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A Mathematical Minimax Optimization Framework for AI-Driven Strategic Decision-Making in Human Resource Management, Marketing, and Finance under Uncertainty

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Abstract
Understanding of allocating strategy resources under uncertainty is an enormous challenge for companies trying to manage their human resource management (HRM), marketing and financial resources. Deterministic methods can often not meet the challenge of uncertain operation conditions and conflicting departmental requirements. This work proposes a mathematical minimax optimization framework for resource allocation in a strategic context with uncertainty. The proposed model uses a normalized budget of 100, three decision variables of departments, and five levels of uncertainty (0% - 20%). Strong minimax optimization is used to minimize the maximum loss to any department; given a set budget. From the analytical results optimal distribution of 40.00% for HRM, 33.33% for marketing and 26.67% for finance. The worst case organizational loss is 0.900, or 16.67% and 25.00% less than equal and fixed allocation strategies respectively. These results illustrate that minimax optimization can mathematically handle the problem of making sound strategic decisions in an uncertain world.

Keywords: Minimax Optimization, Robust Decision-Making, Strategic Resource Allocation, Artificial Intelligence, Mathematical Programming, Uncertainty Analysis.

1. Introduction

In the field of human resource management (HRM), marketing and finance, for example, competing priorities demand coordinated investment decisions, and to ensure a superior performance in all of these functions, it is necessary to allocate resources strategically. Organizations work in conditions of uncertainty regarding productivity, demand of its products, expenditure, financial risks etc. of the workforce. Therefore, in order to make a good decision some mathematical methods have to be used that can meet the requirement of departments, and of course, financial feasibility. Mathematical optimization can be used to systematically

allocate scarce resources, and artificial intelligence (AI) can be used as assistance to uncertainty assessment and strategic planning using computational decision support systems.

Traditional resource allocation methods are often based on hard-to-satisfy deterministic assumptions, on departmental budgets, and on independent optimization strategies. These approaches can fail to consider interactions between organizational units and can be less effective when the context of the operations shifts. Restricted budgets and divergent departmental goals exacerbate strategic planning challenges, and make the need for strong optimization techniques that take undesirable events into account even more crucial. To overcome this, it can be solved by minimax optimization, which aims to allocate the resources in such a way that the maximum loss in the organization is minimized under the given uncertainty conditions.

Although there has been progress with mathematical programming and decision-making using Artificial Intelligence, minimax formulations that tackle the domains of HRM, marketing and finance under a single allocation structure are still significant research avenues. This study formulates a mathematical minimax optimization model by incorporating loss function of each department, budget restraint and the uncertainty adjusted parameters. Five conditions of uncertainty are taken into account, from 0% up to 20%, with a framework based on a normalized budget of 100 units. A comparison of three allocation strategies - equal allocation, fixed allocation, and robust minimax optimization - is made. Main contributions are optimal departmental allocations, analysis of uncertainty sensitivity, budget feasibility and quantification of worst-case organizational loss reductions. The framework proposed builds a clear mathematical basis for joint strategic resource allocation when uncertainty exists.

2. Related Work

Minimax optimization and robust decision theory offer mathematical tools for decision making under uncertainty of operating conditions which are characterized by minimizing worst losses over uncertainties of the operating conditions [1, 4, 9]. Robust mathematical programming with uncertainties and feasibility constraints has been developed to find solutions that are effective over adverse scenarios [1, 4, 12]. Efficient solution procedures and analytical characterization of optimal decisions are also facilitated by convex optimization [4, 9]. For strategic resource allocation, with scarce resources and different priorities, it is important to analyze organizational risks and trade-offs systematically [7], [8], [12].

AI has been bringing significant advances in predictive modelling, uncertainty estimation and optimisation-based strategic planning at the level of computational decision support [2, 5, 6]. Mathematical models with AI can help decision makers detect the parameters that are uncertain and assess the different approaches to resource allocation [5, 11, 13, 14]. But in terms of decision making, uncertainty alone cannot guarantee a strong decision, which is why it is important to combine the uncertainty assessment with mathematically formulated optimization and constraints [2], [10], [15].

In HRM applications, optimization methods are used for workforce planning, employee development investment and distribution of resources in operations [3]. Advertising expenditure, allocation of the advertising budget, and uncertainty over demand are some of the factors that must be optimized by the marketing function, while budget planning, allocation of investments in the budget, and exposure to risk are some of the elements that must be optimized by the financial function [7, 8, 10]. While these applications illustrate the value of mathematical programming, decisions made by departments are often analysed separately from one another, which may fail to account for the opposing demands on departments' attention and shared resources [3, 7, 8].

Most current solutions also use deterministic inputs or focus on a desired (average) performance rather than a maximum loss that can be imposed on departments [1]–[2] [9]. Therefore, mathematical optimization tools which can synchronize HRM, marketing and financial aspects via a single worst case optimization criterion deserve to be studied further [3, 4, 12]. This study fills this methodological gap by presenting a constrained minimax model that allows for the inclusion of departmental loss functions and uncertainty-adjusted coefficients of the model, besides a shared budget. It can be analytically evaluated to offer a clear foundation for allocating strategies, understanding sensitivity to uncertainty and worst-case organizational performance.

3. Proposed Mathematical Minimax Optimization Framework

3.1 Research Design and Integrated Computational Architecture

The study proposed here will be a mathematical-based research with a computational design to build an integrated minimax optimization framework for strategic resource allocation in human resource management (HRM), marketing and finance. The framework is based on the assumption of a total budget of 100 normalized units that are split into three departmental decision variables—workforce development, marketing, and financial management. Each department has a mathematical loss function for allocating resources to their department and measuring the performance of the departments. Five operating conditions are considered, ranging from 0% to 20% uncertainty. The proposed framework utilizes the powerful minimax decision criterion to minimize the maximum departmental loss with respect to satisfying a total budget constraint and minimum allocation constraint. Figure 1 shows the integrated computational architecture which starts with the strategic allocation of budget across the three departments, and then the evaluation of loss in each department, the representation of uncertainty, and the robust minimax optimization. The solution from the analytical solution allocates 40.00 units to HRM, 33.33 units to marketing, and 26.67 units to finance. The architecture also lays the groundwork for future AI-based decision support systems, such as uncertainty estimation and adaptive resource planning. It is an integrated formula that allows for the systematic analysis of departmental priorities, budget feasibility and worst-case organizational performance over different levels of uncertainties.

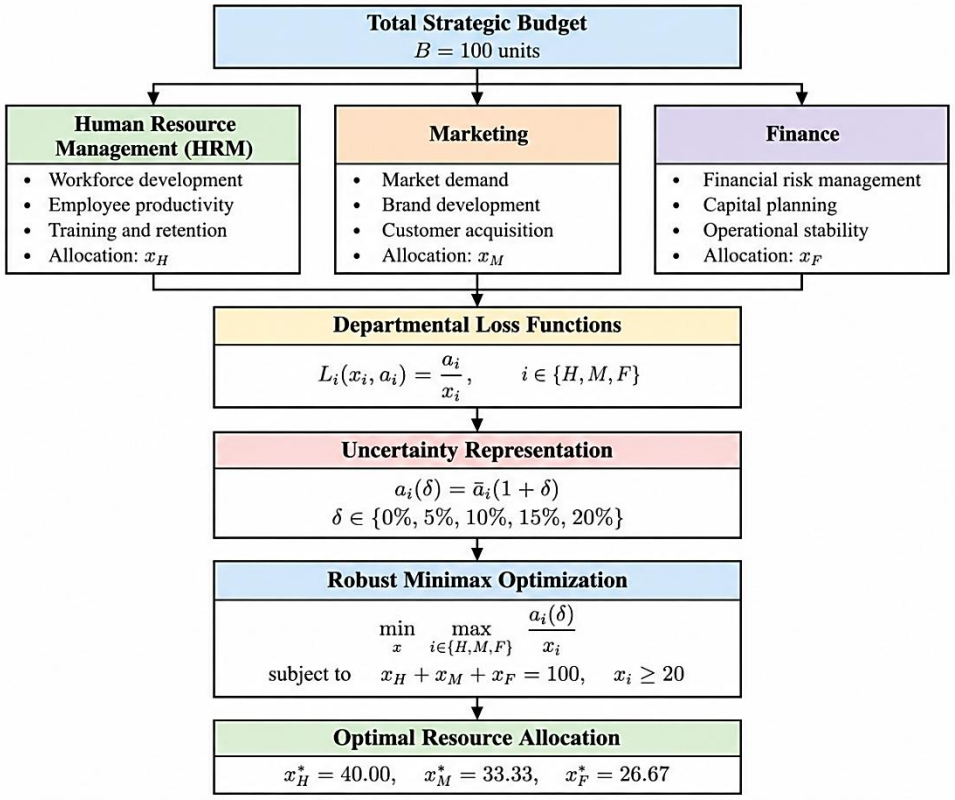


Figure 1. Architecture of the Proposed Minimax Optimization Framework

3.2 Input Parameters, Decision Variables, and Budget Constraints

The proposed mathematical minimax optimization framework assumes that 100 units of resources will be divided between human resource management (HRM), marketing and finance. The allocations of resources, x_H, x_M, and x_F, to the different departments are decision variables. There must be at least 20 units in each department for operational feasibility requirements. To describe the relative contributions of HRM, marketing and finance to the mathematical loss model, the nominal loss coefficients are assumed to be 30, 25 and 20 respectively. To assess the sensitivity to allocation, five uncertainty conditions ranging from 0% to 20% are considered. The numerical setup also sets 500 evaluation scenarios, maximum solver iterations of 1000, a numerical tolerance of $10^{-6}$and planned 30 numerical replications for computational evaluation. The conditions for the mathematical evaluation are summarised in Table 1 and are defined here.

Table 1. Input Parameters and Numerical Configuration

Parameter	Value

Total strategic budget	100 units
Minimum HRM allocation	20 units
Minimum marketing allocation	20 units
Minimum finance allocation	20 units
HRM nominal loss coefficient	30
Marketing nominal loss coefficient	25
Finance nominal loss coefficient	20
Uncertainty conditions	5
Uncertainty range	0–20%
Scenario evaluation configuration	500
Maximum solver iterations	1,000
Numerical tolerance	10^{-6}
Planned numerical replications	30

The strategic budget constraint states that the total budget of the different departments must be equal to the total budget allocated to them (as given by Equation (1)).

$$x_H + x_M + x_F = 100, \quad (1)$$

Each departmental allocation is limited to a minimum of 20 units (as defined by Equation (2)) to prevent resource deprivation and to keep minimum operational requirements.

$$x_H \geq 20, \quad x_M \geq 20, \quad x_F \geq 20, \quad (2)$$

These requirements are applied together to yield the feasible region for the proposed minimax optimization model, in which all the budget is used and the departmental requirements for resources are met.

3.3 Departmental Loss Functions and Mathematical Uncertainty Modelling

The framework is designed to include departmental loss functions which measure the relationship between organizational performance under uncertainty and the allocation of resources in the organization. Each department has a separate loss function, with each function corresponding to an allocation of resources as human resource management (HRM), marketing, finance. There are individual loss functions, each representing a different department and a reduction in the corresponding department's loss function corresponding to an increase in the allocation of the resource. The nominal loss coefficients are determined to be 30 for HRM, 25 for marketing, and 20 for finance. The preselected departmental loss parameters in the mathematical model are these coefficients. The loss function of this department is written as the following equation (3).

$$L_i(x_i, a_i) = \frac{a_i}{x_i}, \quad i \in \{H, M, F\}, \quad (3)$$

where $L_i$denotes the departmental loss, $x_i$represents the allocated resources, and $a_i$denotes the uncertainty-adjusted loss coefficient. The operating conditions are considered as unknown, and the nominal coefficients are changed by introducing a proportional uncertainty factor (PUF), as shown in Equation (4).

$$a_i(\delta) = \bar{a}_i(1 + \delta), \quad (4)$$

where $\bar{a}_i$represents the nominal departmental loss coefficient and δ denotes the uncertainty level. The nominal coefficient vector is defined as $\bar{a} = (30,25,20)$, while five uncertainty conditions are considered:$\delta \in \{0,0.5,0.10,0.15,0.20\}$. The change of uncertainty in departmental loss coefficients is shown in figure 2. As

uncertainty grows from 0% to 20%, the HRM coefficient climbs to 36, the marketing coefficient grows to 30, and the finance coefficient goes up to 24. The proportional increases maintain the structure of the departments in coefficient order and increase the risk of losing a department. Accordingly, condition C5 has the highest uncertainty, and is used as the most adverse coefficient configuration for subsequent worst case minimax optimization. This mathematical tool helps to evaluate uncertainty sensitivity and departmental loss exposure on a consistent basis in the integrated strategic resource allocation framework.

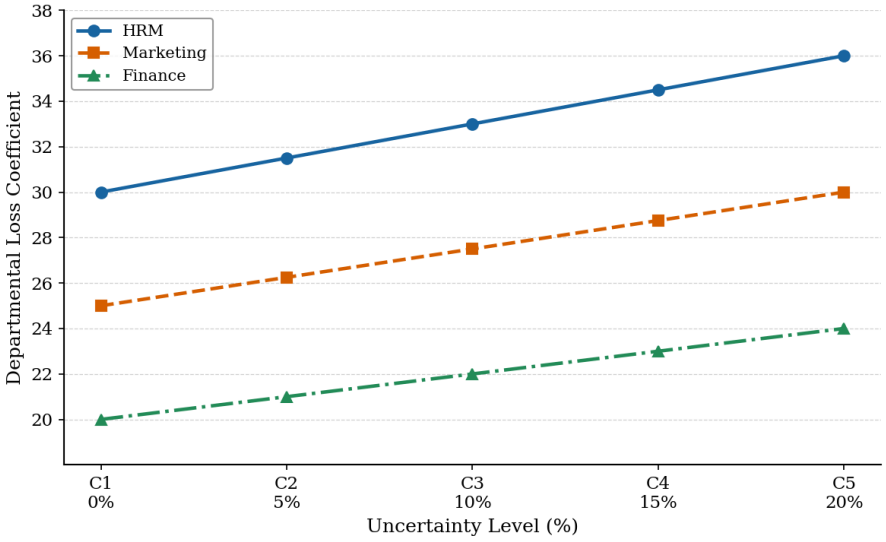


Figure 2. Variation of Departmental Loss Coefficients Across Five Uncertainty Conditions

3.4 Robust Minimax Formulation and Analytical Optimal Allocation

The proposed framework uses the robust minimax optimization to find optimal allocation of strategic resources between human resource management (HRM), marketing and finance under uncertain operating conditions. The point is to minimize maximum loss per department subject to budget constraints and minimum requirement for resources. The minimax method differs from the conventional fixed allocation methods by finding a distribution of the resources that minimizes the "worst-case" losses in each department. The goal of the mathematical component is defined in equation (5).

$$\min_{x \in X} \max_{i \in \{H,M,F\}, a_i \in \mathcal{U}_i} \frac{a_i}{x_i}, \quad (5)$$

where $x = (x_H, x_M, x_F)$represents the departmental allocation vector, X denotes the feasible allocation set, and $\mathcal{U}_i$ represents the uncertainty set associated with each departmental loss coefficient. For mathematical analysis, the minimax objective is restated in terms of an auxiliary variable t, which is the worst case loss incurred by the departments. The equivalent epigraph optimization formulation is given in the following equation (6) is presented.

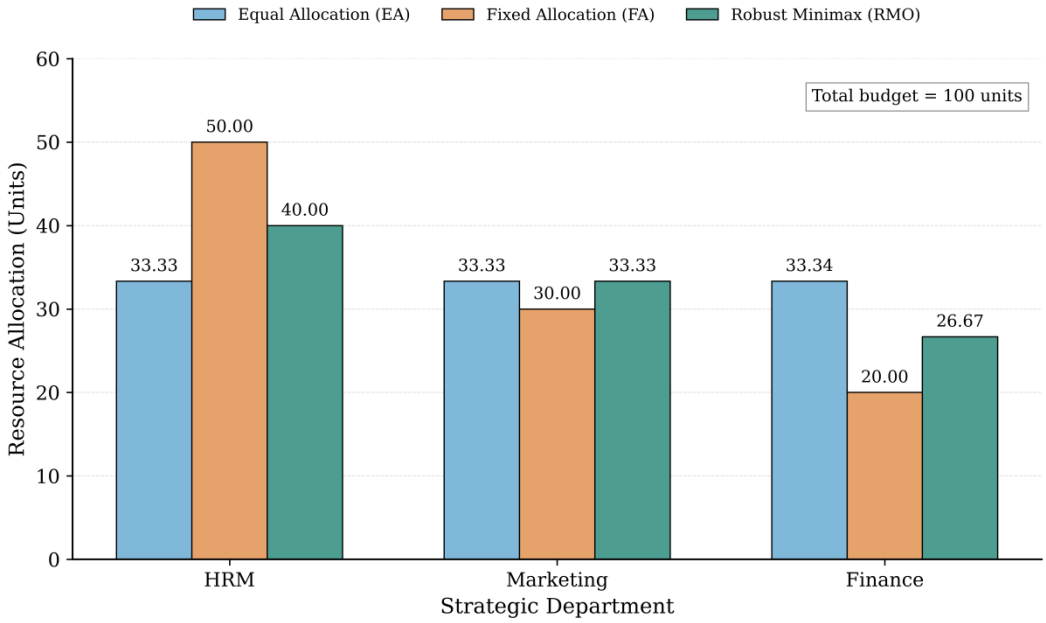
$$\min_{x,t} t \quad subject\ to \quad \frac{(1+\delta)\bar{a}_i}{x_i} \le t, \quad \forall_i \quad , \quad \sum_i x_i \quad x_i \ge 20 \quad (6)$$

The formula is designed to reduce the number of units which is lost by the department and yet meet the need for a total allocation of 100 units. If both the loss coefficients are positive (as they are in this case), and they are not restricted by any outside factors, then the losses for the departments are equalized and the analytical rule for allocating comes out as Equation (7).

$$x_i^* = \frac{100 a_i}{\sum_{j \in \{H,M,F\}} a_j}, \quad (7)$$

A maximum of uncertainty of 20% results in departmental loss coefficients of 36, 30 and 24. Using Equation (7) will lead to optimal levels of HRM of 40.00, marketing of 33.33 and finance of 26.67 units. All that compares

with the minimum requirement of 20 units with a total of 100 units. This yields the required organization's worst-case loss of 0.900, which is the lowest possible loss that can be achieved for the model. Hence, the analytical solution meets the feasibility requirements and offers a mathematically sound resource allocation policy for the given uncertainty where uncertainty is considered.



4. Numerical Evaluation and Performance Metrics

The numerical evaluation analyzes how effective the proposed robust minimax optimization framework is in the distribution of strategic resources among the human resource management (HRM), marketing and finance departments in different uncertainty conditions. Five uncertainty conditions are modelled (C1, 0%; C2, 5%; C3, 10%; C4, 15% and C5, 20%), with 100 normalised resources across the entire uncertainty budget and at least 20 resources allocated to the department. Three allocation methods are investigated: Equal Allocation (EA), Fixed Allocation (FA) and Robust Minimax Optimization (RMO). The EA strategy allocates 33.33, 33.33 and 33.34 units to HRM, marketing and finance, respectively while FA allocates 50, 30 and 20 units to HRM, marketing and finance, respectively. The optimal solution of 40.00, 33.33 and 26.67 units determined by the analytical minimax solution is proposed as the RMO strategy. Three major performance measures are used for the evaluation: worst case organizational loss, worst case loss reduction, and budget utilization. The maximum value of the loss sustained by the department in the case of a particular uncertainty condition is called the worst case organizational loss, and is expressed in Equation (8).

$$L_{max} = \max_{i \in \{H,M,F\}} \frac{a_i}{x_i}, \quad (8)$$

where a_i represents the uncertainty-adjusted departmental loss coefficient and x_i denotes the corresponding resource allocation. RMO's percentage improvement over a baseline strategy is computed by Equation (9).

$$WLR = \frac{L_{baseline} - L_{RMO}}{L_{baseline}} \times 100, \quad (9)$$

The utilization of budget measures the percentage of the utilization of the three departments as specified in Equation (10).

$$BU = \frac{x_H + x_M + x_F}{100} \times 100, \quad (10)$$

The comparative evaluation is done under the maximum uncertainty condition with HRM Loss coefficient is 36, marketing is 30 and finance is 24. The organizational losses and corresponding resource allocations of the three strategies are shown in Table 2.

Table 2. Comparative Resource Allocation and Worst-Case Loss at 20% Uncertainty

Method	HRM	Marketing	Finance	Worst-case loss
Equal Allocation (EA)	33.33	33.33	33.34	1.080
Fixed Allocation (FA)	50.00	30.00	20.00	1.200
Robust Minimax (RMO)	40.00	33.33	26.67	0.900

The analytical results show that RMO's worst case organizational loss is 0.900 while EA and FA are 1.080 and 1.200 respectively. This results in the reductions in losses of 16.67% and 25.00% respectively. The results of the comparative resource allocation patterns are displayed in Figure 3, where the patterns vary from the equal resource allocation approach to the fixed resource allocation approach to the minimax approach. The allocation under the FA strategy is the highest for HRM, while under RMO the resources are distributed according to the loss coefficient of the department adjusted for its level of uncertainty; aiming for equal maximum departmental losses. All three strategies fully fill the 100 unit budget and meet the lower limits of the departmental allocations. The numerical evaluation process includes the calculation of uncertainty adjusted departmental coefficients, departmental feasible allocations, departmental maximum losses, calculation of comparative losses and the checks of budget use. From a mathematical point of view, the resulting comparisons of the three allocation strategies give a relative worst-case performance measure for each strategy, and also give a consistent basis for the sensitivity analysis and discussion of the results undertaken in Section 5.

5. Results and Discussion

5.1 Optimal Strategic Resource Allocation Results

The analytical outcomes of the proposed robust minimax optimization framework show that strategic resources are optimally allocated among human resource management (HRM), marketing and finance, given 20% maximum uncertainty. For the normalized total budget of 100 units, the optimal allocation assigns 40.00 units (40.00%) to HRM, 33.33 units (33.33%) to marketing, and 26.67 units (26.67%) to finance. The departmental loss coefficients are 36, 30 and 24, respectively, indicating that the resources are distributed in proportion to their degree of uncertainty. The level of losses for those departments is then balanced out at around 0.900, which provides a worst-case loss that the department can achieve under the given maths constraints. The framework allocates the budgeting of the departments individually and adds up the allocations to meet the total budget constraint of 100 units, and output of 100 units is achieved. Also, the three departmental allocations are greater than the minimum 20 units required, and this demonstrates the analytical solution's feasibility. Results show that the minimax approach aims at balancing the investment strategy by minimizing the maximum departmental loss instead of focusing the investment of each department. This mathematical outcome signifies the framework's capacity to ensure resources remain feasible and to limit the injury potential of the organisation under the uncertainty and budget defined.

5.2 Comparative Worst-Case Loss Performance

The comparative analysis is carried out for comparing the most damage to the organizations for three strategic resource allocation schemes: Equal Allocation (EA), Fixed Allocation (FA), and Robust Minimax Optimization (RMO). The worst case loss for the EA strategy with maximum uncertainty of 20% is 1.080, and the highest loss for the FA strategy is 1.200 under the maximum uncertainty case of 20%. However, for the same mathematical conditions, the proposed RMO framework achieves the lowest worst case organizational loss of 0.900, showing its ability to minimise WDL in the departments under the RMO framework. The minimax solution outperforms both EA and FA with a reduction of 16.67% and 25.00% respectively, suggesting that it performs best in worst cases. The differences between the three allocation approaches are emphasized in Figure 4 which shows the comparative Worst case Organizational losses and the corresponding minimax Performance improvements. The relative loss of FA is caused by the uneven distribution of resources, specifically the least allocation for finance, while EA distributes resources evenly without taking into account the loss coefficient of the departments. On the other hand, RMO assigns resources in proportion to uncertainty adjusted loss coefficients, which lead to equal losses for departments and minimize the maximum loss of the organization. The analytical results showed that the proposed minimax framework is mathematically efficient in allocating resources while still ensuring full resource utilization and meeting departmental resource constraints. The observed improvements depend on the defined losses, assumptions of uncertainty and allocation bases.

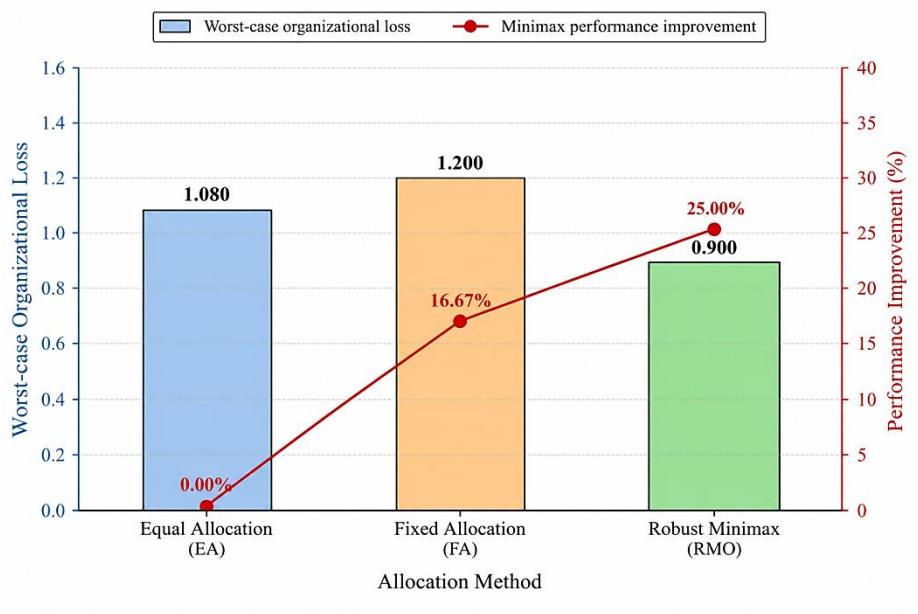


Figure 4. Worst-Case Loss and Minimax Performance Improvement

5.3 Sensitivity Analysis Across Uncertainty Conditions

The sensitivity analysis first investigates how increasing uncertainty changes the process of optimal strategic resource allocation and worst case organizational loss to form an optimization minimax process. The five uncertainty conditions are evaluated while keeping total budget fixed at 100 units (normalized). The analytical sensitivities findings are shown in Table 3, which shows that the best resource allocations are fixed at 40.00% human resources management (HRM), 33.33% marketing and 26.67% finance in all levels of uncertainty. This allocation stability is achieved with a proportional change in departmental loss coefficients, thus maintaining the proportion of sizes. But, the optimum worst case organizational loss grows steadily as uncertainty grows, up from 0.7500 for C1, to 0.7875 for C2, to 0.8250 for C3, to 0.8625 for C4, and to 0.9000 for C5.

Table 3. Sensitivity Analysis of Minimax Allocation Under Uncertainty

Condition	Uncertainty	HRM (%)	Marketing (%)	Finance (%)	Optimal loss
C1	0%	40.00	33.33	26.67	0.7500
C2	5%	40.00	33.33	26.67	0.7875
C3	10%	40.00	33.33	26.67	0.8250
C4	15%	40.00	33.33	26.67	0.8625
C5	20%	40.00	33.33	26.67	0.9000

The sensitivity of optimal worst case organizational loss to growth in uncertainty is shown in figure 5, with sensitivity being constant at 0.0375 on average for each 5% increase in uncertainty. The overall rise in the optimal loss from 0.7500 to 0.9000 is 20% more than the nominal loss. Although the departmental allocation proportions have increased, there is no overall change in these proportions as all of the loss coefficients have been multiplied by the same uncertainty factor. The results here prove that the proposed minimax solution has allocation stability in the presence of proportional uncertainty without the loss achieved being worse than the worst case, and how increased. The results are mathematically grounded in order to interpret the sensitivity to uncertainty and to assess the robustness of a strategic allocation of resources subject to the assumptions of the model.

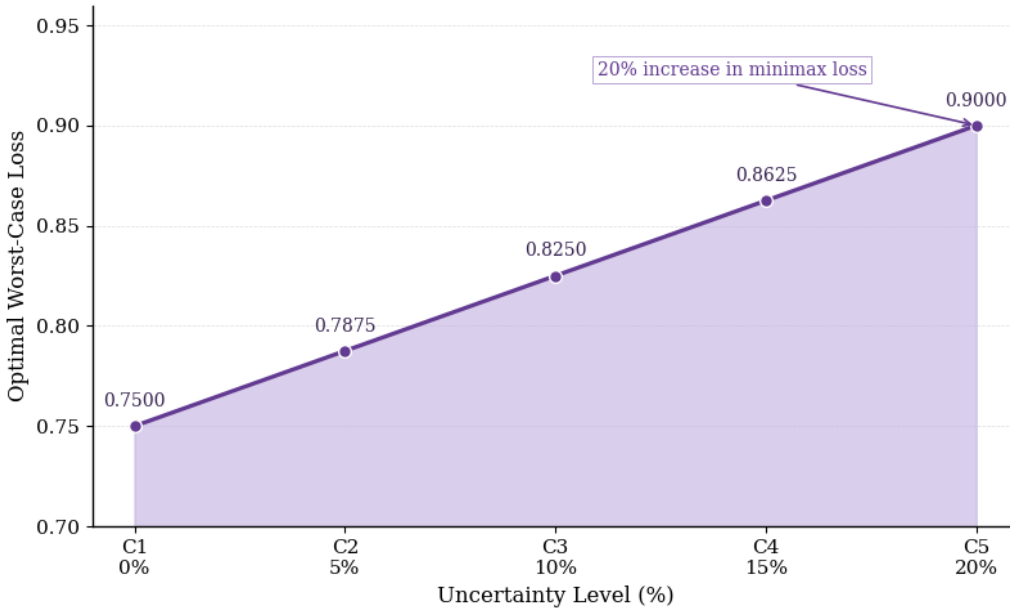


Figure 5. Sensitivity of Optimal Worst-Case Organizational Loss to Increasing Uncertainty

5.4 Mathematical Interpretation and Strategic Implications

Under the proposed budget and uncertainty constraints, the mathematical interpretation of the robust minimax optimization approach shows that the optimal strategic resource allocation is obtained by making the departmental worst case loss the same across the departments. Allocation of 40.00% to human resource management (HRM) along with 33.33% to marketing and 26.67% to finance implies loss for each of the departments at maximum uncertainty as 0.900. This outcome is the proportionality of the uncertainty adjusted loss coefficients and optimal resource allocations. Moreover, the optimal allocation does not change under the five different uncertainty conditions since the optimal allocation departmental coefficients increase proportionately, keeping the same relationship between their contribution values to the minimax objective. Under the above set mathematical conditions, proposed framework mathematically proved as effective organizational loss reduction as compared to equal allocation and fixed allocation strategies, respectively of 16.67% and 25.00%. The framework offers a grounded plan to set priorities for workforce development, marketing investments, and financial resource planning in order to preserve budget feasibility from a strategic standpoint. The allocation mechanism can assist organizational decision makers in balancing competing departmental needs, and managing the maximum potential for loss. Moreover, the mathematical formulation provides the possibility to integrate with intelligent decision-support tools like AI models to forecast uncertainty and guide decisions on resource allocation in adaptive management frameworks. But this integration needs to be further developed and tested in terms of the computation. Overall, the results suggest that minimax optimization could be a clear, consistent and mathematically valid method for strategic resource planning as concerns uncertainty.

5.5 Research Limitations

There are some limitations in the proposed mathematical minimax optimization framework which should be kept in mind for interpreting the analytical results. First, the departmental loss functions use simple reciprocal links between uses of resources and organizational loss, which might miss out on the more complex relationships to be found in a mix of HRM, marketing and finance. Second, the uncertainty model requires the assumption of proportional variations in departmental loss coefficients, which restricts it to capturing departmental disturbance(s) and correlated risks. Third, the framework assumes a single period budget allocation without taking into account time-variant resource reallocations or changing priority setting over time. In addition, the allocation outcomes are not directly generalizable from the organization to the numbers since the numerical values of the coefficients are not empirical and but a mathematical value. While the framework offers a mathematical basis for strategic decision-making with the help of AI, there is no implementation or evaluation of an AI-based uncertainty prediction model. Moreover, the comparative analysis is restricted to two types of allocation: “equal” and “fixed” allocation, excluding the benchmark of independent optimization of stochastic programming and other robust optimization scenarios. The loss reductions reported here, therefore, provide a

mathematical improvement measures against the given baselines, not a generally agreed upon improvement measure of the organization. The constraints guide the further development of the framework by advanced uncertainty model, adaptive optimization, AI integration and empirical testing.

6. Conclusion and Future Research Directions

In this research, an integrated mathematical minimax optimization framework for strategic resource allocation in human resource management (HRM), marketing and finance areas is developed under uncertain conditions. The organization loss minimization framework proposed here integrated a series of departmental loss functions, uncertainty adjusted cost coefficients, and budget constraints. For each of the five uncertainty conditions (IC) from 0% to 20% uncertainty, the analytical solution arrived at the optimal allocation of 40.00% of the budget to HRM, 33.33% to marketing, and 26.67% to finance. However, in the case of the maximum uncertainty, the framework minimized the organizational loss to 0.900, which is 16.67% and 25.00% lower than the equal allocation and fixed allocation, respectively. Moreover, the solution achieved BLM utilization of 100% and met all the minimum BLM constraints for the departments. When the proportions were uncertain proportionally, with values that were common, it was shown that the optimal allocations did not change, while worst case organizational loss grew with increases in uncertainty. The results provide mathematical justification for the effectiveness of minimax optimization for the solution of problems that combine departmental priorities and limit maximum losses in the model considered. The model could be further extended by integrating advanced feature of Artificial Intelligence (AI), such as uncertainty estimation as well as department specific uncertainty distribution, multiperiod resource optimization and nonlinear interactions between organizational functions, into the model as future research. Further research could compare the proposed technique with stochastic programming and other robust optimization techniques. The use of actual organizational data for validation would add to the utility and generalizability of the framework to promote AI-based strategic decision-making.

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