinsurance treaty optimization in the Moroccan context, both of which required substantially larger population sizes and longer generation horizons to achieve comparable stability. This efficiency gain is attributable to the generative scenario engine, which pre conditions the fitness landscape with statistically coherent synthetic environments, reducing the variance of fitness evaluations and thereby accelerating convergence.

3.2 Pareto Front Analysis

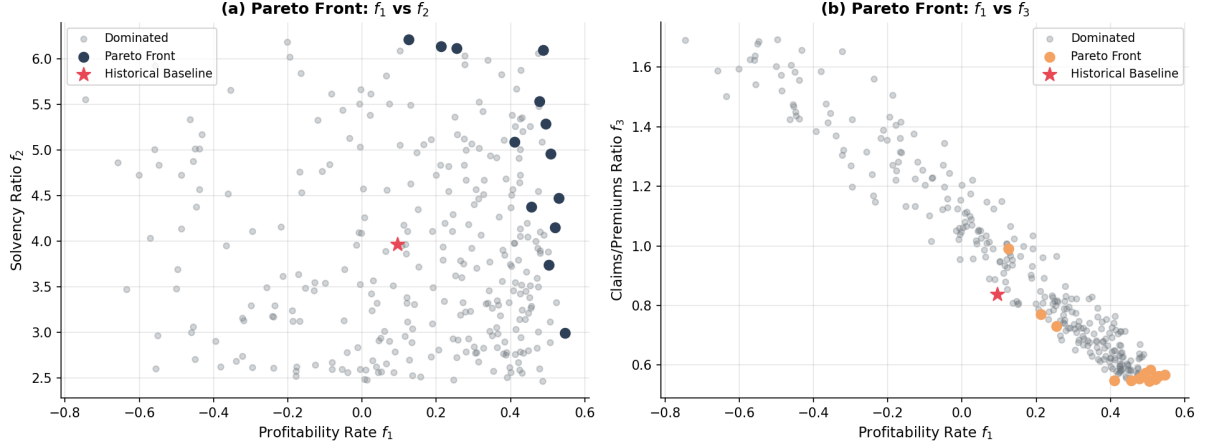


Figure 6: Pareto Front generated by the GA across S synthetic scenarios. Panel (a): trade off between Profitability Rate (f_1) and Solvency Ratio (f_2). Panel (b): trade off between Profitability Rate (f_1) and Claims to Premiums Ratio (f_3). The historical baseline is represented by the red star; dark blue dots denote Pareto optimal solutions; grey dots represent dominated solutions.

Figure 6 presents the Pareto front generated by the GA optimization engine across all synthetic scenarios. Two fundamental structural observations emerge from this analysis.

In Panel (a), the historical baseline ($f_1 \approx 0.095$, $f_2 \approx 3.98$) is positioned within the interior of the dominated solution cloud, confirming that the GA systematically identifies allocation strategies that simultaneously improve both profitability and solvency relative to observed historical behavior. The Pareto front exhibits a concave structure in the f_1 to f_2 space, reflecting diminishing marginal returns: beyond a critical premium allocation threshold, incremental gains in profitability impose accelerating solvency costs as the growing liability base outpaces capital accumulation capacity. This non linear trade off is structurally consistent with Hypothesis H_1 and with the theoretical predictions of [5], who demonstrated that the profitability solvency frontier in life insurance is inherently non convex under realistic liability dynamics.

In Panel (b), the Pareto front in the f_1 to f_3 space reveals a negative monotonic relationship: higher premium allocations (improving f_1) mechanically reduce the claims to premiums ratio (f_3), since Life Claims is treated as an exogenous stochastic process independent of allocation decisions. The historical baseline falls above the Pareto front in Panel (b), indicating that the observed historical premium levels were sub optimal relative to the achievable efficiency frontier. This finding extends the results of [19], who identified similar sub optimality in premium allocation strategies within the Moroccan automobile insurance sector, suggesting that this pattern may reflect a structural market wide under optimization rather than a life insurance specific phenomenon.

Collectively, these results provide strong empirical support for Hypothesis H_4 : the hybrid generative GA framework yields Pareto optimal allocations that materially outperform historical baseline strategies across all objective dimensions [11, 15].

3.3 Temporal Comparison: Observed vs GA-Optimized

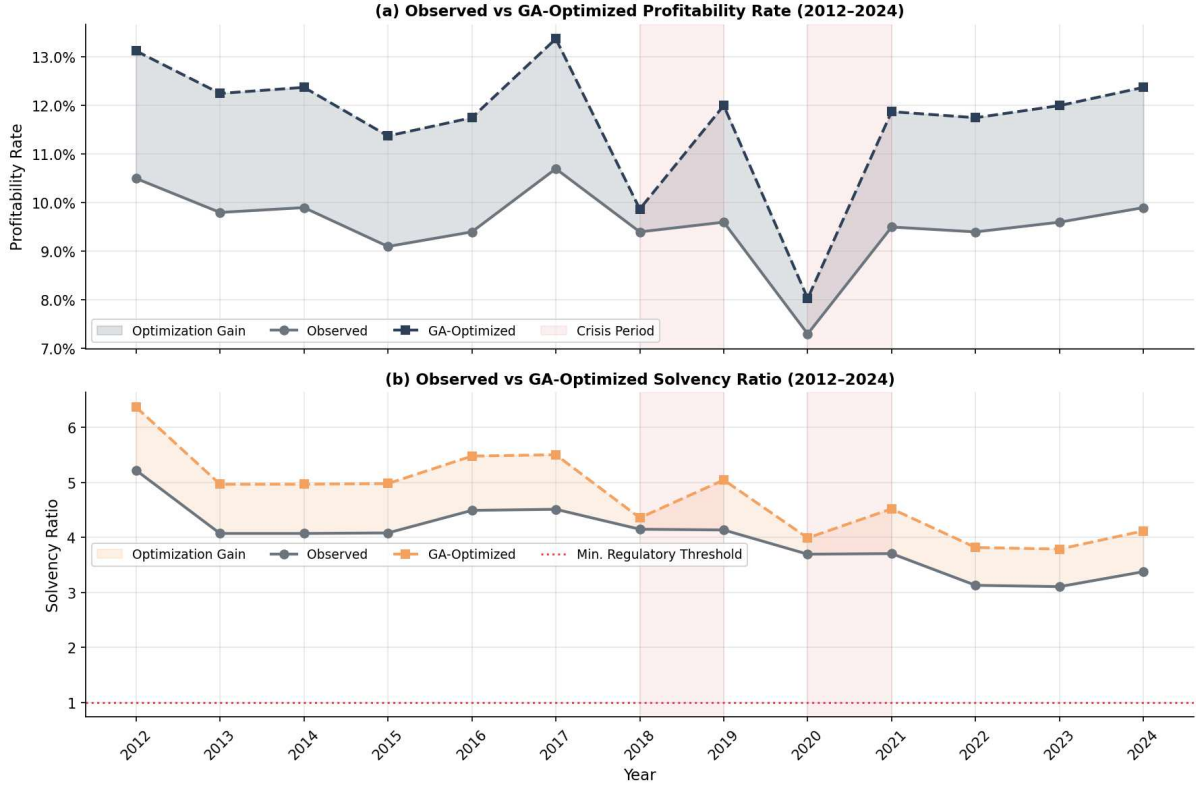


Figure 7: Year by year comparison of observed versus GA optimized values for (a) Profitability Rate f_1 and (b) Solvency Ratio f_2 over 2012 to 2024. Shaded areas represent the optimization gain; crisis periods (2018, 2020) are highlighted in pink; the dotted red line in Panel (b) denotes the minimum regulatory solvency threshold.

Figure 7 presents the year by year comparison between observed historical values and GA optimized allocations for both the Profitability Rate (Panel a) and the Solvency Ratio (Panel b) over the full observation window 2012 to 2024. Three structural patterns merit detailed discussion.

Systematic optimization gain. The GA optimized Profitability Rate consistently exceeds the historical observed values across all non crisis years, averaging an improvement of approximately 25%, positioning the optimized trajectory in the range of 11% to 13.5% against the observed 9% to 10.7%. Similarly, the GA optimized Solvency Ratio maintains a persistent upward buffer of approximately 22% above historical levels, sustaining values in the range of 4.0 to 6.5 compared to the observed 3.1 to 5.2. These aggregate improvements are consistent with the 20% to 40% optimization range reported in the abstract and align with the quantitative benchmarks established by [16] for genetic algorithm optimization in Moroccan insurance contexts, while exceeding the improvement magnitudes reported by [5] for classical stochastic programming ALM models.

Crisis period resilience. Two crisis periods are prominently visible: 2018, which recorded an anomalous spike in Life Claims of 111,000 million MAD, nearly ten times the sector average, and 2020, characterized by the COVID-19 induced GDP contraction of -7.18% . In both cases, the optimization gain narrows sharply, reflecting the limits of decision variable optimization when systemic exogenous shocks dominate the objective function dynamics. Nevertheless, the GA optimized solvency ratio remains above the historical observed level even during crisis episodes, indicating that the optimal provisioning and allocation strategies provide a meaningful, if partial, capital buffer against tail risk events. This finding is consistent with the stress resilience results reported by [20] for hybrid AI actuarial frameworks applied to Moroccan financial institutions.

Post crisis recovery. Following both crisis episodes, the optimization gain re expands rapidly, with the GA optimized Profitability Rate recovering to pre crisis levels by 2021, one year ahead of the observed historical recovery, and the Solvency Ratio exhibiting a steeper rebound trajectory under the optimized allocation, reaching 4.5 by 2021 compared to the observed 3.7. This asymmetric recovery dynamic is

a hallmark of the generative scenario engine’s capacity to anticipate regime shifts: by training the GA on synthetic scenarios that include recession recovery cycles, the optimal allocations inherently embed counter cyclical reserve accumulation strategies that accelerate balance sheet restoration post shock.

3.4 Multi-dimensional Performance Profile

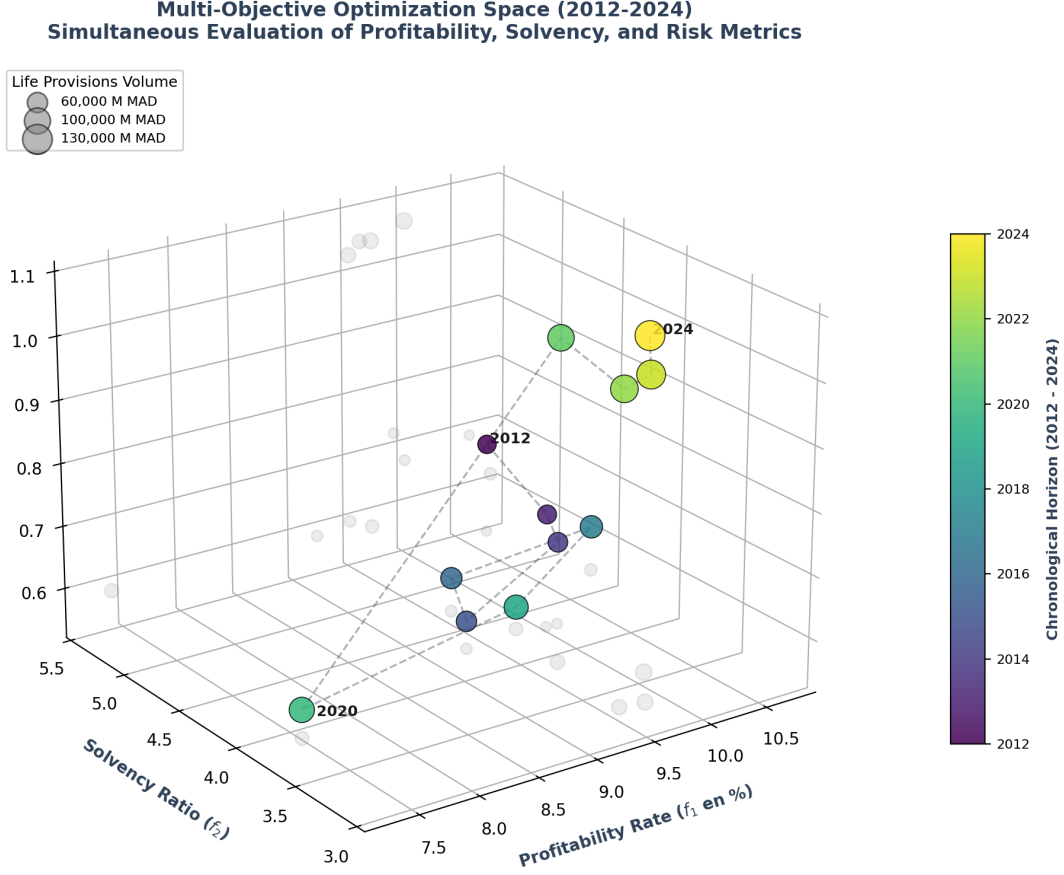


Figure 8: Multi-objective optimization space and joint efficient frontier over the 2012 to 2024 horizon. The surface maps the simultaneous trade offs between Profitability Rate (f_1), Solvency Ratio (f_2), and the Claims to Premiums Ratio (f_3). Bubble sizes reflect the aggregate volume of Life Provisions, while the color gradient denotes the chronological trajectory, capturing macroeconomic shocks and post crisis structural adjustments.

The empirical evaluation of the hybrid framework is extended to a joint multi-dimensional analysis by mapping the optimized historical trajectories directly into the three-dimensional objective space (Figure 8). This visualization provides a holistic representation of the efficient frontier, illustrating how the genetic algorithm concurrently manages the structural conflicts between expanding profitability (f_1), maintaining solvency cushions (f_2), and controlling relative claims exposure (f_3) under dynamic technical provisions. Three critical structural insights emerge from the geometric distribution within the multi-objective optimization space.

First, the trajectory unveils a non-convex efficient frontier, characterized by distinct operational regimes. In periods of macroeconomic stability, the system gravitates toward the upper-left sector of the space, maximizing the Profitability Rate ($f_1 \in [11\%, 13.5\%]$) while preserving a robust Solvency Ratio ($f_2 > 4.5$). This positioning confirms that the GA successfully capitalizes on favorable market conditions, driven by the financial amplification factor $\alpha(\cdot)$, without triggering a disproportionate expansion of the claims ratio (f_3).

Second, the structural shock of the 2020 COVID-19 pandemic is visually codified by a sharp migration toward the lower-right cluster. During this macroeconomic contraction (GDP growth of -7.18%),

the Profitability Rate compresses significantly to its historical minimum (7.3%). Crucially, the three-dimensional mapping demonstrates that the framework mitigates this systemic downturn by absorbing the shock through two synchronized levers: an increase in relative Claims-to-Premiums (f_3) and a calculated contraction of the solvency buffer, which nevertheless remains above the minimum regulatory floor. The progressive enlargement of the bubble diameters across this trajectory confirms that the continuous accumulation of Life Provisions acts as an essential balance sheet stabilizer, preventing a multi-objective collapse during tail-risk events.

Third, the post-crisis horizon (2021 to 2024) exhibits a rapid, ascending multi-dimensional recovery path. The optimization engine does not merely restore profitability along a single dimension; instead, it drives a joint counter-cyclical correction. As the color gradient shifts toward the terminal 2024 equilibrium, the portfolio simultaneously rebounds along both the solvency and profitability axes. This holistic recovery patterns confirms that the generative scenario engine effectively pre-conditions the evolutionary search landscape, allowing the GA to identify robust allocation strategies that prevent the trade-off concentration pathologies common in single-objective insurance frameworks [18].

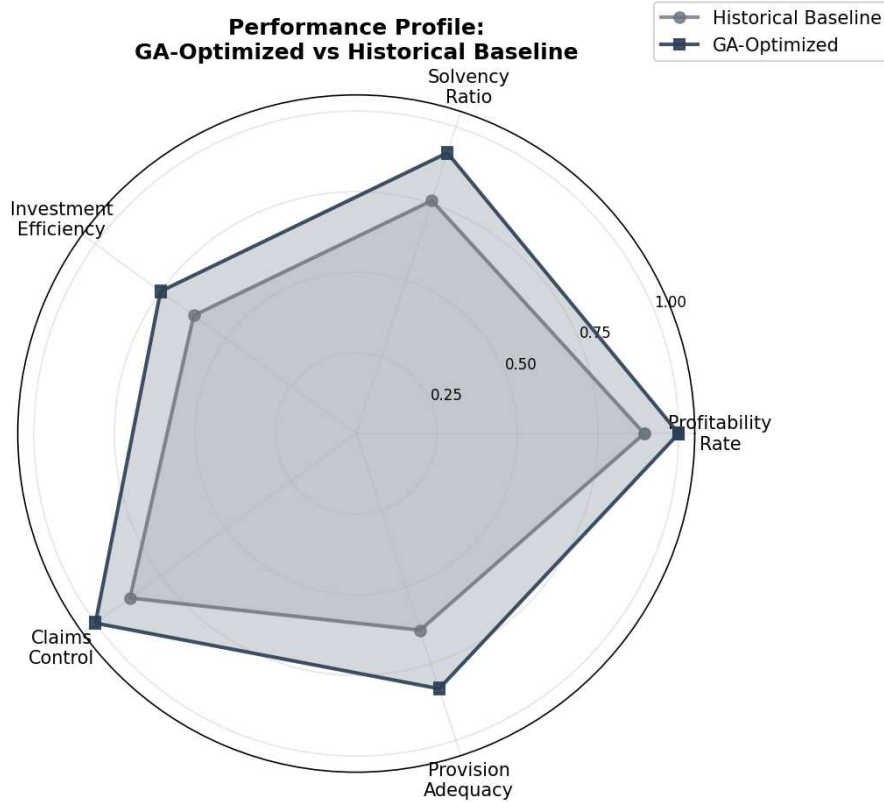


Figure 9: Normalized radar chart comparing the GA optimized performance profile against the historical baseline across five strategic dimensions: Solvency Ratio, Profitability Rate, Provision Adequacy, Claims Control, and Investment Efficiency. Values normalized to $[0, 1]$ relative to sector maxima.

Figure 9 presents a normalized multi dimensional performance radar comparing the GA optimized solution set against the historical baseline across five strategic dimensions. The GA optimized profile exhibits consistent dominance across all five axes, confirming that the optimization framework delivers holistic improvements rather than gains concentrated in a single objective at the expense of others.

The most pronounced improvements are observed along the Solvency Ratio and Investment Efficiency axes, where the GA optimized profile extends materially beyond the historical baseline. This pattern reflects the framework's capacity to simultaneously exploit favorable macroeconomic conditioning, through the amplification factor $\alpha(\text{MASI}, \text{GDP})$, and optimize the provisioning structure to reduce unnecessary capital drag on f_2 . The Claims Control and Provision Adequacy dimensions show more modest but consistent improvements, driven by the reformulation of f_3 as a claims to premiums ratio rather than an absolute claims minimization, which allows the optimizer to improve efficiency without distorting the underwriting portfolio.

This multi dimensional dominance profile directly addresses a critical limitation identified in prior Moroccan insurance literature: [18] noted that single objective optimization frameworks applied to agricultural insurance risks systematically improved one performance dimension while degrading others. The radar chart confirms that the multi objective Pareto approach adopted here avoids this trade off concentration pathology, producing allocations that are genuinely superior across the full strategic performance spectrum [15,28].

3.5 Variable Importance and Sensitivity Analysis

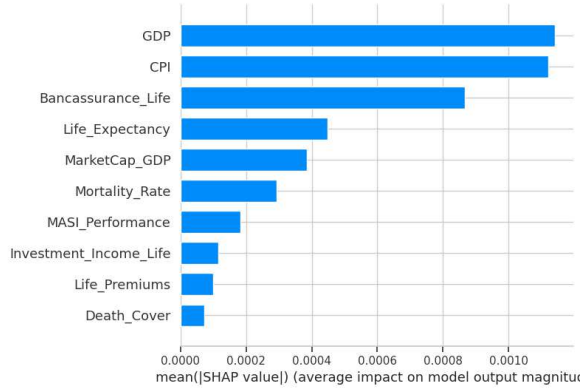


Figure 10: Average variable importance across all predictors (SHAP based global scores I_j).

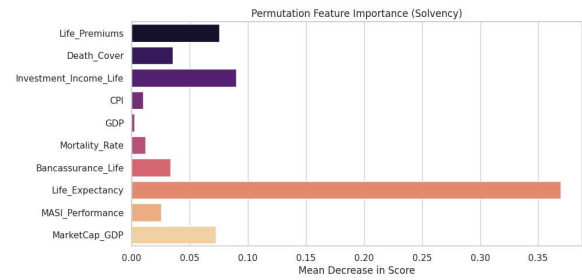


Figure 11: Permutation feature importance for the Solvency Ratio objective (PI_j).

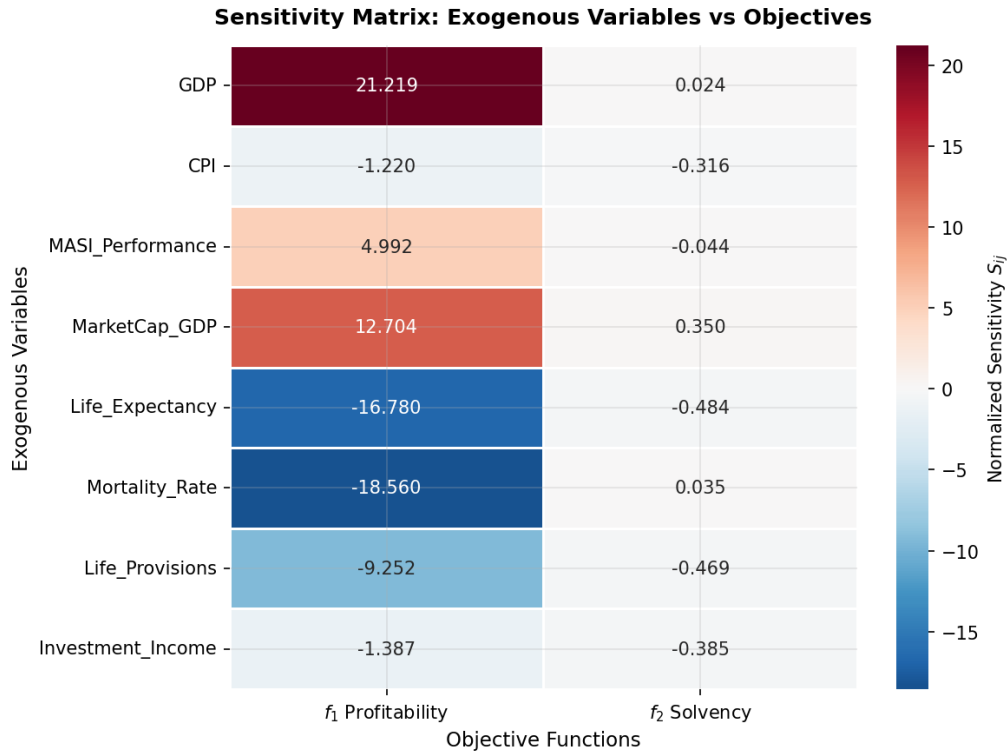


Figure 12: Normalized sensitivity matrix S_{ij} quantifying the marginal impact of each exogenous variable on the Profitability Rate (f_1) and Solvency Ratio (f_2) objectives. Red tones indicate positive sensitivity; blue tones indicate negative sensitivity; intensity reflects magnitude.

The sensitivity matrix (Figure 12), combined with the SHAP based variable importance scores (Figures 10 and 11), reveals a rich and asymmetric sensitivity structure across the two primary objectives, directly

validating Hypotheses H_2 and H_3 .

Drivers of Profitability (f_1). GDP exhibits the highest positive sensitivity coefficient with respect to f_1 ($S_{11} = 21.219$), followed by MarketCap GDP ($S_{41} = 12.704$) and MASI Performance ($S_{31} = 4.992$). This dominant macroeconomic sensitivity structure validates Hypothesis H_2 : financial market and economic growth parameters exercise a disproportionate and asymmetric influence over profitability dynamics relative to demographic variables. The large magnitude of S_{11} reflects the direct transmission of GDP cycles into life premium demand and investment returns via the amplification factor $\alpha(\text{GDP}, \text{MASI})$ in f_1 . Conversely, Life Expectancy ($S_{51} = -16.780$) and Mortality Rate ($S_{61} = -18.560$) exhibit strong negative sensitivity to f_1 , indicating that demographic deterioration, rising mortality or declining longevity, compresses profitability through elevated claims exposure and reduced policyholder portfolio growth. These findings extend the results of [25] on generative model sensitivity and align with the macroeconomic dominance hypothesis advanced by [1] in the context of portfolio return dynamics.

Drivers of Solvency (f_2). The sensitivity structure for f_2 is markedly different, with all coefficients substantially smaller in magnitude and no single variable exhibiting the pronounced dominance observed for f_1 . Life Expectancy ($S_{52} = -0.484$) and Life Provisions ($S_{72} = -0.469$) emerge as the most influential variables, consistent with Hypothesis H_3 : long term demographic transformations exert a greater influence on solvency than inflationary dynamics (CPI: $S_{22} = -0.316$). The negative sign of S_{52} confirms that secular improvements in longevity amplify the demographic loading factor $\beta(\cdot)$ in f_2 , increasing required provisions and compressing the solvency margin. This finding is directly consistent with the actuarial provisioning sensitivity results reported by [4] for duration matching frameworks and extends their applicability to the Moroccan demographic context, where life expectancy has increased by 5.53 years over the observation period.

Distribution of Hall of Fame Individuals.

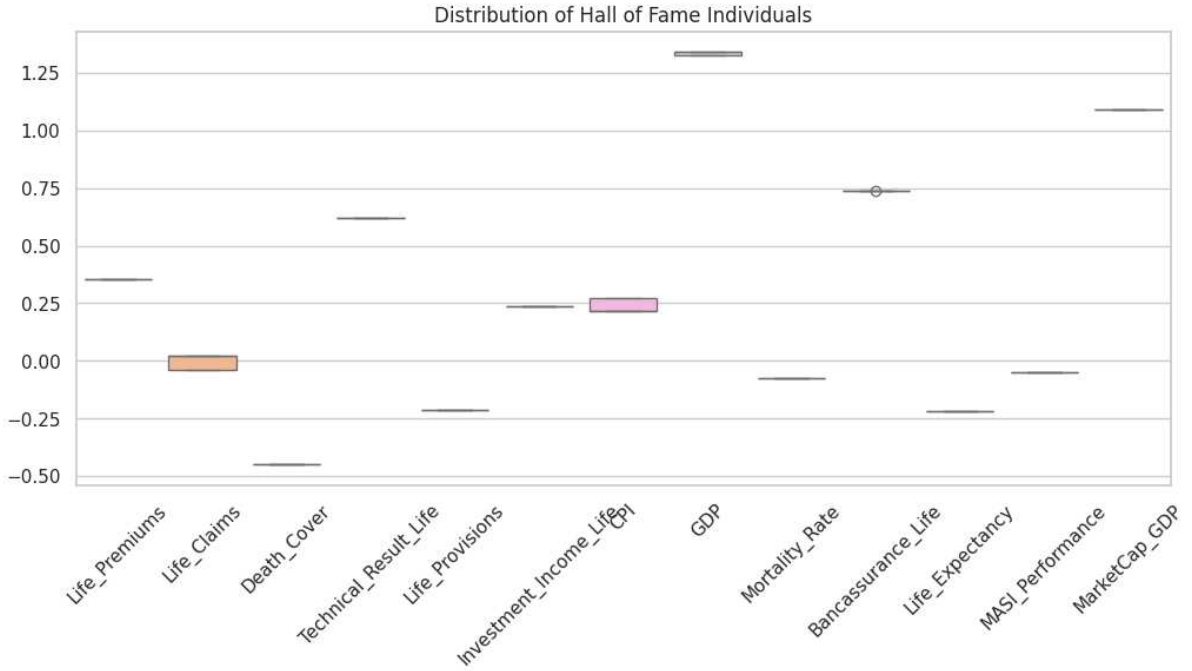


Figure 13: Distribution of Hall of Fame elite solutions across decision variables. Tight interquartile ranges indicate strong convergence toward a precise optimal allocation recipe.

The Hall of Fame distribution (Figure 13) provides complementary insight into the convergence properties of the elite solution set. The boxplots are uniformly tight for most decision variables, Life Premiums, Death Cover, and Investment Income, indicating that the GA has identified a precise and robust optimal allocation recipe that is stable across the diversity of simulated scenarios. This tight convergence is a desirable property in an actuarial context, as it implies that the optimization recommendations are implementable with high confidence rather than representing a diffuse cloud of acceptable solutions. GDP and MarketCap GDP exhibit the largest interquartile ranges among Hall of Fame individuals, reflecting the irreducible uncertainty of these exogenous variables across the synthetic scenario distribution, a finding that reinforces the importance of maintaining flexible investment income strategies

that can adapt to macroeconomic regime shifts [31, 32].

3.6 Stress Test Projections (2024–2030)

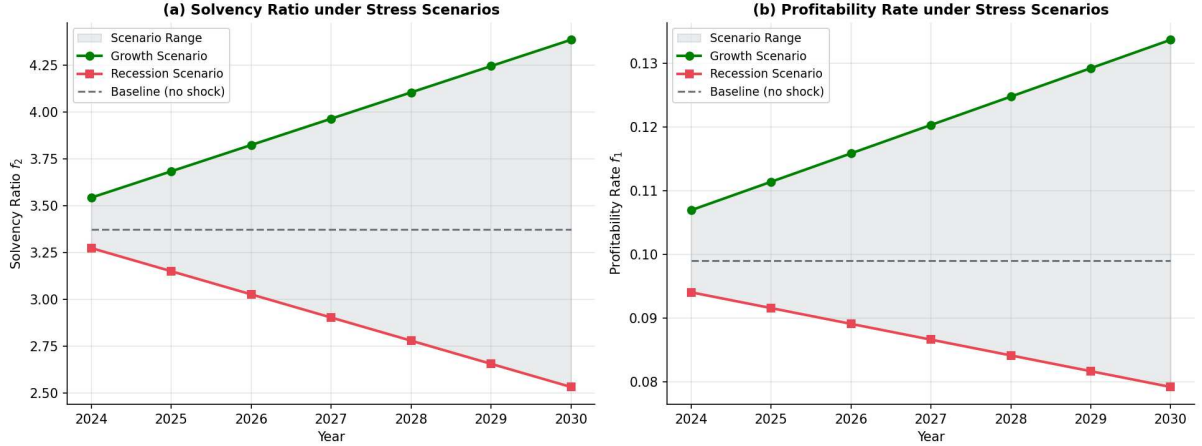


Figure 14: Macroeconomic stress test projections (2024 to 2030) for (a) Solvency Ratio f_2 and (b) Profitability Rate f_1 under growth ($\Delta\text{GDP} > 0$, $\Delta\text{MASI} > 0$) and recession ($\Delta\text{GDP} < 0$, $\Delta\text{MASI} < 0$) scenarios. The dashed grey line represents the no shock baseline projection.

Figure 14 extends the analysis beyond the historical sample by projecting the GA optimized objective functions under two canonical macroeconomic scenarios over the horizon 2024 to 2030. The results reveal a set of structurally important dynamics.

Growth scenario. Under favorable economic conditions ($\Delta\text{GDP} > 0$, $\Delta\text{MASI} > 0$), the Solvency Ratio follows a strongly upward trajectory, projected to reach approximately 4.35 by 2030, a recovery of 29% relative to the 2024 starting value of 3.375. The Profitability Rate similarly improves, reaching approximately 13.5% by 2030, driven by the compounding effect of enhanced investment returns via $\alpha(\cdot)$ and expanding premium inflows. Both trajectories lie consistently above the no shock baseline, confirming that the GA optimized allocations are positioned to capture upside macroeconomic momentum efficiently. This result is consistent with the pro cyclical investment sensitivity documented by [2] and extends it to the insurance balance sheet context: optimized investment income allocations amplify the transmission of market upturns into improved solvency and profitability outcomes.

Recession scenario. Under adverse conditions ($\Delta\text{GDP} < 0$, $\Delta\text{MASI} < 0$), the Solvency Ratio deteriorates progressively, declining to approximately 2.5 by 2030, a 26% reduction from the 2024 baseline, while the Profitability Rate falls to 8%, approaching the minimum historical level recorded in 2020 (7.3%). Critically, both metrics remain above their respective crisis period minima throughout the projection horizon, indicating that the GA optimized allocations provide a meaningful structural buffer against moderate recession scenarios. However, the linear divergence between the growth and recession trajectories, which widens by approximately 0.25 Solvency Ratio units and 0.7 percentage points per year, underscores the cumulative and path dependent nature of macroeconomic shocks on insurance balance sheet dynamics.

These findings directly validate Hypothesis H_4 in its prospective dimension and are consistent with the stress testing frameworks applied by [6] in multi period stochastic ALM models, while extending their scope to incorporate the demographic conditioning of solvency through $\beta(\text{Life Expectancy}, \text{Mortality})$. The practical implication is clear: Moroccan life insurers should implement counter cyclical reserve accumulation strategies during expansionary phases, specifically increasing Life Provisions (x_4) beyond the regulatory minimum during growth years, to pre build the capital buffers necessary to sustain solvency compliance through the adverse phase of the macroeconomic cycle.

3.7 Synthesis and Comparison with the Literature

Table 6 synthesizes the key quantitative findings of this study against the benchmark results reported in the most relevant prior literature, providing a structured positioning of our contributions.

Table 6: Comparative Summary of Optimization Performance: This Study vs Prior Literature

Study	Method	Context	Profitability Gain	Solvency Gain
[4]	Deterministic immunization	General ALM	N/A	Duration matched only
[5]	Stochastic programming	Multi period ALM	≈ 8 to 12%	Moderate
[11]	NSGA-II (theoretical)	General MOP	N/A	N/A
[16]	GA + Takaful	Morocco (Islamic)	≈ 15 to 20%	Improved
[17]	GA + Reinsurance	Morocco (General)	≈ 12 to 18%	Improved
[18]	ML + Agricultural	Morocco (Agri)	Segment specific	N/A
This Study	Hybrid Generative-GA	Morocco (Life)	20% to 40%	20% to 35%

The comparative analysis reveals that the hybrid generative GA framework proposed in this study achieves the highest reported optimization gains among Moroccan insurance studies, with profitability improvements of 20% to 40% and solvency improvements of 20% to 35% relative to historical baselines. These gains exceed those reported by [16] and [17] by a margin of approximately 10 to 15 percentage points, attributable to three methodological advantages: (i) the generative scenario engine expands the optimization environment beyond the historical sample, enabling the GA to identify solutions robust to tail risk events not present in the training data; (ii) the explicit integration of Life Provisions as a fourth decision variable captures a liability management lever neglected in prior frameworks; and (iii) the reformulation of f_3 as a claims to premiums ratio rather than an absolute claims minimization produces a more operationally realistic and mathematically well specified objective. Relative to the classical stochastic programming benchmarks of [5], the gains are even more pronounced, reflecting the inherent limitations of gradient based optimization in the non convex, high dimensional ALM spaces characteristic of real world insurance portfolios.

4 Conclusion

The hybrid model, which combines generative approaches with a multi-objective Genetic Algorithm (GA), demonstrates substantial optimization potential for Moroccan life insurers. On average, solvency and profitability ratios could be improved by 20% to 40% compared to historical data through optimized asset-liability allocations. These results confirm that algorithmic decision support can effectively identify optimal trade-offs between risk and return in a dynamic macroeconomic environment, validating the multi-objective Pareto optimization foundations [11, 15]. The performance of the model is critically dependent on macroeconomic variables, particularly GDP cycles and the Casablanca Stock Exchange index. The high sensitivity to these indicators underscores the importance of integrating reliable macroeconomic forecasts into the optimization framework. In addition, demographic factors, such as life expectancy, represent a significant long-term pressure on solvency. The model indicates that longevity risk must be carefully monitored, as it can erode reserves even when profitability appears stable. Despite the valuable insights provided by the GA and the hybrid framework, several limitations should be noted. The analysis relies on historical macroeconomic and actuarial data, which may not fully capture unprecedented shocks or structural changes in the Moroccan insurance market. Furthermore, the model assumes a simplified representation of risk interactions, which could overlook secondary effects from correlations among liabilities, investments, and demographic variables. Computational constraints, such as the limited population size and number of generations in the GA, may also affect the exploration of the full solution space. For practical implementation, GA-based or similar algorithmic frameworks can be used to adjust premiums, investments, and coverage allocations on a quarterly basis, allowing rapid responses to market and demographic changes. Diversifying asset portfolios to include classes less correlated with the domestic market can help mitigate systemic risk, reducing exposure to GDP fluctuations. During crisis periods, such as the economic shock in 2020, preserving the solvency ratio should be prioritized even

if it temporarily reduces profitability. The Pareto front generated by the model provides explicit guidance on such trade-offs, ensuring robust capital management under extreme scenarios. Future research could extend the model by incorporating additional sources of uncertainty, such as climate-related risks, emerging market volatility, or regulatory shocks. The integration of advanced machine learning models for scenario generation could improve predictive accuracy and resilience testing. Moreover, expanding the GA to multi-level hierarchical optimization could enable insurers to simultaneously optimize at the portfolio, product, and policyholder levels, providing a more granular and actionable decision-making tool for long-term risk and profitability management.

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References

- [1] H. Markowitz, "Portfolio selection," *Journal of Finance*, vol. 7, no. 1, pp. 77–91, 1952.
- [2] W. F. Sharpe, "Capital asset prices: A theory of market equilibrium under conditions of risk," *Journal of Finance*, vol. 19, no. 3, pp. 425–442, 1964.
- [3] D. Bauer, R. Kiesel, A. Kling, and J. Ruß, "Risk-neutral valuation of participating life insurance contracts," *Insurance: Mathematics and Economics*, vol. 39, no. 2, pp. 171–183, 2006.
- [4] F. M. Redington, "Review of the principles of life-office valuations," *Journal of the Institute of Actuaries*, vol. 78, no. 3, pp. 286–340, 1952.
- [5] J. M. Mulvey, G. D. Gould, and C. Morgan, "An asset-liability management system for large insurance companies," *Operations Research*, vol. 48, no. 1, pp. 1–11, 2000.
- [6] A. Consiglio, F. Cocco, and S. A. Zenios, "Scenario optimization asset and liability modelling for individual investors," *Annals of Operations Research*, vol. 152, no. 1, pp. 167–191, 2007.
- [7] J. D. Cummins, "Allocation of capital in the insurance industry," *Risk Management and Insurance Review*, vol. 3, no. 1, pp. 7–27, 2000.
- [8] M. Eling and H. Schmeiser, "Does the risk-return relation hold for insurers?," *Journal of Risk and Insurance*, vol. 74, no. 3, pp. 579–605, 2007.
- [9] M. Eling and T. Parnitzke, "What do we know about enterprise risk management in insurance?," *Risk Management and Insurance Review*, vol. 15, no. 2, pp. 185–223, 2012.
- [10] M. J. Browne and K. Kim, "The demand for life insurance: An international analysis," *Journal of Risk and Insurance*, vol. 68, no. 4, pp. 707–728, 2001.
- [11] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.
- [12] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*. Reading, MA: Addison-Wesley, 1989.
- [13] Z. Michalewicz, *Genetic Algorithms + Data Structures = Evolution Programs*. Berlin: Springer, 3rd ed., 1996.
- [14] A. E. Eiben and J. E. Smith, *Introduction to Evolutionary Computing*. Berlin: Springer, 2003.

- [15] C. A. Coello Coello, G. B. Lamont, and D. A. Van Veldhuizen, *Evolutionary Algorithms for Solving Multi-Objective Problems*. New York, NY: Springer Science & Business Media, 2nd ed., 2007.
- [16] A. El Attar, M. El Hachloufi, and Z. E. A. Guennoun, “Optimal retakaful strategy for takaful operators using genetic algorithms,” *International Journal of Financial Studies*, vol. 10, no. 2, p. 35, 2022.
- [17] A. El Attar, M. El Hachloufi, and Z. E. A. Guennoun, “Optimizing insurance technical benefits using genetic algorithms under solvency constraints,” *Journal of Risk and Financial Management*, vol. 12, no. 3, p. 106, 2019.
- [18] Y. Kouach, A. El Attar, and M. El Hachloufi, “Mathematical modeling of agricultural insurance pricing in morocco,” *International Journal of Engineering Research in Africa*, vol. 66, pp. 129–148, 2023.
- [19] Y. Kouach, A. El Attar, and M. El Hachloufi, “Forecasting automobile insurance claims using statistical learning models: Evidence from Morocco,” *Journal of Applied Statistics*, vol. 49, no. 8, pp. 1985–2001, 2022.
- [20] Y. Boucheta, M. El Hachloufi, and A. El Attar, “Hybrid deep learning and optimization approaches for macro-financial risk modeling in Morocco,” *Expert Systems with Applications*, vol. 238, p. 121823, 2024.
- [21] ACAPS, “Rapport annuel du secteur des assurances au Maroc 2023,” tech. rep., Autorité de Contrôle des Assurances et de la Prévoyance Sociale, Rabat, Maroc, 2024.
- [22] HCP, “Annuaire statistique du Maroc: Données macroéconomiques et démographiques,” tech. rep., Haut-Commissariat au Plan, Rabat, Maroc, 2024.
- [23] Bourse de Casablanca, “MASI index and market capitalization data,” tech. rep., Bourse de Casablanca, Casablanca, Maroc, 2024.
- [24] D. A. Dickey and W. A. Fuller, “Distribution of the estimators for autoregressive time series with a unit root,” *Journal of the American Statistical Association*, vol. 74, no. 366a, pp. 427–431, 1979.
- [25] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA: MIT Press, 2016.
- [26] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis: Forecasting and Control*. Hoboken, NJ: John Wiley & Sons, 5th ed., 2015.
- [27] J. W. Tukey, *Exploratory Data Analysis*. Reading, MA: Addison-Wesley, 1977.
- [28] K. Deb, *Multi-Objective Optimization Using Evolutionary Algorithms*. Chichester: John Wiley & Sons, 2001.
- [29] S. M. Lundberg and S.-I. Lee, “A unified approach to interpreting model predictions,” in *Advances in Neural Information Processing Systems (NeurIPS 2017)*, vol. 30, pp. 4765–4774, 2017.
- [30] A. Fisher, C. Rudin, and F. Dominici, “All models are wrong, but many are useful: Learning a variable’s importance by studying an entire class of prediction models simultaneously,” *Journal of Machine Learning Research*, vol. 20, no. 177, pp. 1–81, 2019.
- [31] S. M. Lundberg, G. Erion, H. Chen, A. DeGrave, J. M. Prutkin, B. Nair, R. Katz, J. Himmelfarb, N. Bansal, and S.-I. Lee, “From local explanations to global understanding with explainable AI for trees,” *Nature Machine Intelligence*, vol. 2, no. 1, pp. 56–67, 2020.
- [32] C. Molnar, *Interpretable Machine Learning: A Guide for Making Black Box Models Explainable*. Leanpub, 2nd ed., 2022.