Gradient-Driven Solution Based on Indifference Analysis (GIA) for Scenario Modelling Optimization Problem

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***Abstract*—This paper introduces an optimization technique for scenario modeling in uncertain business situations, termed the Gradient-Driven Solution Based on Indifference Analysis (GIA). GIA evolves the conventional methods of scenario planning by applying a reverse-strategy approach, where future financial goals are specified, and the path to attain these targets are engineered backward. It adopts economic concepts to construct gain indifference curves and loss indifference lines, which aid in making strategic decisions and refining financial plans. This method employs gain and loss gradients to assess and improve the efficiency of decision-making processes. The GIA algorithm's effectiveness has been confirmed through its application in a real-world project, where it adeptly navigated the intricacies of scenario modeling by proposing variable adjustments that streamline efforts and curtail losses. The outcomes reveal that GIA not only addresses scenario modeling challenges but also augments existing financial plans.**

***Keywords*—Scenario Modelling, Optimization, Consumer Theory, Gradient-Driven Solution Based on Indifference Analysis (GIA)**

I. Introduction

In today's rapidly evolving business landscape, organizations encounter increasing uncertainties, highlighting the need for robust strategic planning tools. Scenario modelling has emerged as a key strategy, enabling companies to probe and prepare for a range of potential future scenarios, thereby enhancing their strategic decision-making and adaptability [1, 2]. This approach has become widely acknowledged and adopted across various business sectors [3].

While conventional scenario modelling has been instrumental in providing a forward-looking view, facilitating "what if" analyses and sensitivity assessments [4-17], it falls short in exploring scenarios from a reverse standpoint. The focus of this paper, the "inverse" scenario modelling, adopts a novel approach. Rather than merely forecasting future outcomes from present-day actions, it enables organizations to set a desired future state or objective and retrospectively determine the optimal path and actions to attain that goal. This method is especially pertinent to financial planning optimization, where firms establish specific financial objectives and seek a strategic and operational route to reach these goals.

There exists a rich corpus of research on optimization issues in diverse sectors [18, 19], with significant attention to optimization within trading and investment contexts [20-25]. However, the particular challenges of applying scenario modelling to business operations, especially from an inverse perspective, have not been extensively examined. The Gradient-Driven Solution Based on Indifference Analysis (GIA) methodology introduced in this paper aims to address the issue, providing a structured and quantitatively rigorous framework that not only enables the envisioning of various future scenarios but also delineates the most effective strategies to achieve predetermined financial objectives.

The GIA methodology synthesizes classical scenario modelling with economic theory, particularly adopting the economic constructs of utility indifference curves and budget lines in consumer theory [32-35], to tackle optimization challenges in business. The method introduces gain indifference curves and loss indifference lines into strategic business planning, allowing for the comparison of various strategy combinations that yield equivalent financial results or costs, thus aiding in the optimization of strategic planning and operational efficiency.

Utilizing these concepts, The GIA approach presents a framework that not only visualizes the problem but also addresses it through a systematic and sequential process, utilizing the concepts of gain and loss gradients for effective resolution. It allows companies to strategically navigate towards their future financial aspirations, providing a refined tool for scenario planning that aligns business strategies with financial and operational objectives, thereby improving decision-making in complex business situations.

Beyond addressing scenario modelling challenges, the GIA method offers a means to refine existing financial plans. It enhances efficiency by identifying areas where effort can be reorganized, achieving equivalent financial targets with less exertion. This is accomplished by intelligently reallocating attention to modifiable variables, optimizing their impact on the overall plan.

Furthermore, GIA has proven to be an effective tool beyond theoretical applications, as it has been successfully implemented in a real-world project. This practical application underscores GIA's utility in navigating and optimizing complex scenario modelling challenges in actual business environments, demonstrating its potential to enhance existing financial plans and strategic decision-making processes.

This paper is organized as follows. Section 2 presents an example to elaborate the scenario modelling problem. Section 3 delves into the GIA methodology, presenting its underlying theory and outlining the detailed steps of the implementation process. Section 4 evaluates the effectiveness of the GIA methodology in solving scenario modelling issues and improving existing financial plans, using both a hypothetical scenario and a practical real-world application. Section 5 concludes the paper, summarizing the findings and suggesting avenues for future research.

II. Problem Statement

This section delineates the scenario modeling problem by elucidating relevant concepts via a hypothetical example, thereby establishing a foundational understanding necessary for comprehending the subsequent discussions.

A. *Baseline*

The initial phase of the scenario modelling problem is established through a baseline, which is essentially a forecast encompassing predictions regarding the quantities and prices of a product portfolio over forthcoming periods, with revenues being the product of these quantities and prices.

Notably, the sales are subscription based, hence the quantities and prices carry over from one period to the next, adding the complexity of the problem.

Tab 1 exemplifies a hypothetical baseline forecast, extending over the upcoming three months, with Month 1 delineated in Columns C-E, Month 2 in Columns G-I, and Month 3 in Columns K-M. The ensuing discourse will concentrate on Month 1 to elucidate the example.

Tab 1: A hypothetical example of the baseline

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1				Month 1				Month 2				Month 3			TOTAL
2			begin	addition	all		begin	addition	all		begin	addition	all		
3															
4	quantity	product A	200	30	230		230	40	270		270	50	320		
5		product B	100	40	140		140	20	160		160	70	230		
6		total	300	70	370		370	10	430		430	120	550		
7															
8	price	product A	$28.00	$30.00	$28.26		$28.26	$24.00	$27.63		$27.63	$35.00	$28.78		
9		product B	$54.00	$40.00	$50.00		$50.00	$56.00	$50.75		$50.75	$58.00	$52.96		
10		total	$24.00	$35.71	$36.49		$36.49	$208.00	$36.23		$36.23	$48.42	$38.89		
11															
12	revenue	product A	$5,600	$900	$6,500		$6,500	$960	$7,460		$7,460	$1,750	$9,210		$23,170
13		product B	$5,400	$1,600	$7,000		$7,000	$1,120	$8,120		$8,120	$4,060	$12,180		$27,300
14		total	$11,000	$2,500	$13,500		$13,500	$2,080	$15,580		$15,580	$5,810	$21,390		$50,470

Tab 2: Baseline formulas

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1				Month 1				Month 2				Month 3			TOTAL
2			begin	addition	all		begin	addition	all		begin	addition	all		
3															
4	quantity	product A	200	30	=C4+D4		=E4	40	=G4+H4		=I4	50	=K4+L4		
5		product B	100	40	=C5+D5		=E5	20	=G5+H5		=I5	70	=K5+L5		
6		total	=SUM(C4:C5)	=SUM(D4:D5)	=SUM(E4:E5)		=SUM(G4:G5)	10	=SUM(I4:I5)		=SUM(K4:K5)	=SUM(L4:L5)	=SUM(M4:M5)		
7															
8	price	product A	28	30	=E12/E4		=E8	24	=I12/I4		=I8	35	=M12/M4		
9		product B	54	40	=E13/E5		=E9	56	=I13/I5		=I9	58	=M13/M5		
10		total	24	=D14/D6	=E14/E6		=G14/G6	=H14/H6	=I14/I6		=K14/K6	=L14/L6	=M14/M6		
11															
12	revenue	product A	=C4*C8	=D4*D8	=C12+D12		=G4*G8	=H4*H8	=G12+H12		=K4*K8	=L4*L8	=K12+L12		=E12+I12+M12
13		product B	=C5*C9	=D5*D9	=C13+D13		=G5*G9	=H5*H9	=G13+H13		=K5*K9	=L5*L9	=K13+L13		=E13+I13+M13
14		total	=SUM(C12:C13)	=SUM(D12:D13)	=SUM(E12:E13)		=SUM(G12:G13)	=SUM(H12:H13)	=SUM(I12:I13)		=SUM(K12:K13)	=SUM(L12:L13)	=SUM(M12:M13)		=E14+I14+M14

This forecast incorporates projections for two products, designated as Product A and Product B, and includes their combined predictions. Structurally, the forecast is segmented into three distinct categories for each month: quantities are detailed in Rows 4-6, prices in Rows 8-10, and revenues in Rows 12-14, providing a comprehensive view of the forecasted financial landscape for each product.

In the quantity segment, delineated within Rows 4-6, subscription data for each product is presented across three columns for each month. These columns chronicle the number of subscribers at the start of the month (Column C), the increment in subscribers during the month (Column D), and the total subscriber count at the month's end (Column E).

Similarly, the price segment, outlined in Rows 8-10, employs three columns to capture the pricing dynamics: the average monthly subscription rate at the beginning of the month (Column C), the average rate for new subscribers added within the month (Column D), and an aggregated average rate for all subscribers, both existing and new, for the entire month (Column E).

Parallel to this, the revenue segment, captured in Rows 12-14, uses three columns to reflect financial outcomes: the revenue from subscribers at the start of the month (Column C), revenue derived from new subscribers during the month (Column D), and the total revenue accrued from all subscribers by the month's conclusion (Column E).

It is imperative to highlight that within Tab 1, certain values are projections derived directly from the established forecast. These values, totalling 12, are marked with a green highlight within the table, for example, the projected number of new subscribers in Cell D4. Such values are amenable to modifications within the scenario modelling context, thereby classifying them as decision variables.

Conversely, other values within Tab 1 are outcomes of static formulas that encapsulate specific business rules, as expounded in Tab 2. A case in point is the formula in Cell D12, represented as "=D4*D8." This formula demonstrates that the revenue for Product A in Month 1 (D12) is determined by multiplying the number of new subscribers (D4) by the average subscription rate for these new subscribers (D8). These resultant values, being products of predefined formulas, are not subject to direct alterations within the scenario modelling framework.

It is essential to recognize that the scenario presented in Tab 1 serves as a simplified illustration. Actual business contexts might exhibit greater complexity, potentially involving an expanded array of products, a more extensive assortment of items within each month, and additional forecasting periods. Despite these complexities, the fundamental approach to handling these scenarios remains consistent with the methodology demonstrated in the given example.

B. *Objective variable*

Within the framework of the baseline forecast, the goal of the scenario modelling is to empower the user to identify a specific variable and designate a target value for it, diverging from the baseline figure. For instance, if the forecasted total revenue over three months is $50,470, as noted in cell O14 of Tab 1 highlighted in orange, a user might aspire to surpass this figure. Consequently, in this context, the three-month total revenue becomes the objective variable, around which the scenario modelling is cantered.

C. *Objective*

The objective within the scenario modelling framework is defined as the target value that the user aims to achieve. In the context provided, the user's goal is to attain a total revenue of $51,470 over three months, representing an increase of $1,000 from the baseline figure of $50,470. Thus, the specified target of $51,470 becomes the focal point or the objective of the scenario modelling exercise.

D. *Decision variables*

To attain the specified objective, it is necessary to adjust the values that were initially forecasted in the baseline. These adjustable values are termed decision variables. In the provided example, the 12 values marked in green in Tab 1, which are direct predictions from the baseline, qualify as decision variables. Altering these decision variables will consequently lead to modifications in other values within the table, due to the interconnected formulas, thereby enabling the achievement of the desired objective. Hence, these decision variables serve as the pivotal elements or the solutions within the scenario modelling framework.

E. *Implicit objective*

Given the scenario with one objective variable and 12 decision variables, the relationship can be encapsulated in the following mathematical function:

$$f(Q_{A1}, Q_{A2}, Q_{A3}, Q_{B1}, Q_{B2}, Q_{B3}, P_{A1}, P_{A2}, P_{A3}, P_{B1}, P_{B2}, P_{B3}) = R \quad (1)$$

where

QA1, QA2, QA3, QB1, QB2, QB3, PA1, PA2, PA3, PB1, PB2, PB3 are the 12 decision variables that can be adjusted. For example, QA1 denotes the quantity, specifically the number of additional subscribers for Product A in Month 1, as shown in Cell D4 of Tab 1. Similarly, PA1 represents the price, specifically the rate for additional subscribers of Product A in Month 1, indicated in Cell D8 of Tab 1;

R is the objective variable, which in this case is the total revenue over three months, recorded in Cell O14 of Tab 1;

f is the function that transforms the input decision variables into the output R, embodying the underlying business rules governing the scenario.

From (1), the followings can be deduced:

$$df = 12 \quad (2)$$

$$n_c = 1 \quad (3)$$

where

df is the degree of freedom within the problem, corresponding to the quantity of decision variables, which in this context is 12.

n_c is the number of constraints within the problem, equating to the count of objectives, which is 1 in this case.

From (2) and (3), it can be derived that

$$df \gg n_c$$

This indicates a significantly higher degree of freedom compared to the number of constraints. Consequently, it leads to a scenario where potentially infinite solutions exist. By altering any combination of the 12 decision variables, one can achieve myriad outcomes, all satisfying the objective for the total revenue over three months.

Nonetheless, it is critical to acknowledge that not all solutions hold equal value or feasibility. Certain solutions, particularly those involving balanced adjustments across several decision variables, may be more advantageous or practical than others that propose drastic changes to a single variable. This introduces an implicit objective in scenario modelling: to sift through the possible solutions and identify the most optimal or “preferred” one based on certain criteria.

III. METHODOLOGY

The scenario modelling problem under discussion is fundamentally a mathematical optimization challenge, where the objective is to identify optimal values for decision variables that maximize or minimize a given function. This process involves systematically selecting inputs for the decision variables from a permissible range and computing the function’s value to satisfy the specified objective [26, 27].

While there exists a plethora of methodologies to address optimization problems [28-31], and a variety of mature computational tools available in programming languages and spreadsheet applications, a gap is identified for the specific scenario modelling challenge at hand. This gap is particularly pronounced when addressing problems characterized by loss gradient functions that adopt a format of progressively increasing segmented linear functions, which will be detailed in the ensuing sections. The prevailing solutions in this context are observed to be either excessively slow, prone to instability, or exhibit convergence issues, indicating the necessity for a novel solution.

To address this nuanced challenge, this paper introduces an innovative approach by integrating a concept from economics, resulting in the development of the Gradient-Driven Solution Based on Indifference Analysis (GIA). This methodology is specifically tailored for the scenario modelling optimization problem, aiming to offer a more efficient, stable, and convergent solution compared to existing methods.

A. *Inspiration from the economics theory*

Note: the following review and figures of the economics concepts in this section are referenced from https://www.economicshelp.org/blog/glossary/indifference-curves/ with slight modifications by the paper.

In economics, consumer theory is a pivotal concept that elucidates the decision-making processes of rational consumers, who make choices based on the utility derived from goods or services [32]. This theory posits that a consumer's decision point is located at the tangency between a utility indifference curve and a budget constraint [33-35].

A utility indifference curve represents all combinations of two goods that provide the same level of utility to the consumer, illustrating a state of indifference between different bundles of goods. Fig 1 exemplifies such a curve, showcasing the trade-off between two goods, apples and bananas, where the curve’s convexity reflects diminishing marginal utility.

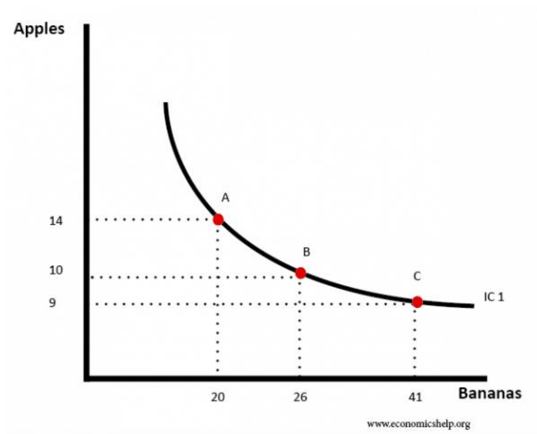

Fig 1: Utility indifference curve. It represents all combinations of two goods that provide the same level of utility to the consumer.

Fig 2 presents a utility indifference curve map, illustrating various indifference curves, each denoting a different level of utility. For instance, all points on curve I2 yield identical utility, which is superior to that of I1 and inferior to I4, with I4 representing the highest utility.

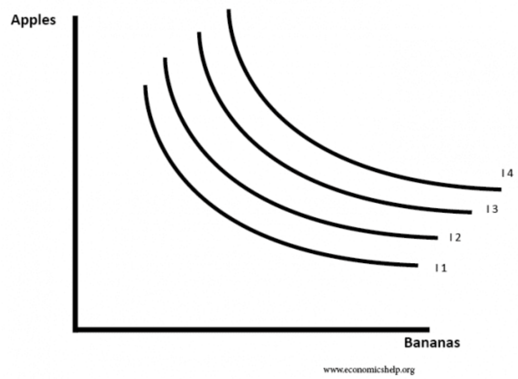

Fig 2: Utility indifference curve map. It illustrates various utility indifference curves, each denoting a different level of utility.

The budget line, as depicted in Fig 3, illustrates all possible combinations of two goods that a consumer can purchase within the confines of their budget. For example, with a budget of £40, and given the prices of apples and bananas, the line delineates all purchasable combinations of these fruits.

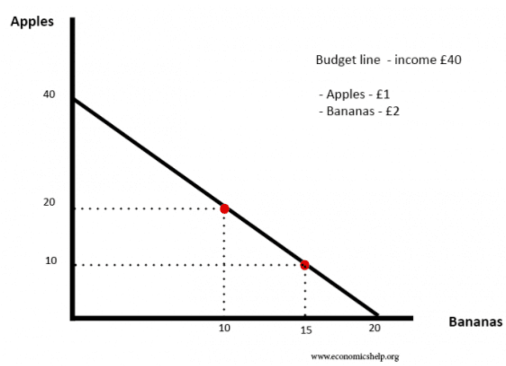

Fig 3: Budget line. It illustrates all possible combinations of two goods that a consumer can purchase within the confines of their budget.

Fig 4 visualizes the optimal consumption choice, where the consumer achieves maximum utility at the point where the highest attainable indifference curve is tangent to the budget line, indicating the most preferred combination of goods within budgetary limits.

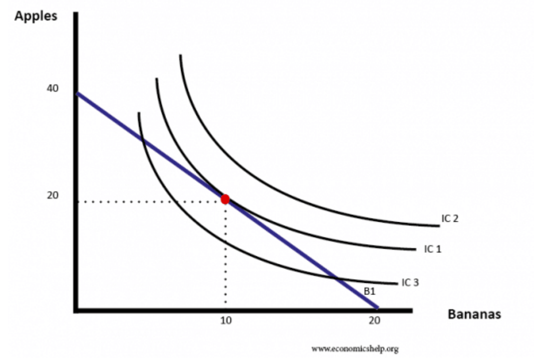

Fig 4: Optimal consumption choice. The consumer achieves maximum utility at the point where the highest attainable indifference curve is tangent to the budget line.

Furthermore, Fig 5 introduces an income-consumption curve, indicating how a consumer's optimal choice of goods evolves with increasing income, allowing them to reach higher utility levels as depicted by the upward and rightward shift along the curve in blue colour.

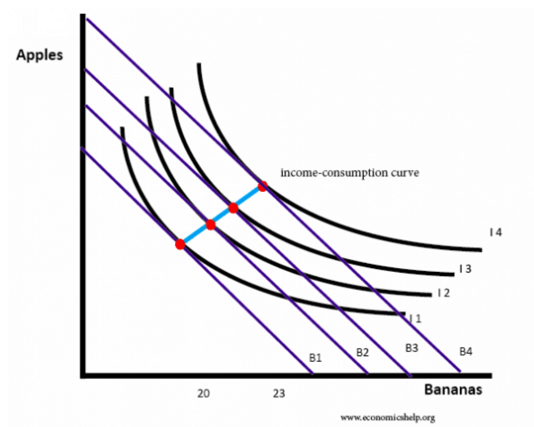

Fig 5: Income-consumption curve. It indicates how a consumer's optimal choice of goods evolves with increasing income, allowing them to reach higher utility levels as depicted by the upward and rightward shift along the curve in blue colour.

By leveraging these foundational concepts from consumer theory, this paper adapts a similar analytical framework to address the scenario modelling problem, introducing analogous concepts that will be detailed in subsequent sections to construct a comprehensive solution methodology.

B. Gain indifference curve

Drawing on the economic principle of the utility indifference curve, this paper proposes the analogous concept of a gain indifference curve, exemplified in Fig 6. At any point on this curve, the interplay between the price and quantity of a product yields a consistent revenue level, thereby delineating the trade-off between these two variables in the context of revenue generation.

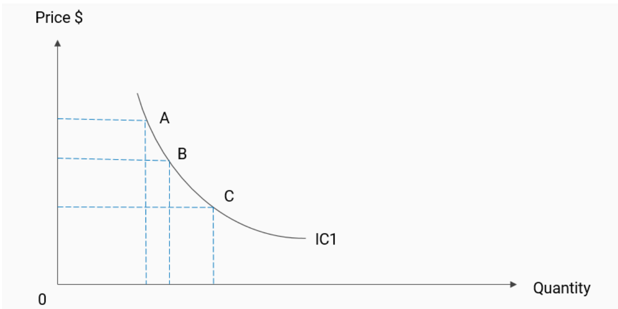

Fig 6: Gain indifference curve. On this curve, the relationship between a product's price and quantity consistently results in a stable revenue outcome.

Characteristically, the gain indifference curve is convex, taking on a hyperbolic shape, a reflection of the constancy in the product of price and quantity along the curve's trajectory.

In Fig 7, a map of multiple gain indifference curves is presented. Each curve, such as I2, signifies a series of price-quantity combinations that culminate in identical revenue figures, with revenue levels escalating as one moves to higher curves—evidenced by I4 generating the highest revenue among the illustrated curves.

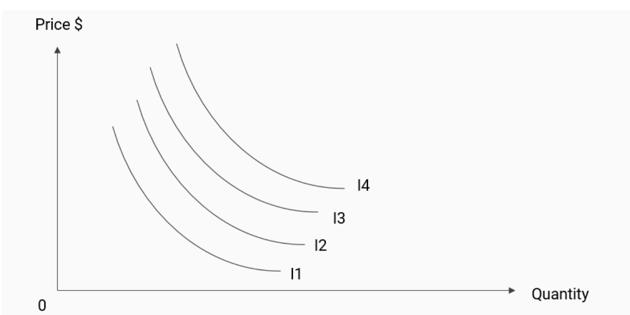

Fig 7: Gain indifference curve map. It illustrates various gain indifference curves, each denoting a different level of revenue.

The essence of this concept is that higher gain indifference curves correlate with increased revenue outcomes.

It is crucial to note, however, that Figs 6 and 7 present a simplified view, focusing on the price and quantity dynamics of a singular product. Real-world scenarios, akin to those depicted in Tab 1, typically involve multiple products, necessitating an expanded consideration of diverse price and quantity variables. Consequently, in a more complex scenario, the gain indifference curve would extend into a convex hyperplane within a multidimensional space. Nevertheless, for clarity and ease of exposition, a two-dimensional representation is employed in this discussion.

C. ***Gain gradient***

The concept of gain gradient is defined as the incremental revenue generated when there is a unit increase in either the price or quantity of a product. For instance, if increasing the product quantity from 100 to 101 leads to a revenue increase of $20, the gain gradient at a quantity of 100 is determined to be 20. This metric is crucial for assessing the potential benefits associated with modifications in a product's price or quantity parameters.

D. ***Loss***

The concept of loss is integrated into the scenario modelling framework, where loss quantifies the effort or adversity a business encounters to attain a specific revenue level. Unlike more tangible metrics, loss is interpreted here as a largely psychological measure, emphasizing that its absolute value may not hold standalone significance. Instead, the comparative analysis of varying loss levels provides actionable insights.

E. ***Implicit objective: total loss minimization***

The introduction of loss as a concept enables the pursuit of the implicit objective within scenario modelling: the identification and selection of the optimal solution from a potentially infinite set, where "optimal" is defined as the scenario that minimizes total loss. This objective is mathematically framed as the minimization of the aggregate loss experienced in adjusting the pricing and quantity variables to meet the revenue target.

Detailed exploration of this implicit objective, including its mathematical underpinnings and practical implications, is presented in subsequent sections of the paper.

F. ***Loss indifference line***

Building on the economic concept of the budget line, this paper introduces the novel concept of a loss indifference line, depicted in Fig 8. This line represents various combinations of a product's price and quantity that result in the same level of loss for the business.

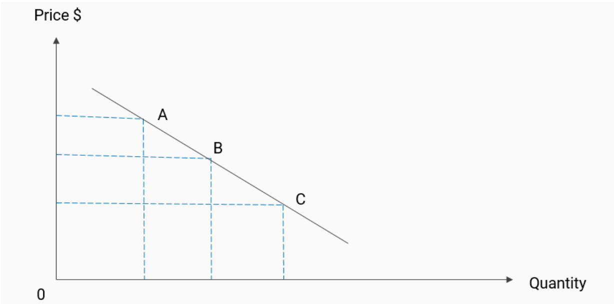

Fig 8: Loss indifference line. It represents various combinations of a product's price and quantity that result in the same level of loss for the business.

To construct a loss indifference line, one can apply linear regression to historical data of price and quantity combinations, as shown in Fig 9. Here, the grey dots represent historical price and quantity data points, with the linear regression line defining the loss indifference line. This approach assumes that the business exerted a consistent level of effort across different periods, with any deviations around the regression line attributed to random fluctuations. By employing regression analysis, these random effects are mitigated, revealing the core loss indifference line.

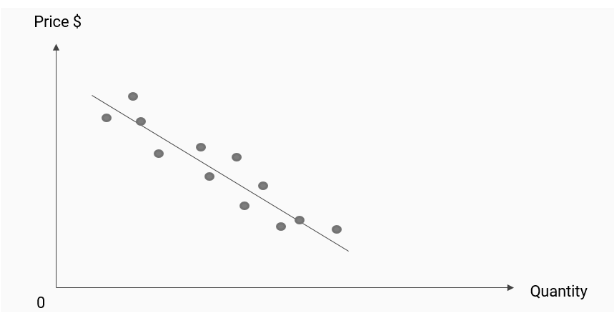

Fig 9: Loss indifference line derived from linear regression on historical data of price and quantity combinations. The grey dots represent historical price and quantity data points.

Typically, a loss indifference line exhibits a negative slope, indicating that an increase in price tends to decrease sales volume and vice versa, illustrating the loss trade-off between price and quantity. This observation aligns with real-world data where price-quantity relationships for various products demonstrate similar negative trends, validating the loss indifference line concept.

The practical value of the loss concept is primarily in its comparative analysis, as illustrated by the loss indifference line map shown in Fig 10. This figure demonstrates that lines situated lower on the graph signify a reduced level of loss, thus being more favourable for the business. Such insights underscore the significance of the loss indifference line in facilitating strategic decision-making within the context of scenario modelling.

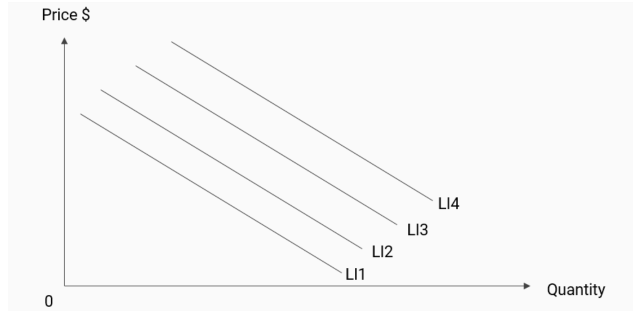

Fig 10: Loss indifference line map. The practical value of the loss concept is primarily in its comparative analysis. Lines situated lower on the graph signify a reduced level of loss, thus being more favourable for the business.

G. *Loss gradient*

The concept of the loss gradient quantifies the additional effort required by a business when either the price or quantity of a product is incremented by one unit. To illustrate, if escalating the quantity of a product from 100 to 101 results in a 10 unit increase in loss, the loss gradient at a quantity of 100 is determined to be 10 units.

This metric, the loss gradient, is instrumental in assessing the challenges associated with altering a product's price or quantity. It facilitates a comparative analysis, enabling businesses to gauge the relative difficulty of modifying the price versus the quantity of a particular product or to compare these challenges across different products.

H. *Universal measure for loss comparison: standard deviation*

In the context of scenario modelling, where multiple products are analysed, it is crucial to consider a diverse array of prices and quantities. Consequently, the loss indifference concept extends into a multidimensional space, forming a hyperplane rather than a simple line.

A significant challenge arises in comparing loss changes across various products, as the ease of altering price or quantity can vary significantly from one product to another.

To address this, the paper proposes utilizing the reciprocal of the standard deviation of historical price-quantity data as a metric to gauge the loss gradient, which is the relative difficultness of making such changes. A higher standard deviation indicates greater historical volatility in price or quantity, suggesting that deviations from the regression line are more feasible.

This concept is represented in Fig 11. In Fig 11(a), three loss indifference lines for Product A are shown, with the central line derived from linear regression on historical data and the flanking lines representing one standard deviation above and below the regression line. Similarly, Fig 11(b) illustrates three corresponding lines for Product B.

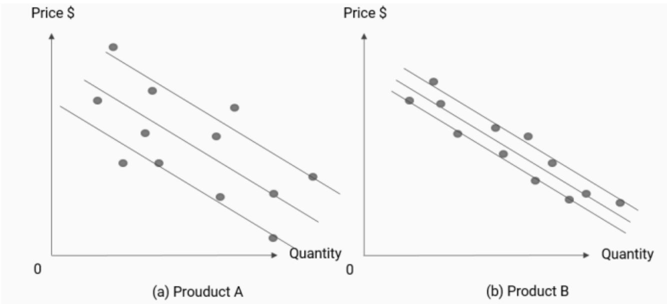

Fig 11: Loss comparison across products. In (a), there are three loss indifference lines for Product A: the middle line is based on linear regression of historical data, and the other two lines are one standard deviation away from this central line. In (b), similar lines for Product B are displayed. Product A's wider spacing between lines, due to a higher standard deviation, suggests it has more price or quantity flexibility than Product B. By comparing these loss gradients, we can discern which product's attributes, like price or quantity, are easier to adjust, aiding in strategic decision-making.

The comparison between Product A and Product B reveals that Product A, with its higher standard deviation, has experienced greater historical volatility, implying that it is generally easier to adjust Product A's price or quantity to meet new objectives. The spacing between the loss indifference lines for Product A is larger than that for Product B, suggesting differing levels of effort required to achieve changes in loss.

By analysing the loss gradient for each decision variable across different products, one can make nuanced comparisons. For instance, if Product A's quantity has a lower loss gradient than Product B's quantity, as depicted in Fig 11, it indicates a relative ease in adjusting Product A's quantity over Product B's. This comparative approach allows for a more informed and strategic decision-making process regarding price and quantity adjustments across a range of products.

I. *Loss gradient function*

The loss gradient function is a pivotal tool in scenario modeling, assigned to each decision variable to define the loss gradient across all potential values of that variable. This function can adopt various forms, with this paper specifically utilizing a progressively increasing segmented linear function to illustrate the concept. Tab 3 provides an example of loss gradient functions for four decision variables (QA1, QB1, PA1, PB1) in Month 1, as referenced in Tab 1.

Tab 3: Loss gradient functions of decision variables

	A	B	C	D	E	F
16		QA1			QB1	
17		Threshold	loss gradient		Threshold	loss gradient
18		16	2		12	1
19		24	4		28	2
20		28	8		36	4
21		30	16		40	8
22		32	32		44	16
23		36	64		52	32
24		44	128		68	64
25						
26		PA1			PB1	
27		Threshold	loss gradient		Threshold	loss gradient
28		$ 23.00	1		$ 26.00	2
29		$ 27.00	2		$ 34.00	4
30		$ 29.00	4		$ 38.00	8
31		$ 30.00	8		$ 40.00	16
32		$ 31.00	16		$ 42.00	32
33		$ 33.00	32		$ 46.00	64
34		$ 37.00	64		$ 54.00	128

Consider QA1 from Tab 3: its loss function is divided into segments such as 16-23, 24-27, and so forth, with distinct loss gradients assigned to each range (e.g., a gradient of 2 for the 16-23 segment). These segments allow the consideration of values both below and above the baseline (30 for QA1), extending the analysis to a broad spectrum of potential values.

The loss gradient at the baseline is derived from the reciprocal of the standard deviation of historical data, indicating that variables with more historical volatility are deemed easier to adjust. The segmented nature of the loss gradient function, with consistent values within a segment but increasing between segments, aids in guiding a search algorithm towards a balanced solution by incrementally adjusting multiple variables rather than excessively altering a single one.

This nuanced approach encourages the algorithm to distribute adjustments across various decision variables, aiming for a solution that harmonizes the increments rather than relying on disproportionate increases in a few variables.

While Tab 3 sets a framework for these functions, it's important to note that the actual application of thresholds and loss gradients can be adjusted by domain experts to tailor the scenario modeling process to specific contexts or objectives, enhancing the model's relevance and applicability.

J. *Theoretical solution*

In a manner akin to consumer theory within economics, the methodology to ascertain the optimal solution in scenario modelling entails identifying the lowest loss indifference line that intersects tangentially with the gain indifference curve symbolizing the target objective value, as depicted in Fig 12. At this juncture, the desired objective is attained with minimal business effort.

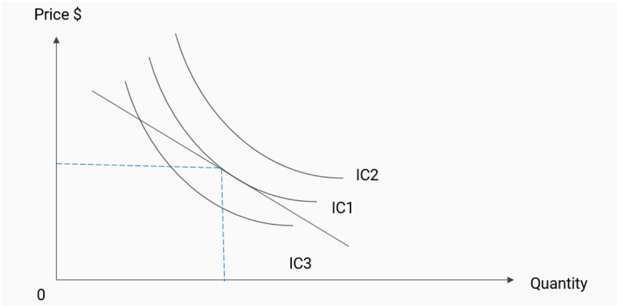

Fig 12. Theoretical solution. The lowest loss indifference line that intersects tangentially with the gain indifference curve IC1 symbolizing the target objective value. At this juncture, the desired objective is attained with minimal business effort.

Fig 13 showcases a loss-gain curve, illustrating that with an increase in loss, the business is positioned to realize higher revenues corresponding to elevated gain indifference curves. This dynamic suggests that the most favourable choice transitions towards the upper-right quadrant, delineating an upward trajectory of revenue in response to escalating loss, represented by the blue loss-gain curve in the diagram. This graphical representation elucidates the interplay between loss and gain, guiding towards an optimal balance where the business objective is met efficiently.

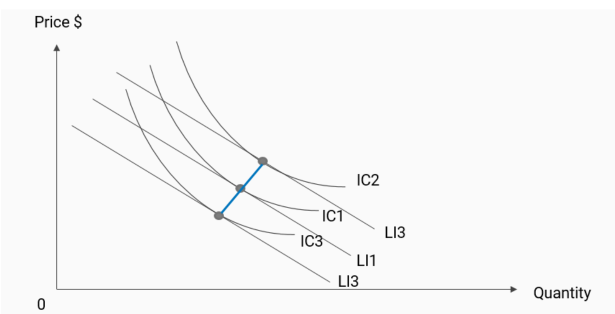

Fig 13. Loss-gain curve. It illustrates that with an increase in loss, the business is positioned to realize higher revenues corresponding to elevated gain indifference curves. The most favourable choice transitions towards the upper-right quadrant, delineating an upward trajectory of revenue in response to escalating loss, represented by the blue loss-gain curve in the diagram.

K. Loss-gain-gradient-ratio (LGR)

The Loss-Gain-Gradient-Ratio (LGR) is a novel metric defined as the ratio of the loss gradient to the gain gradient. This ratio quantifies the incremental effort required by a business to generate an additional dollar in revenue. In essence, LGR offers a nuanced perspective on the efficiency of resource allocation in revenue generation.

Within the framework of an iterative search algorithm, LGR serves as a critical metric for evaluating and comparing decision variables at each iteration. The strategy is to prioritize the adjustment of the variable with the lowest LGR, suggesting that this variable offers the most cost-effective opportunity for revenue enhancement at that point in the algorithm. Adopting this approach ensures that the algorithm's progression aligns closely with the optimal trajectory delineated by the loss-gain curve illustrated in Fig 13, guiding the search towards the most resource-efficient solution.

L. Overall solution represented in a figure

Fig 14 illustrates the comprehensive methodology applied in scenario modelling. Here, the baseline scenario starts with a revenue prediction marked at $5 million, shown as a blue dot. The objective set forth is to escalate this figure to $6 million.

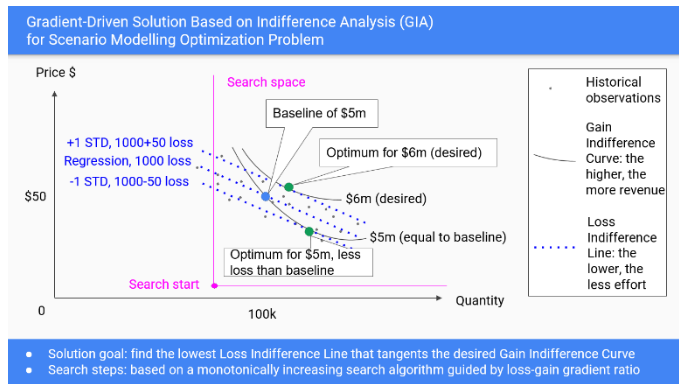

Fig 14: Overall view of the Gradient-Driven Solution Based on Indifference Analysis (GIA) for scenario modelling optimization problem.

In the depiction, two gain indifference curves correspond to the $5 million and $6 million revenue benchmarks, with the curve for $6 million positioned above the $5 million curve, indicating higher revenue levels.

Historical data points for price and quantity are represented by grey dots, and their collective trend is captured by a blue dotted line, signifying a loss indifference line at 1000 loss units. It's important to note that the specific value of 1000 units is less critical than its comparative context against other loss indifference lines.

Additionally, two parallel blue dotted lines delineate a variance of plus or minus one standard deviation from the main loss indifference line, quantified as 50 loss units to signify a standard deviation change. This standardization is crucial for ensuring equitable comparison across different products regarding the effort required to enhance revenue uniformly.

In this framework, the primary loss indifference line at 1000 units intersects rather than tangents the $5 million gain indifference curve, suggesting that achieving the $5 million revenue target can be optimized to require less effort. The optimal point for the $5 million target is marked by a green dot, where a lower loss indifference line at 950 units meets the gain curve, indicating a more efficient solution with 50 units less loss.

For the aspirational $6 million target, the optimal solution is identified where the loss indifference line at 1050 units—representing an incremental effort—tangentially meets the $6 million gain indifference curve, marked by another green dot. This intersection represents the strategic point where the desired $6 million revenue can be achieved with minimal additional loss, showcasing the model's capability to guide towards the most resource-efficient solution.

M. Search space and staring point

Fig 14 outlines the search space utilized by the search algorithm of GIA to identify the optimal solution. The process initiates from a search starting point, depicted as a purple dot within the figure. The designated search space is the region above and to the right of this starting point, as demarcated in the diagram.

The selection of the search starting point is somewhat discretionary, yet it is advisable to opt for a "conservative" starting position. This entails setting initial price and quantity values lower than those in the baseline, ensuring that no potential solutions with prices or quantities below the baseline are overlooked during the search.

Tab 4 presents a set of example starting values: QA1 at 28, QB1 at 36, PA1 at $29, and PB1 at $38. These values are intentionally set below the baseline figures from Tab 1, where QA1 is 30, QB1 is 40, PA1 is $30, and PB1 is $40, to encompass a broader range of potential solutions.

Tab 4: Search starting values

variable	value
QA1	28
QB1	36
PA1	$29.00
PB1	$38.00

With the search space established, the algorithm proceeds through a series of monotonically increasing steps, systematically exploring the space to converge on the most favorable solution.

N. Practical process to seek the best solution

This section outlines an iterative method to identify the optimal solution for the scenario modeling issue. The procedure involves two nested loops: an outer loop (Steps 7-18) and an inner loop (Steps 9-13), with specific examples provided at each stage.

Step 1

Action: Create a spreadsheet that integrates baseline predictions and variable relationships as per the established business rules.

Example: Tabs 1 and 2.

Step 2

Action: Identify the objective variable for the scenario modeling task, as chosen by the user.

Example: The user selects the total revenue over three months, displayed in Cell O14 of Tab 1, as the objective variable.

Step 3

Action: Specify the target value for the objective variable, defining the objective of the scenario modeling task. This objective is user-defined.

Example: The user sets the objective at $51,470, which exceeds the baseline value of $50,470 (noted in Cell O14 of Tab 1) by $1,000. This target is consistently referred to throughout the iterative process, as illustrated in Tab 5, for example in Cell A59.

Step 4

Action: Define the decision variables that can be directly changed by the model. Their values will be overwritten through the process and finally become the output of the scenario modelling problem when reaching the objective.

Example: For the sake of simplicity, this example only takes the four variables highlighted in green in Month 1 in Cells D4, D5, D8, D9 of Tab 1 as the decision variables of the problem. The other eight variables highlighted in green in the rest two months are ignored.

Step 5

Action: Establish loss gradient functions for each of the decision variables, utilizing a progressively increasing segmented linear function to define the relationship between variable adjustments and associated loss.

Example: Tab 3.

Step 6

Action: Assign starting values to each decision variable for the commencement of the search process. These starting values are ideally set below the baseline to ensure a comprehensive exploration of potential solutions. The initial combination of these values represents a preliminary, suboptimal solution that will undergo iterative enhancements.

Example: Tab 4.

Step 7

Action: Initiate the outer loop, which encompasses Steps 8-18. This loop will iterate until the predefined objective is met as outlined in Step 18.

Example: In Tab 5, this outer loop is demonstrated, where it cycles through eight iterations to arrive at the desired solution.

Step 8

Action: Record the current value of the objective variable at the beginning of each outer loop iteration.

Example: For Loop 1, the objective variable value is noted as 49,510, located in Cell A61 of Tab 5.

Step 9

Action: Execute the inner loop, focusing on each decision variable sequentially. Within this loop, Steps 10-13 are performed for every variable to evaluate and potentially adjust their values.

Example: In the first iteration of the inner loop, the focus is on variable QA1, as illustrated in row 58 of Tab 5.

Step 10

Action: Determine the loss gradient for the chosen decision variable from Step 9, utilizing its respective loss gradient function outlined in Step 5.

Example: For QA1 during Loop 1, the loss gradient is determined to be 8, as shown in Cell F58 of Tab 5. This value is derived by considering QA1's value of 28 from Cell C58 in Tab 5 and referencing the loss gradient function for QA1 in Tab 3, where the loss gradient for a value of 28 is listed as 8 in Cell C20.

Step 11

Action: Compute the cumulative loss for the selected decision variable, employing the same loss gradient function.

Example: The cumulative loss for QA1 in Loop 1 is calculated to be -16, shown in Cell E58 of Tab 5. This figure is calculated by taking QA1's loop value of 28 from Cell C58, then consulting the loss gradient function for values between 28-29, which is 8 (found in Cell C20 of Tab 3). Assuming the baseline (30) incurs zero loss, a decrease to 28 (2 units less) results in a cumulative loss of -16 (calculated as -2 multiplied by 8).

Step 12

Action: Determine the gain gradient for the decision variable highlighted in Step 9, following the detailed steps from 12.1 to 12.4.

Example: For QA1 in Loop 1, the gain gradient is identified as $87.00, as calculated in Step 12.3.

Step 12.1

Action: Temporarily increase the value of the decision variable chosen in Step 9 by one unit, ensuring that the values of all other decision variables remain constant.

Example: In Loop 1, QA1's original value is 28 (shown in Cell C58 of Tab 5). This value is temporarily increased by one unit to 29. This updated value of 29 is not permanently recorded in the table as it is provisional and will be reverted to its original in Step 12.4.

Step 12.2

Action: Record the updated value of the objective variable after the increment made in Step 12.1.

Example: Post the adjustment of QA1 in Loop 1, the objective variable's new value is noted as 49,597. This figure is temporary for the purpose of calculation and is not permanently entered into the table, as it will be reverted in Step 12.4.

Step 12.3

Action: Determine the gain gradient for the decision variable selected in Step 9. This is done by subtracting the original objective variable value recorded in Step 8 from the new objective variable value documented in Step 12.2.

Example: For QA1 in the Loop 1, the gain gradient is computed as $87.00, showcased in Cell G58 of Tab 5. This value is derived by subtracting the original objective variable value (49,510 from Step 8) from the new objective variable value (49,597 from Step 12.2).

Step 12.4

Action: Revert the decision variable's value to its original state as recorded before the increment in Step 12.1.

Example: QA1's value, initially altered in the process, is reset to 28 in Cell C58 of Tab 5, reversing the temporary change made in Step 12.1.

Step 13

Action: Compute the loss-gain-gradient-ratio (LGR) for the decision variable chosen in Step 9. This is done by dividing the loss gradient calculated in Step 10 by the gain gradient determined in Step 12. This step concludes the inner loop initiated in Step 9.

Example: For QA1 in Loop 1, the LGR is calculated to be 0.09, as shown in Cell H58 of Tab 5. This value results from dividing the loss gradient (8 from Step 10) by the gain gradient (87.00 from Step 12).

Step 14

Action: Determine the total loss for the current provisional solution by aggregating the cumulative losses for all decision variables calculated in Step 11. This total loss serves as a measure of the effort required from the business to attain the solution. A lower total loss signifies a more efficient solution, when the gain remains constant. Thus, comparing total loss figures can help in evaluating the effectiveness of different solutions.

Example: For Loop 1, the total loss is computed as -52, as recorded in Cell E62 of Tab 5. This figure is the sum of all cumulative losses for the decision variables, as shown in Cells E58:E61. The negative value of -52 suggests that the interim solution offers a 52-unit saving in effort compared to the baseline. However, since the objective has not yet been met, further iterations of the outer loop will be necessary, increasing both the objective variable and the total loss.

Step 15

Action: Evaluate all the LGRs computed in Step 13 for each decision variable and identify the one with the smallest LGR value. The variable with the lowest LGR is chosen for the next adjustment, as it represents the most efficient option for increasing revenue with the least additional loss.

Example: In Loop 1, QB1 is selected because its LGR value, 0.04, noted in Cell H59 of Tab 5, is the lowest among all calculated LGRs for the decision variables within that loop, as shown in Cells H58:H61.

Step 16

Action: Adjust the value of the decision variable identified in Step 15 by a predetermined increment to enhance the provisional solution, moving the objective variable closer to the target. The magnitude of this increment can be chosen flexibly; a smaller increment is generally preferred for a more refined solution, reducing the total loss and mitigating the non-linear impacts of loss and gain gradients. However, smaller increments mean the outer loop will need to be executed more frequently, extending the overall computation time. For decision variables defined by a progressively increasing segmented linear function, the increment can be set to reach the start of the next segment in the loss function.

Example: Transitioning from Loop 1 to Loop 2, QB1's value is increased from 36 to 40, as indicated by moving from Cell 59 to Cell 67 in Tab 5. This adjustment is based on the loss function for QB1, detailed in Cells E17:F24 in Tab 3, where the subsequent segment threshold after 36 is identified as 40 in Cell E21.

Step 17

Action: Record the updated value of the objective variable after implementing the changes decided in the previous steps.

Example: In Loop 2, the updated objective variable value is noted as 49,966, shown in Cell A69 of Tab 5.

Step 18

Action: Evaluate whether the updated objective variable meets the target set in Step 3. If the updated value is still below the target, initiate another iteration of the outer loop starting from Step 7. If the target is met, conclude the outer loop and proceed to finalize the solution in the subsequent step.

Example: Since the updated value of 49,966 from Step 17 is below the target of 51,470 set in Step 3, the process returns to Step 7 for additional iterations. This loop continues until the objective variable value reaches 51,470, at which point the outer loop concludes.

Step 19

Action: Document the definitive solution, which is delineated by the final values of the decision variables. These values represent the resolution to the scenario modeling challenge.

Example: The conclusive solution is presented in Cells C122:C125 of Tab 5, where the values are listed as QA1 at 30, QB1 at 45, PA1 at $31, and PB1 at $42.

Step 20

Action: Compute the total loss for the final solution by following a similar approach to Step 14. This total loss should approximate the minimum feasible loss across all potential solutions, reflecting the optimized state of the model.

Example: The total loss for the ultimate solution is recorded as 93 in Cell E126 of Tab 5, indicating that the business incurs an additional 93 units of loss to meet the objective. This figure is expected to be the minimal necessary loss to achieve the set objective.

Tab 5: Process steps to seek the best solution for the higher objective

	A	B	C	D	E	F	G	H	I
56	Loop 1	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
57								= loss g / gain g	
58	Goal:	QA1	28	30	-16	8	$87.00	0.09	
59	51470	QB1	36	40	-16	4	$114.00	0.04	** SELECTED **
60	Current:	PA1	$ 29.00	$ 30.00	-4	4	$84.00	0.05	
61	49510	PB1	$ 38.00	$ 40.00	-16	8	$108.00	0.07	
62		total loss			-52				
63									
64	Loop 2	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
65								= loss g / gain g	
66	Goal:	QA1	28	30	-16	8	$87.00	0.09	
67	51470	QB1	40	44	-	8	$114.00	0.07	
68	Current:	PA1	$ 29.00	$ 30.00	-4	4	$84.00	0.05	** SELECTED **
69	49966	PB1	$ 38.00	$ 40.00	-16	8	$120.00	0.07	
70		total loss			-36				
71									
72	Loop 3	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
73								= loss g / gain g	
74	Goal:	QA1	28	30	-16	8	$90.00	0.09	
75	51470	QB1	40	44	-	8	$114.00	0.07	
76	Current:	PA1	$ 30.00	$ 31.00	-	8	$84.00	0.10	
77	50050	PB1	$ 38.00	$ 40.00	-16	8	$120.00	0.07	** SELECTED **
78		total loss			-32				
79									
80	Loop 4	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
81								= loss g / gain g	
82	Goal:	QA1	28	30	-16	8	$90.00	0.09	
83	51470	QB1	40	44	-	8	$120.00	0.07	** SELECTED **
84	Current:	PA1	$ 30.00	$ 31.00	-	8	$84.00	0.10	
85	50290	PB1	$ 40.00	$ 42.00	-	16	$120.00	0.13	
86		total loss			-16				
87									
88	Loop 5	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
89								= loss g / gain g	
90	Goal:	QA1	28	30	-16	8	$90.00	0.09	** SELECTED **
91	51470	QB1	44	52	32	16	$120.00	0.13	
92	Current:	PA1	$ 30.00	$ 31.00	-	8	$84.00	0.10	
93	50770	PB1	$ 40.00	$ 42.00	-	16	$132.00	0.12	
94		total loss			16				
95									
96	Loop 6	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
97								= loss g / gain g	
98	Goal:	QA1	30	32	-	16	$90.00	0.18	
99	51470	QB1	44	52	32	16	$120.00	0.13	
100	Current:	PA1	$ 30.00	$ 31.00	-	8	$90.00	0.09	** SELECTED **
101	50950	PB1	$ 40.00	$ 42.00	-	16	$132.00	0.12	
102		total loss			32				
103									
104	Loop 7	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
105								= loss g / gain g	
106	Goal:	QA1	30	32	-	16	$93.00	0.17	
107	51470	QB1	44	52	32	16	$120.00	0.13	
108	Current:	PA1	$ 31.00	$ 33.00	8	16	$90.00	0.18	
109	51040	PB1	$ 40.00	$ 42.00	-	16	$132.00	0.12	** SELECTED **
110		total loss			40				
111									
112	Loop 8	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
113								= loss g / gain g	
114	Goal:	QA1	30	32	-	16	$93.00	0.17	
115	51470	QB1	44	52	32	16	$126.00	0.13	** SELECTED **
116	Current:	PA1	$ 31.00	$ 33.00	8	16	$90.00	0.18	
117	51304	PB1	$ 42.00	$ 46.00	32	32	$132.00	0.24	
118		total loss			72				
119									
120	Finished!	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
121	Total loops: 8							= loss g / gain g	
122	Goal:	QA1	30	32	-	16	$93.00	0.17	
123	51470	QB1	45	52	53	16	$126.00	0.13	
124	Current:	PA1	$ 31.00	$ 33.00	8	16	$90.00	0.18	
125	51470	PB1	$ 42.00	$ 46.00	32	32	$135.95	0.24	
126		total loss			93				

Tab 6: Process steps to seek the best alternative solution for the baseline

	A	B	C	D	E	F	G	H	I
56	Loop 1	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
57								= loss g / gain g	
58	Goal:	QA1	28	30	-16	8	$87.00	0.09	
59	50470	QB1	36	40	-16	4	$114.00	0.04	** SELECTED **
60	Current:	PA1	$ 29.00	$ 30.00	-4	4	$84.00	0.05	
61	49510	PB1	$ 38.00	$ 40.00	-16	8	$108.00	0.07	
62		total loss			-52				
63									
64	Loop 2	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
65								= loss g / gain g	
66	Goal:	QA1	28	30	-16	8	$87.00	0.09	
67	50470	QB1	40	44	-	8	$114.00	0.07	
68	Current:	PA1	$ 29.00	$ 30.00	-4	4	$84.00	0.05	** SELECTED **
69	49966	PB1	$ 38.00	$ 40.00	-16	8	$120.00	0.07	
70		total loss			-36				
71									
72	Loop 3	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
73								= loss g / gain g	
74	Goal:	QA1	28	30	-16	8	$90.00	0.09	
75	50470	QB1	40	44	-	8	$114.00	0.07	
76	Current:	PA1	$ 30.00	$ 31.00	-	8	$84.00	0.10	
77	50050	PB1	$ 38.00	$ 40.00	-16	8	$120.00	0.07	** SELECTED **
78		total loss			-32				
79									
80	Loop 4	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
81								= loss g / gain g	
82	Goal:	QA1	28	30	-16	8	$90.00	0.09	
83	50470	QB1	40	44	-	8	$120.00	0.07	** SELECTED **
84	Current:	PA1	$ 30.00	$ 31.00	-	8	$84.00	0.10	
85	50290	PB1	$ 40.00	$ 42.00	-	16	$120.00	0.13	
86		total loss			-16				
87									
88	Finished!	variable	value	next threshold	loss	loss gradient	gain gradient	lgr: loss-gain ratio	
89	Total loops: 4							= loss g / gain g	
90	Goal:	QA1	28	30	-16	8	$90.00	0.09	
91	50470	QB1	42	44	12	8	$120.00	0.07	
92	Current:	PA1	$ 30.00	$ 31.00	-	8	$84.00	0.10	
93	50470	PB1	$ 40.00	$ 42.00	-	16	$124.50	0.13	
94		total loss			-4				

O. Better solution for baseline

While the prior steps focused on achieving a user-defined objective surpassing the baseline, it's noteworthy that an enhanced solution can also be identified for the baseline scenario itself. This concept is demonstrated through an alternative scenario modeling process presented in Tab 6.

In Tab 6, the procedure mirrors that of Tab 5, with the critical distinction being the objective is aligned with the baseline figure of 50,470, instead of an elevated target of 51,470. This objective of 50,470 is consistently referenced throughout each loop iteration, such as in Cell A59 during Loop 1. The process requires four loops to navigate the search space and pinpoint the optimal solution.

The total loss calculated for this optimal solution is -4, as shown in Cell E94. This negative value signifies that the business can reduce effort by 4 units while still attaining the baseline revenue target. The solution reveals a strategic adjustment between QA1 and QB1: it recommends reducing QA1 from its baseline of 30 (Cell D4 in Tab 1) to 28 (Cell C90 in Tab 6) and augmenting QB1 from its baseline of 40 (Cell D5 in Tab 1) to an adjusted value of 41.5, which is rounded to 42 as shown in Cell C91 of Tab 6. This nuanced trade-off between QA1 and QB1 exemplifies how strategic adjustments can lead to efficiency gains, even when the goal is to meet existing baseline figures.

IV. RESULT

A. Optimized solution to the scenario modelling problem

The iterative method outlined previously offers a strategy to ascertain the optimal solution in scenario modelling, emphasizing a balanced approach where multiple decision variables are incrementally adjusted. This contrasts with strategies that rely on significant changes to a single variable.

To appraise the effectiveness of the identified solution, this analysis juxtaposes it with four alternative solutions delineated in Tab 7. These alternatives, while achieving the same target objective of $51,470, adopt a disproportionate strategy by altering only one decision variable and maintaining the others at their baseline levels.

Tab 7: Comparison of solutions for a desired objective of $51,470

variable	best solution	solution 1	solution 2	solution 3	solution 4
QA1	30	41	30	30	30
QB1	45	40	49	40	40
PA1	$ 31.00	$ 30.00	$ 30.00	$ 41.00	$ 30.00
PB1	$ 42.00	$ 40.00	$ 40.00	$ 40.00	$ 48.50
Tatol loss	93	480	104	424	320

Tab 7 reveals that each of these alternative strategies results in a greater total loss compared to the algorithm-derived solution. This comparative analysis substantiates the efficacy of the algorithmic approach, confirming it as the superior method for minimizing total loss in the context of scenario modelling.

B. *Better alternative to the existing plan*

The GIA methodology not only serves to surpass a set objective but also to refine an existing baseline plan. By applying the outlined approach, an enhanced alternative to the baseline can be identified, demonstrating potential for broader application in strategic planning and optimization.

Tab 8 showcases a comparison between the original baseline and the optimized alternative solution. While both solutions attain the same revenue target of $50,470, the alternative approach adjusts the decision variables to achieve this outcome more efficiently.

Tab 8: Comparison of baseline vs the best alternative solution for the baseline revenue of $50,470

variable	best alternative	baseline
QA1	28	30
QB1	42	40
PA1	$ 30.00	$30.00
PB1	$ 40.00	$40.00
Tatol loss	-4	-

The analysis in Tab 8 indicates a reduction of 4 units of loss in the alternative solution compared to the baseline. This signifies that the algorithm-derived solution offers a more loss-efficient strategy, validating the approach's capability to enhance existing plans by minimizing the total loss.

This methodology's utility extends beyond mere scenario modelling, offering insights into strategic business planning. Often, the baseline configurations of business plans are not optimized for loss minimization. Through the iterative search and optimization process, it's possible to uncover superior strategies that maintain revenue targets while reducing operational loss, thereby optimizing resource allocation and enhancing overall business performance.

C. *Real-world project application*

The GIA algorithm was employed to address complex scenario modelling challenges in a real-world context, specifically within a subscription-based revenue framework encompassing multiple products.

In this practical application, the complexity was notably higher than in the simplified examples. The products involved had interrelated constraints, and each period presented a multitude of decision variables that could be adjusted. This complexity rendered manual identification of the optimal strategy nearly impossible.

The GIA algorithm's application facilitated efficient identification of the most effective path to reach the set objectives. It proved adept at not only striving for targets beyond the baseline but also enhancing the baseline itself. In both scenarios—aiming for higher objectives and refining the existing baseline—the GIA algorithm demonstrated its effectiveness, delivering substantial improvements in decision-making and optimization for the business.

This real-world application underscores the GIA algorithm's potential as a powerful tool for businesses facing intricate scenario modelling challenges, offering a systematic approach to navigate and optimize complex decision-making landscapes.

V. Conclusion

The Gradient-Driven Solution Based on Indifference Analysis (GIA) introduces a novel approach to scenario modeling, offering a framework that allows organizations to effectively navigate and optimize their financial planning. By employing an inverse methodology that integrates economic theories with practical business applications, GIA provides a robust tool for organizations to achieve their financial targets through a systematic analysis of decision variables and strategic options.

This methodology's application extends beyond traditional scenario planning, demonstrating its potential to refine financial strategies and enhance decision-making processes. By identifying efficient resource allocations and minimizing losses, GIA supports businesses to adapt an environment of uncertainty.

The application of GIA has proven successful not only in theoretical constructs but also in real-world projects, showcasing its efficacy in practical settings. This success story underscores GIA's capacity to not only achieve heightened financial objectives but also to enhance existing plans without necessarily targeting higher goals, by optimizing resource allocation and minimizing losses in uncertain environments.

Future research avenues present opportunities to broaden the understanding and utility of GIA across a spectrum of industry contexts. By delving deeper into its application in varied sectors, researchers can uncover insights into how different industries can harness GIA to navigate their unique challenges and uncertainties, using it as a strategic tool to forecast and plan for future scenarios effectively. This exploration will illuminate the adaptability and impact of GIA across sectors, potentially uncovering new use cases and benefits.

In addition to exploring industry-specific applications, there is potential in enhancing the versatility and robustness of GIA by integrating a variety of loss function formats. Currently, GIA utilizes a particular set of loss functions to model and solve scenario planning problems; however, by expanding this repertoire to include diverse loss function formats, the methodology could be tailored more precisely to specific industry needs or scenario complexities. This enhancement would not only broaden the scope of GIA's applicability but also improve its precision and effectiveness in different planning contexts.

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