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Utilization of Operational Research and Machine Learning to Analyze Decision Making Procedures

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Abstract:

This research paper explores the synergistic integration of Operational Research (OR) and Machine Learning (ML) techniques to enhance the analysis of decision-making procedures across diverse domains. Decision-making is a critical aspect of problem solving in various fields, and the combination of OR and ML offers a powerful framework for optimizing, automating, and gaining deeper insights into decision processes. This study delves into the methodologies, applications, and advantages of utilizing OR and ML in decision analysis, providing a comprehensive overview of how these two disciplines can complement each other. Through real-world case studies and practical examples, we illustrate the potential for improved decision-making, resource allocation, and efficiency in complex decision scenarios. By examining the intersection of OR and ML, this research contributes to a deeper understanding of the transformative potential of these methodologies in modern decision analysis. By consistently delving into and adjusting these approaches, we can anticipate a future where decision-making processes become more streamlined, precise, and adept at addressing the evolving challenges of our swiftly transforming world.

Keywords: Operational Research, Machine Learning, Decision-Making Procedures, Optimization, Automation, Decision Analysis, Resource Allocation.

1.Introduction

Decision-making is a fundamental process that permeates virtually every aspect of human endeavour, ranging from business operations to healthcare, logistics, finance, and beyond. The quality of decisions made within an organization often directly correlates with its success and efficiency.

In the 1950s, Herbert Simon and James March presented an innovative decision-making framework to investigate the behaviour of organizations. While expanding upon the bureaucratic framework and emphasizing individual contributions within rationalized organizations, their model introduced a novel viewpoint: acknowledging the constraints of human rationality. This novel approach offered a more practical option compared to the conventional assumption of full rationality in decision-making. This alignment with the behavioural perspective better reflects how individuals and organizations operate.

The model proposed that when a person makes a decision, they consider only a restricted range of potential choices instead of evaluating every option at hand. They tend to settle for options that are satisfactory or good enough, rather than demanding the absolute best choice.

Simon [3] outlined a decision-making model consisting of four steps, which include the phases of intelligence, design, choice, and review. The perspective known as "satisficing," which is process-oriented, draws heavily from Simon's [5] research on bounded rationality. It acknowledges that rational decision-makers may not always possess complete information and that achieving optimal choices is not always necessary. As Simon, H. [15] , "Human rational behaviour is influenced by a pair of factors: the structure of task environments and the computational abilities of the decision-maker." These factors, like a pair of scissors, limit the problem space, making it more manageable for exploration. Bounded rationality is defined by the actions of searching for information and settling for satisfactory solutions.

Davis, G.B., & Olson, M.H. [7], The Management Information System (MIS) excels at pinpointing issues and aiding managers in comprehending them to arrive at appropriate and accurate choices. However, its primary drawback is its lack of customization for individual and group decision-makers' specific requirements. Frequently, MIS fails to deliver precisely the information essential for resolving problems in individual and group decision-making processes. In contrast, The Decision Support System is designed to cater to the specific needs of both individual and groups of managers. As a result, DSS can provide comprehensive comfort across the enduring stages of decision-making, including objective and criteria established, alternative exploration, alternative assessment, decision-making, and decision review.

DSS plays a greater part in the processes of decision-making and addressing issues compared to MIS, as pointed out by Raymond in [16]. This claim is supported by additional scholars, such as Uma [31], who defines a Decision Support System as an extensive set of computer tools that enables decision makers to interact directly with computers to obtain vital information for making decisions that may be only partially structured or entirely unstructured. Examples of such decisions encompass choices like mergers and acquisitions, expanding operations, introducing new products, managing portfolios, and making marketing decisions.

Cao, Baker, and Hoffman, [38], the concept of alignment is a substantial theme investigated in strategic management, operations management, information systems, and production research. Within the realm of production research, certain studies delve into product design, (Dou, Zhang, and Nan, [46]), while others examine production & supply chain aspects, (Ivanov, Das, and Choi 2018[49]). Additionally, Bullinger and Schweizer [28]conducted research into the concept of product economy.

Importantly, within production research, integrating marketing strategy into production planning is recognized to lead to a notable reduction in overall costs and a substantial boost in profits (Leitch [2]).

Embedded within a marketing strategy, relationship marketing strives to forge enduring connections with consumers, suppliers, and merchandiser by fostering mutually advantageous interactions. The central focus of this method is dedicated to nurturing and maintaining their enduring favour, allegiance, and business commitment (Buttle [11]; Foss and Stone [21], Cavusgil, S. Tamer, and Shaoming Zou[10]; Peck et al. 1999[18]).

Over the past few decades, IT has made significant progress in terms of its capabilities and speed, motivating organizations to develop IT strategies aimed at efficiently managing operational expenses (Chen, Tu, and Lin [26] Piercy, Nigel F, Lloyd C Harris, Linda D Peters[13]). Venkatraman [14], IT stratification promotes the optimization of global connectivity and information exchange within companies. This, in turn, enables the reduction of redundant data and enhances operational efficiency.

The rising technological progress and the growing complexity of the market necessitate that every organization leverages strategic alignment. It underscores the significance of aligning the priorities of businesses and functions with various corporate strategies, including production, marketing, technology, and operations, In the quest to achieve their goals (Ritson ,[37]).

In the dynamic and fast-changing business environment fuelled by technology, achieving strategic alignment is crucial for the success and prosperity of many service providers and manufacturers. Henriques and colleagues [50], who explored the potential of using artificial intelligence (AI) integration to attain and fortify the sought-after strategic alignment.

Machine learning is utilized in different aspects of production and operations management, such as improving production, quality control, and packaging processes to increase overall efficiency. According to Visinescu, Jones, and Sidorova[47], this powerful analytical approach provides valuable insights for decision-makers in production and operations. These insights would be unattainable without the incorporation of advanced technologies and business intelligence.

Its applicability extends to the realms of warehousing and transportation, offering valuable analytical insights. As an illustration, Lee et al. [42] harnessed ML techniques to predict two parameters within the Bass model prior to the introduction of a new item, demonstrating that this AI-driven estimation method surpassed conventional models in performance. As demonstrated by Li et al. [43], the effectiveness of AI as an analytical tool is dependent on its accuracy in analysis. They employed data mining and ML techniques to analyze the scarce information accessible in the preliminary phase of a new product's development, occurring prior to mass production.

In this era of data abundance and increasing complexity, the integration of OR and ML has materialized as a powerful approach to analyse and optimize decision-making procedures.

OR has traditionally been employed to solve complex decision problems through mathematical modeling, optimization, and simulation. ML, on the other hand, leverages data-driven algorithms to uncover patterns, make predictions, and automate tasks. By combining these two disciplines, organizations can achieve a synergistic effect, leading to more informed, efficient, and automated decision processes.

Decision-making is a fundamental aspect of organizational management and problem solving across diverse industries. Operational research, with its rich history, has played a pivotal role in aiding decision-makers in formulating optimal solutions to complex problems. However, in today's data-driven world, the sheer volume and complexity of available data have posed new challenges for traditional operational research techniques.

This has led to an increasing need to incorporate machine-learning methodologies to extract valuable insights from data and support more informed decision-making.

The aim of this scholarly article is to illuminate how OR and ML can be applied in decision analysis. We will delve into the methodologies and techniques that underpin this synergy, displaying how it can be applied across various domains. Real-world case studies and practical examples will be used to illustrate the benefits of this integrated approach, such as improved resource allocation, cost reduction, and enhanced decision-making precision.

2. Literature Review:

Singla [45] emphasized that Operations Research (OR) is the primary method for aiding decision-makers by providing them with data to make informed choices. It involves breaking down complex issues into their fundamental components for effective problem solving. Kothari [29], further clarified that OR is not only a valuable tool for decision-making but also enhances intuition and judgment. It can be considered a modeling technique frequently used by decision-makers.

Jemison [6] has investigated the field of strategic decision-making theory, primarily focusing on its implementation in the context of operations management, specifically within manufacturing companies.

In line with previous research, our present investigation extends the principles of strategic decision-making theory to construct our research framework and hypotheses. Afterward, we conducted a thorough examination of existing literature to explore the correlation between Information Technology and marketing strategies in the domains of both strategic management and operations management. We also reviewed previous studies that have leveraged Machine Learning (ML) in the context of operations management, as well as the analytical techniques of Structural Equation Modeling.

Likert [1] highlighted in early studies on strategic positioning the importance of ensuring that the functional priorities and overall business objectives are in harmony with the organization's strategies.

Earlier research has also emphasized the significance of aligning the external challenges and opportunities in the environment, together with the internal strengths of the organization, with the overall business strategy, as exemplified by Cao and Hoffman [35].

Lingle and Schliemann [12], along with Hrebiniak and Joyce [8], have demonstrated a correlation between business performance and alignment. In the realms of strategic management and operations management, there is a prevailing assumption that inadequate alignment is likely to have adverse effects on a company's performance, a viewpoint endorsed by Schniederjans and Cao [33].

According to a study by Mollenkopf, Diane A and Ivan Russo [36], many companies fail to achieve their strategic business goals, partly because they struggle with functional shortcomings. For instance, the absence of efficient coordination among a company's diverse strategies, such as marketing and other functional approaches, is perceived as a lack of alignment, as observed by Berry, Hill, and Klompmaker[17]. Attaining alignment involves striking a suitable equilibrium between a company's operational performance and the requirements of the market, as elucidated by Slack and Lewis [41]. Additionally, Piercy et al. [13] underscore that the execution and evolution of a marketing strategy directly influence functions such as production, finance, and personnel. Understanding how these strategies integrate with each other is crucial for making informed operational decisions.

The well-documented consensus on the positive influence of integrating marketing and IT on corporate performance is widely recognized. Analyzing the effectiveness of IT strategies entails reviewing how businesses integrate market information systems, such as gathering data on competitors and customers, to enhance their overall business strategies(Sabherwal and Chan[25]; Venkatraman [9]). Borges, Hoppen, and Luce [32] have emphasized the importance of utilizing emerging internet-based technologies to improve production and distribution processes. The strategic use of IT can also positively impact marketing strategies by offering assistance for marketing activities, such as enhancing business performance through markets facilitated by the internet (Min, Song, and Keebler [27]).

A significant body of research has explored methods for aligning strategies with an organization's overarching strategic objectives (Baker [30]; Berry, Hill, and Klomp- maker [17],Cavusgil and Zou [10]) in order to enhance overall performance. Marketing strategy involves making decisions concerning the creation and sustenance of a competitive edge, as well as the implementation of diverse marketing initiatives.(V.Rajan, J.Chandran, and C.White [22]). Marketing involves a range of activities, including product development, research and development, product promotion, and pricing strategy formulation. These activities play a crucial role in evaluating external factors like competitors and customers. The marketing strategy focuses on the methods a company can use to differentiate itself from competitors and leverage its distinctive strengths to deliver outstanding value to customers in a specific market (Jain [19]).

Papageorgiou [4], pointed out that OR found applications in the field of medicine during the 1960s and 70s. Romero-Conrado, Castro-Bolaño, Montoya-Torres & Jiménez-Barros [48],expanded on this, noting that in the mid-20th century, OR experienced significant growth, becoming instrumental in solving problems across various sectors. Berner [34] added that in the 21st century, OR continued to evolve, especially in the form of decision-support systems. Chwelos, [20], Dexter [23] and McCowan [24] succinctly emphasized that OR models became a dominant force in the functionality of computer tools.

Singh[39] highlighted that Knowledge Management (KM) involves three key activities: creation, transfer, and storage. Sharma [44]provided a technical perspective, defining OR as a theory of applied decision-making that employs mathematical, scientific, or logical methods to address the challenges faced by executives in their pursuit of rational decision-making.

Abdurrahman Al-Surmi, Mahdi Bashiri, and Ioannis Koliousis[51], introduced a comprehensive decision-making framework in three phases. This framework aims to derive the most effective marketing and IT strategies across various business sectors, offering methodological, theoretical, and practical insights.

In the subsequent sections of this paper, we will explore the foundations of OR and ML, their respective roles in decision analysis, and the potential for collaboration between the two disciplines. By doing so, we hope to provide valuable insights into how organizations can harness the power of OR and ML to analyze decision-making procedures more effectively and adapt to the ever-evolving challenges of the modern world.

3. Mathematical Operational Research Model: We have employed a mathematical operations research model to define the issue, and we have incorporated these models into machine learning to enhance our outcomes.

3.1 Mathematical Model of Linear Programming Problem: LPP is a mathematical modeling technique used in various decision-making scenarios. It finds applications in resource allocation, production planning, and supply chain optimization, among others. LPP helps organizations maximize profits, minimize costs, and make efficient use of resources.

The general LP model is defined by n decision variables and m constraints, and can be articulated in the following manner:

Optimize (Max. or Min.)

$$Z = c_1x_1 + c_2x_2 + \cdots \ldots \ldots \ldots + c_nx_n$$

Bound by the linear limitations,

$b_{11}y_1 + b_{12}y_2 + \cdots \ldots \ldots \ldots . +b_{1n}y_n <=> d_1$

$b_{21}y_1 + b_{22}y_2 + \cdots \ldots \ldots \ldots . +b_{2n}y_n <=> d_2$

$b_{m1}y_1 + b_{m2}y_2 + \cdots \ldots \ldots \ldots . +b_{mn}y_n <=> d_n$

and $y_1, y_2, \ldots \ldots, y_n \geq 0$

These values represent the amount of a resource, labelled as "i," consumed for every unit of the variable (activity) "y_j." These coefficients may take on positive, negative, or zero values. The "d_i" values signify the total availability of the "i^{th}" resource.

The term "resource" is employed in a broad sense, encompassing any numerical value linked to the right-hand side of a constraint. It is presupposed that all "bi" values are greater than or equal to 0. In the event that any "bi" is less than 0, both sides of constraint "i" are multiplied by -1. This is done to ensure that "bi" becomes greater than 0 and to invert the inequality of the constraint [44].

In the context of the general linear programming problem, the symbols (≤, =, ≥) indicate that each individual constraint in any particular problem can assume one of three potential formats:

(i) Equal to or less than. (≤), (ii) Equal to (=)

(iii) Equal to or greater than (≥)

3.2 Mathematical Model for Replacement of Machine:

Theorem1: The machine's maintenance cost is described as a function that grows over time, while its scrap value remains constant.

(a) When measuring time continuously, the most cost-effective annual average can be achieved by replacing the machine as soon as the cumulative average cost matches the current maintenance cost.

(b) When assessing time in discrete increments, achieving the best annual average cost involves replacing the machine as soon as the maintenance cost for the next period surpasses the current average cost.

Proof: This analysis aims to find the best time to replace a piece of equipment with increasing running costs while assuming a constant value of money over the period (i.e., disregarding changes in value). Let

C = initial purchase cost of the new equipment

S = value of the equipment when sold or salvaged at the end of t years

R(t) = annual running cost of the equipment in year t

n = the age at which the equipment should be replaced.

(a) When the variable 't' represents continuous time, the total cost accrued over a period of 't' years due to equipment usage can be expressed as follows:

Total Cost=Initial expense (or acquisition cost) - Residual value after t years + Operational expenses over the course of t years = $C - S + \int_0^n R(t)dt$

Hence, the mean cost per unit of time expended throughout a span of n years is:

$ATC_n = \frac{1}{n}\{C - S + \int_0^n R(t)dt\}$ (1)

To find the value of 'n' that minimizes ATC_n, you can calculate the derivative of ATCn with respect to 'n' and then set this derivative equal to zero. This process helps identify the point at which ATC_n reaches its minimum.

$$\frac{d}{dn}ATC_n = -\frac{1}{n^2}(C - S) + \frac{R(n)}{n} - \frac{1}{n^2}\int_0^n R(t)dt = 0$$

$R(n) = \frac{1}{n}\{(C - S) + \int_0^n R(t)dt\}, n \neq 0$ (2)

$R(n) = ATC_n$

Therefore, by utilizing Eq. (2), we can formulate the subsequent replacement strategy.

Replace the equipment when the cumulative annual expenses over a period of 'n' years reach the same level as the current yearly operating costs.

i.e. $R(n) = \frac{1}{n}\{(C - S) + \int_0^n R(t)dt\}$.

(b) When we treat time't' as a discrete variable, the average cost incurred over the period of 'n' can be articulated in the following manner:

$ATC_n = \frac{1}{n}\{C - S + \sum_{t=0}^{n} R(t)\}$ (3)

Policy 1: states that if the operational expenses for the upcoming year, R (n + 1), exceed the average cost of the previous year, ATC_n, and then it is cost-effective to consider replacement at the conclusion of the n-year period.

i.e. $R(n + 1) > \frac{1}{n}\{C - S + \sum_{t=0}^{n} R(t)\}$

Policy 2: If the current year's operational expenses are lower than the average costs of the previous year (ATC_{n-1}), then refrain from carrying out a replacement[44].

i.e. $R(n) < \frac{1}{n-1}\{C - S + \sum_{t=0}^{n-1} R(t)\}$

3.4 Mathematical Model of Linear Regression:

Linear regression is a statistical technique employed to represent the connection between a target and one or more features . This is achieved by establishing a linear equation that best fits the observed data.The simple linear regression model, which relates a single independent variable to the dependent variable, can be expressed as follows:

Target: Y

Feature: X

The L E is: $Y = \beta_0 + \beta_1 X + \varepsilon$

Y serves as the outcome variable, while X functions as the predictor variable. The intercept, denoted as β_0, signifies the value of Y when X is 0. The slope, represented by β_1, reflects the alteration in Y associated with a one-unit shift in X. ε denotes the error term, encompassing the variability in the data not accounted for by the model [42,52,53].

The objective of linear regression is to determine the values of β_0 and β_1 in a way that minimizes the sum of squared residuals, which is the total of the squared deviations between the observed and predicted Y values.

Multiple Linear Regression: When dealing with multiple independent variables, one can employ multiple linear regression to formulate the model as follows:

$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \varepsilon$

Y is the target. $X_1, X_2, \ldots, X_p$ are the features. β_0 represents the intercept, while $\beta_1, \beta_2, \ldots, \beta_p$ denote the coefficients corresponding to the independent variables. ε signifies the error term. The objective persists: to determine the coefficients' values ($\beta_0, \beta_1, \beta_2, \ldots, \beta_p$) that minimize the sum of squared residuals [42,52,53].To find the values of the coefficients, you typically use a method like the least squares method, which minimizes the sum of squared residuals. This can be done using various algorithms, including matrix algebra and optimization techniques.

In practical terms, we typically employ statistical software or a programming language such as Python, utilizing libraries like NumPy, Pandas, SciPy, or scikit-learn to execute linear regression. This allows us to calculate and determine the coefficients based on the provided data.

3.5 Mathematical Model of Logistic Regression:

Logistic regression serves as a statistical technique applied in scenarios involving binary classification. It aims to characterize the connection between a binary outcome variable (0 or 1) and one or multiple independent variables by predicting the probability of the dependent variable falling into a specific category. The logistic regression model employs the logistic function, also called the sigmoid function, to convert the linear combination of independent variables into a probability value. This function is articulated as follows:

$$P(Y=1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \ldots + \beta_n X_n)}}$$

Where: P(Y=1) is the probability of the dependent variable Y being equal to 1. β_0 is the intercept. $\beta_0, \beta_1, \beta_2, \ldots, \beta_n$ are the coefficients for the independent variables $X_1, X_2, \ldots \ldots X_n$. e is the base of the natural logarithm (approximately 2.71828).

The logistic regression model is trained to estimate the values of the coefficients $(\beta_0, \beta_1, \beta_2, \ldots, \beta_n)$ that maximize the likelihood of the observed data. The likelihood function is typically the product of the probabilities for each data point in the training dataset, given the model parameters. The logistic regression model can be represented mathematically as:

$$ln\left(\frac{P(Y=1)}{1 - P(Y=1)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

In this equation, the natural logarithm of the odds ratio on the left-hand side is modeled as a linear combination of the independent variables on the right-hand side[40].

The coefficients $(\beta_0, \beta_1, \beta_2, \dots, \beta_n)$ are typically estimated using optimization techniques like maximum likelihood estimation (MLE). Once the coefficients are estimated, the logistic regression model can be used to predict the probability of the dependent variable being 1 for new data points. If the predicted probability is greater than a chosen threshold (e.g., 0.5), the model predicts the outcome as 1; otherwise, it predicts the outcome as 0.

4. Role of Operations Research in decision-making:

Operations Research (OR) plays a critical role in decision-making across various fields and industries by providing quantitative and analytical methods to optimize complex processes, allocate resources efficiently, and make informed choices. OR tools aid in project scheduling, resource allocation, and risk assessment to ensure that projects are completed on time and within budget. OR is applied in agriculture for optimizing crop planting and harvesting schedules, managing resources like water and fertilizers efficiently, and addressing supply chain challenges. Some key roles of Operations Research in decision-making:

4.1 Resource Allocation: OR helps in allocating limited resources, such as time, money, and work force, effectively. This is especially crucial in situations where there are multiple competing demands for resources, and decisions must be made to maximize their utilization.

For example, a production firm manufactures two product varieties, namely Product A and Product B. The manufacturing process involves the utilization of two machines, Machine X and Machine Y, both with hourly production limits:

Machine X can manufacture either 10 units of Product A or 5 units of Product B per hour.

Machine Y has the capability to produce 8 units of Product A or 4 units of Product B per hour.

The company wants to determine the optimal allocation of machine hours to maximize their total production output. They also want to ensure that the total production does not exceed the demand for each product, which is as follows:

The demand for Product A is 60 units per day.

The demand for Product B is 40 units per day.

Mathematical modelling: Let us represent the decision variables:
x = Number of hours allocated to Machine X
y = Number of hours allocated to Machine Y
The objective function to maximize would be the total number of products produced:
Z=10x+8y (for Product A)
Z=5x+4y (for Product B)
Subject to the following constraints:
10x+8y≤60 (Machine X capacity for Product A)
5x+4y≤40 (Machine Y capacity for Product B)
x,y≥0 (Non-negativity constraint)

```
Optimal Solution:
Hours allocated to Machine X (x): 3.0 hours
Hours allocated to Machine Y (y): 3.75 hours
Maximum Production Output (Z): 60.0 units
```

We solved above example by python and ML to allocate best resource to maximize the production while respecting the limitations of available resources

4.2 Effective Decisions

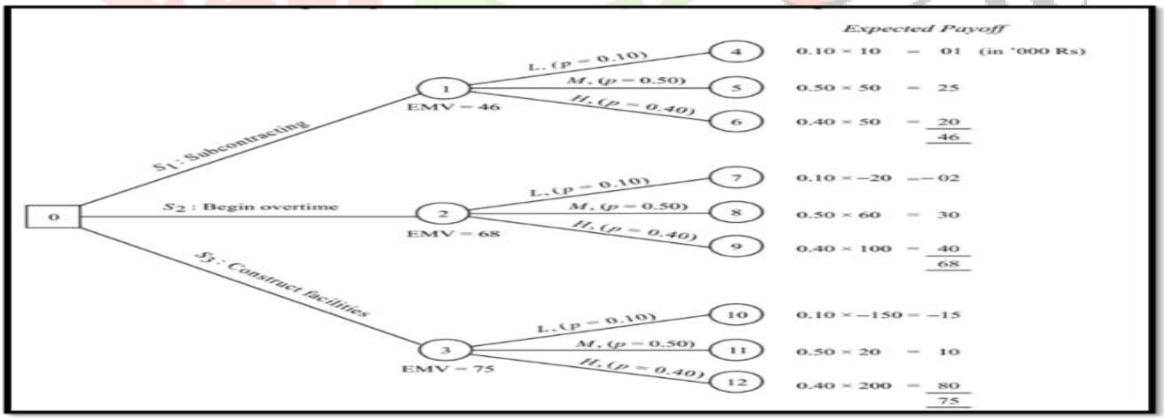
Operation Research plays a pivotal role in aiding managers in making informed and efficient decisions. It provides managers with a range of options to choose from, enabling them to evaluate these alternatives along with their associated risks and the outcomes of their implementation. Additionally, it facilitates an analysis of how each alternative affects overall management. As a result, Operation Research streamlines the decision-making process, allowing for quicker and better-informed choices.

For example, a crystal-focused glass manufacturing plant is facing a growing backlog of orders, prompting the company's management to explore three potential solutions: subcontracting (S1), implementing overtime production (S2), and constructing new facilities (S3). The most suitable option hinges on anticipated future demand, which could be categorized as either low, moderate, or high. After deliberation, the management collectively assesses the likelihood of each scenario at 0.10, 0.50, and 0.[40], respectively. A thorough cost analysis has been conducted to evaluate how these choices will impact the company's profits, as illustrated in the table below:

Demand	Probability	Course of Action		
		S1 (Subcontracting)	S2 (Begin Overtime)	S3 (Construct Facilities)
Low (L)	0.10	10	-20	-150
Medium (M)	0.50	50	60	20
High (H)	0.40	50	100	200

Represent this decision scenario using a decision tree and identify the optimal decision along with its associated expected value.

In below Figure, there is a decision tree illustrating potential actions and various scenarios. To evaluate the tree, we begin by working in reverse, starting from the terminal nodes. At decision node 0, the best course of action is identified by calculating the anticipated value for each decision branch and selecting the path with the highest expected value.



As node 3 exhibits the highest Expected Monetary Value (EMV), the decision at node 0 will consequently favour selecting course of action S3, which entails building new facilities[44].

5. Integration of Operations Research models with Machine Learning models:

Integration of Operations Research (OR) models with Machine Learning (ML) models is a powerful approach that combines the strengths of both disciplines to tackle complex decision-making problems.The integration of OR models with ML models provides a synergistic approach to decision-making. It enhances optimization processes, facilitates better forecasting, adapts to dynamic conditions, and enables data-driven, personalized, and more informed decision support across various industries. This interdisciplinary approach has the potential to revolutionize how organizations address complex challenges and make more effective, efficient decisions.

5.1 Integration of Operations Research (OR) with python in Decision-Making:

Integration of Operations Research (OR) techniques with Python is a powerful combination for decision-making in various fields such as supply chain management, finance, healthcare, and more. Python offers a wide range of libraries and tools that make it easy to implement OR models, solve complex optimization problems, and analyze the results. Here is how you can integrate OR with Python for decision-making:

Let us explore this integration with a numerical example:

Data: Each unit of Product A is priced at Rs.1000, requiring 2 hours of labour, 3 units of raw materials, and 1 hour of machine time for production. In contrast, Product B is priced at Rs.1500 per unit and involves 1 hour of labour, 2 units of raw materials, and 2 hours of machine time in its manufacturing process. The available resources for the company include 50 hours of labour, 100 units of raw materials, and 80 hours of machine time. The market demand is 200 units for Product A and 150 units for Product B.

Decision variables include x, representing the quantity of Product A to manufacture, and y, representing the quantity of Product B to produce.

Mathematical Modelling of Data:

Apply the chosen optimization library to solve your OR problem. This typically involves setting up the model, invoking the solver, and retrieving the results. For example, if you are solving a linear programming problem with PuLP.

Goal Function: The aim is to optimize financial gain, and this can be expressed as:

Maximize $Z=10x+15y$ (Total Revenue)$-(2x+y)$ (Labor Cost)$-(3x+2y)$ (Raw Material Cost)$-(x+2y)$ (Machine Cost)

Constraints:

Labor constraint: $2x+y\leq 50$ (Available labor hours).

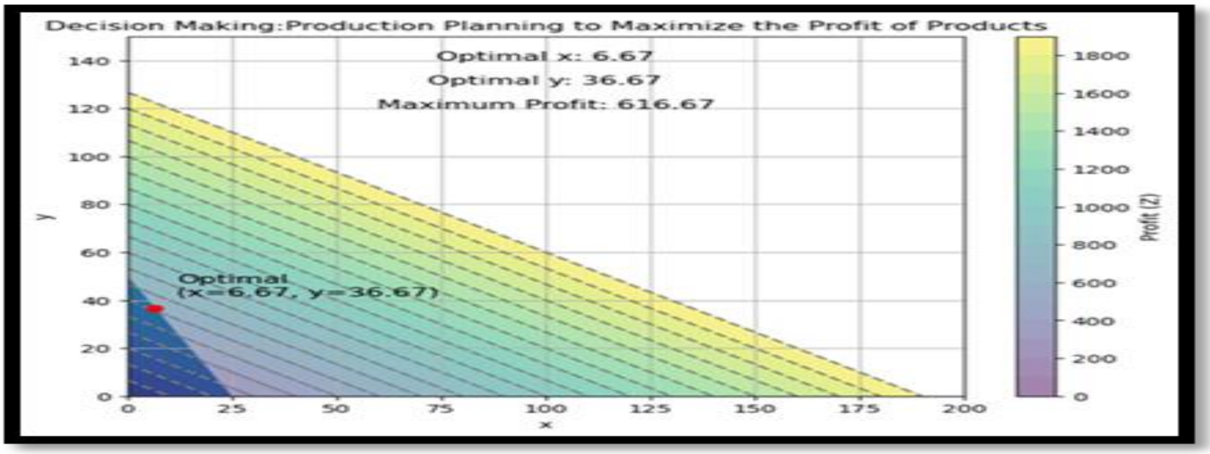
Raw material constraint: $3x+2y\leq 100$ (Available raw materials).

Machine constraint: $x+2y\leq 80$ (Available machine hours).

Demand constraint for Product A: $x\leq 200$ (Market demand for Product A).

Demand constraint for Product B: $y\leq 150$ (Market demand for Product B).

Non-Negativity Constraints:$x\geq 0$ and $y\geq 0$ (You cannot produce a negative quantity of a product). We employed LP methods to identify the most favourable values for x and y, aiming to maximize profit while adhering to all specified constraints.



The combination of OR and Python has the potential to enhance decision-making by making it more efficient and based on data analysis. This hybrid approach allows organizations to leverage the strengths of both fields to solve complex problems and make better-informed decisions.

5.2 Integration of OR with Linear Regression and Logistic Regression models:

Integrating machine learning with operational research (OR) models can indeed lead to more robust and effective decision-making processes. Operational research is a discipline focused on optimizing complex systems, while machine learning excels at making predictions and identifying patterns within data. By combining these two approaches, you can enhance decision-making in various domains.

Employ machine learning algorithms to make predictions or classifications related to your OR problem. For example, we can use regression models for demand forecasting, classification models for quality control, or time series forecasting for inventory management.

Sharma[44], OR , (Theorem 17.1) The machine's maintenance cost is described as a function that grows over time, while its scrap value remains constant.

(a)When measuring time continuously, the most cost-effective annual average can be achieved by replacing the machine as soon as the cumulative average cost matches the current maintenance cost. Then Replace the equipment when the cumulative annual expenses over a period of 'n' years reach the same level as the current yearly operating costs.

i.e. $R(n) = \frac{1}{n}\{(C - S) + \int_0^n R(t)dt\}$ (1)

(b) When time 't' is considered as a discrete variable, the average cost accrued during the duration of 'n' can be expressed as follows: $ATC_n = \frac{1}{n}\{C - S + \sum_{t=0}^{n} R(t)\}$

Policy 1: states that if the operational expenses for the upcoming year, R (n + 1), exceed the average cost of the previous year, ATC_n, and then it is cost-effective to consider replacement at the conclusion of the n-year period.

i.e. $R(n+1) > \frac{1}{n}\{C - S + \sum_{t=0}^{n} R(t)\}$ (2)

Policy 2: If the current year's operational expenses are lower than the average costs of the previous year (ATC_{n-1}), then refrain from carrying out a replacement.

i.e. $R(n) < \frac{1}{n-1}\{C - S + \sum_{t=0}^{n-1} R(t)\}$ (3)

We employed an Operational Research model to determine the optimal machine replacement time in the following example. To validate the accuracy of our findings, we subsequently utilized regression and logistic models. These methods aided in analyzing the problem and making an informed decision about machine replacement timing. Consequently, integrating Operational Research and Machine Learning can be beneficial in various domains, enhancing decision-making processes.

Example: A company is contemplating the substitution of a machine with an initial cost of Rs 12,200 and a salvage value of Rs 200. Based on experience, the expenses associated with its operation and maintenance are as follows:

Year :	1	2	3	4	5	6	7	8
Running cost (Rs):	200	500	800	1200	1800	2500	3200	4000

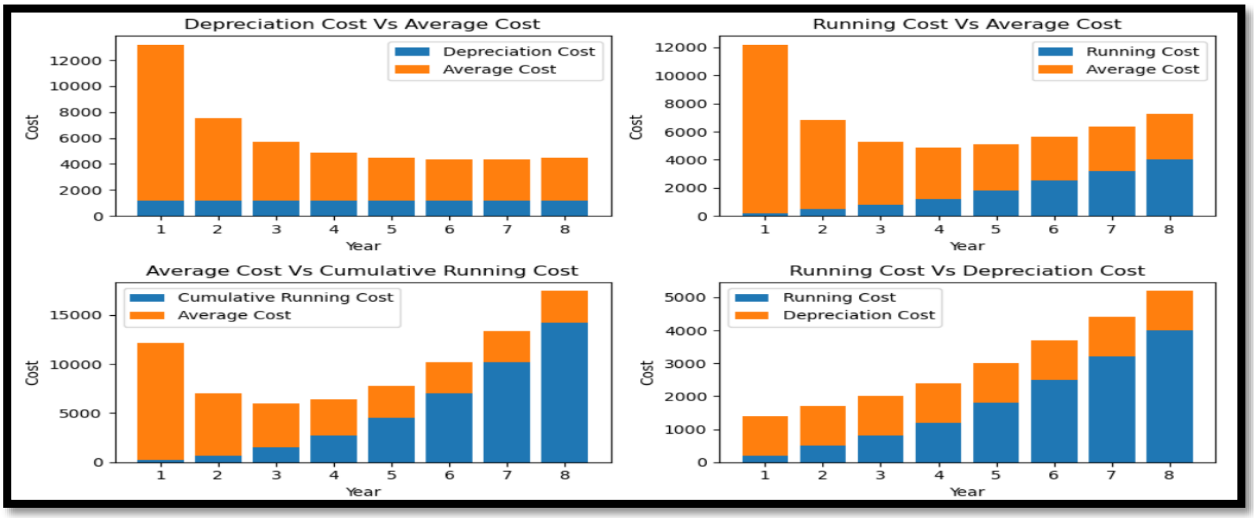
Given the machine's cost (C = Rs 12,200), running cost (R(n)), and scrap value (S = Rs 200), our objective is to find the ideal replacement time (n).

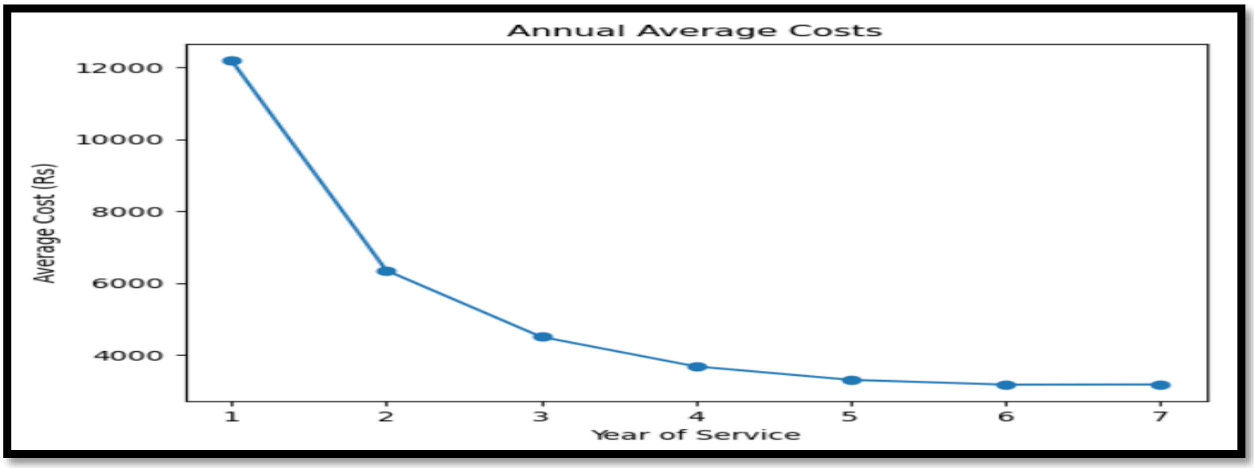
To do this, we start by computing the annual average cost over the machine's lifespan, as illustrated in the table:

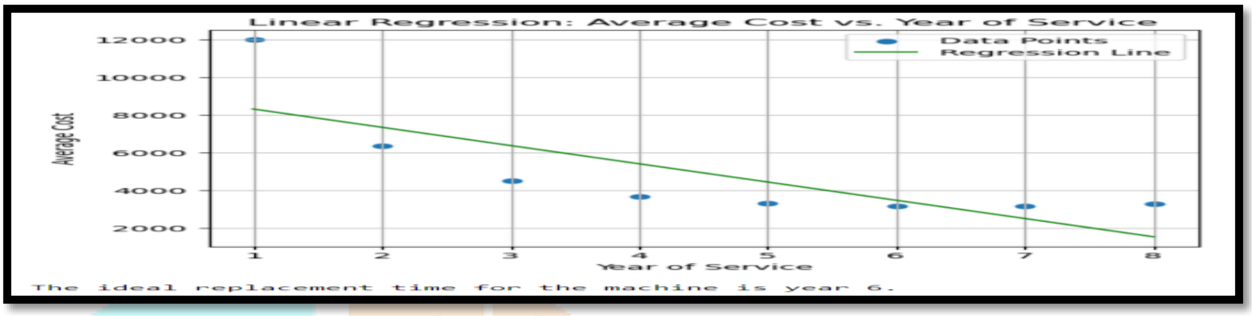
Year of Service (n)	Running Cost (Rs) R(n)	Cumulative Running Cost (Rs) ∑R(n)	Depreciation Cost (Rs) (C-S)	Total Cost (Rs) TC	Average Cost (Rs) ATCn
1	200	200	1200	12200	12000
2	500	700	1200	12700	6350
3	800	1500	1200	13500	4500
4	1200	2700	1200	14700	3675
5	1800	4500	1200	16500	3300
6	2500	7000	1200	19000	**3167**
7	3200	10200	1200	22200	3171
8	4000	14200	1200	26200	3275

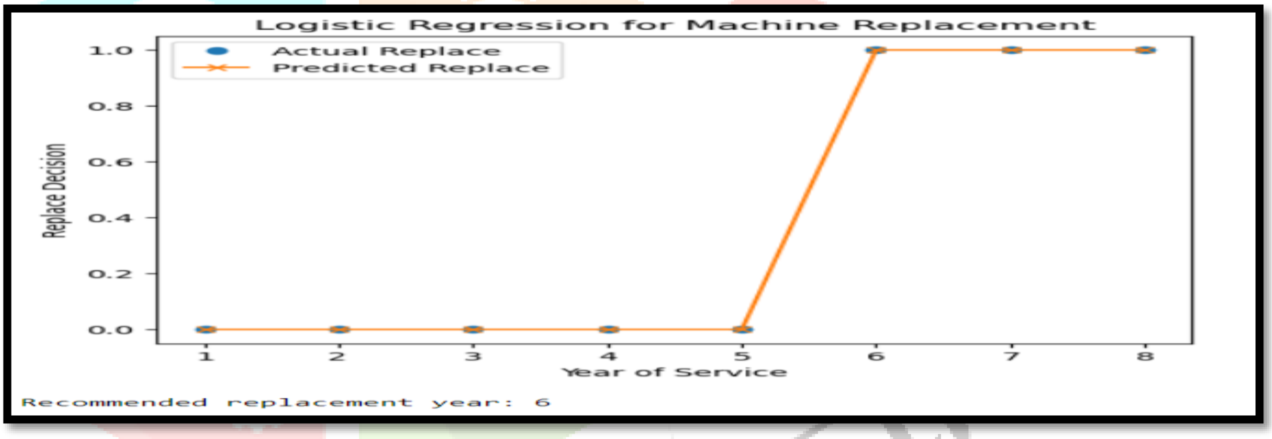
The table above illustrates that the minimum annual average cost, ATCn = Rs 3,167, occurs in the sixth year. Furthermore, the seventh-year average cost of Rs 3,171 surpasses the cost in the sixth year. Consequently, it is advisable to replace the machine every six years.

To validate the accuracy of our findings, we subsequently utilized regression and logistic models. These methods aided in analyzing the problem and making an informed decision about machine replacement timing.









The output of both the regression and logistic regression models has confirmed the finding of the OR model, indicating a six-year lifespan for the replacement of the machine.

Integrating machine learning with operations research models enables us to enhance decision-making processes, making them more precise, flexible, and responsive. This synergy harnesses the respective advantages of both methodologies to efficiently address intricate real-world challenges.

6. Conclusion:

In conclusion, the integration of operational research and machine learning represents a powerful approach for analysing decision-making procedures across a wide range of industries and applications. This synergy between traditional analytical methods and cutting-edge artificial intelligence techniques has the potential to revolutionize how organizations make critical decisions.

Through this study, we have highlighted the numerous advantages of leveraging operational research and machine learning, including enhanced predictive capabilities, optimized resource allocation, improved efficiency, and the ability to handle complex, data-rich environments. Furthermore, we have emphasized the importance of a multidisciplinary approach, involving domain experts, data scientists, and decision-makers, to successfully implement these techniques and extract meaningful insights.

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