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The Optimization of Production and Inventory Management Processes in Tissue Paper Production: The Goal Programming Approach

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ABSTRACT

This paper aimed to apply the Goal Programming approach to optimize important parameters in the production and inventory management processes of tissue papers and paper towel manufacturing. A real-life scenario problem was formulated and solved, and a sensitivity analysis was conducted to examine the effects of changes in goal priorities and target values. The goal programming solution optimized the company's profit while meeting the demand and also minimizing raw material and labor usage. The results show the optimal inventory levels for the four products as determined by market demand in the target month to be: I_1^* = 215 tons (SSTP), I_2^* = 380 tons (MSTP), I_3^* = 550 tons (JSTP), and I_4^* = 275 tons (PT). The sensitivity analysis reveals that changes in goal priorities and target values have significant effects on optimal production and inventory levels, thereby highlighting the importance of careful goal setting and prioritization. The findings from the research revealed that a 50-tonne increase in production will increase the profit margin by ten percent for jumbo-size toilet paper. The proper understanding of the production implications will enable the mill to optimize its production, manage resources, and also maximize profit.

Keywords: optimization, production, inventory management, tissue paper, goal programming, manufacturing

Definition of Symbols/Nomenclature			
Symbol/ Parameter	Meaning/Implication	Symbol/ Parameter	Meaning/Implication
SSTP	Small size Toilet Paper	u.d.	Undated or not dated
MSTP	Medium Size Toilet Paper	X	Quantity of production material
JSTP	Jumbo Size Toilet Paper	X_i	Quantity of material for product
PT	Paper Towel	I	Inventory level
$d+$, $d-$	Deviational variables that represent over-achieving, under-achieving at the desired level of a goal	i	Number 1, 2, 3 or 4 referencing SSTP, MSTP, JSTP, or PT respectively.
d_i+	Deviational variables that represent over-achieving the desired level of a goal	I_i^*	Optimal inventory level of an i^{th} material.
d_i-	Deviational variables that represent under-achieving the desired level of a goal		

INTRODUCTION

Tissue Paper Production – A Brief Overview

In the tissue paper production process, wood chips or recycled paper are converted into pulp, followed by the impurities removal process known as screening. The pulp is then refined, bleached, and formed into a sheet with the application of a fourdrinier machine. Water is pressed out of the sheet after which it begins to take the desired shape. The sheet is later dried with the application of heat from a series of hot air blowers. The dried sheet is then cut to the desired size and properly packaged for distribution.

Various products can also be manufactured from tissue paper production. These products include toilet paper, paper towels, handkerchiefs, napkins, and facial tissues. The production process of each of these products may vary due to some reasons. Additionally, some manufacturers may use more advanced technologies or sustainable practices, such as the application of recycled fibers or biogas energy.

Importance of Optimization in Production and Inventory Management

According to Okpala et al. (2021), the need to enhance productivity through optimization is a crucial challenge for all establishments. They pointed out that this is because productivity which is a determinant of a firm's success is a major factor in the economic well-being and growth of an enterprise and any nation. The importance of optimization in production and inventory management cannot be over-emphasized. The application of this technique is crucial for several reasons, which include reduction in the cost of production through waste reduction, energy consumption, and labor costing; increase in production efficiency by optimizing production and inventory processes, thereby leading to improved productivity, reduced lead times, and enhanced supply chain efficiency; improvement in quality of production by consistently identifying and addressing potential defects or bottlenecks; and enhancement of customer satisfaction by ensuring timely delivery of products, and meeting customer demands and expectations.

More so, companies that optimize production and inventory management can gain a competitive edge in the market. Optimization helps to identify and mitigate potential risks, such as stockouts, overstocking, or supply chain disruptions and also provides insights and data to support informed decision-making. Optimized processes can adapt to changing market conditions, demand fluctuations, or new product introductions. Besides, optimization can help organizations to maintain optimal inventory levels, reduce storage costs, and minimize the risk of obsolescence.

Okpala et al. (2020), observed that as the greatest asset of any company is its staff, efforts should be made by manufacturing companies to recruit knowledgeable workers who will bring their experience to bear in their day-to-day activities. They explained that this is because human skills and expertise like effective communication, teamwork, capability, problem-solving, and analytical skills are crucial factors for successful optimization of any company's production processes. By optimizing production and inventory management, businesses can achieve significant benefits, thereby enhancing growth, profitability, and sustainability.

The Goal Programming Approach

Goal Programming (GP) is a multi-objective optimization approach that helps decision-makers to achieve multiple, conflicting goals by minimizing deviations from desired target values. The application steps in the GP approach include,

- *Define goals:* Identify multiple objectives (goals) to be achieved.
- *Set target values:* Establish desired target values for each goal.
- *Assign weights:* Allocate weights to each goal, reflecting their relative importance.
- *Formulate constraints:* Define constraints that limit the feasible solutions.
- *Develop objective function:* Create an objective function that minimizes deviations from target values.
- *Solve the model:* Use optimization techniques (e.g., linear programming) to find the optimal solution.

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Key components of GP include expression of the goals as constraints with target values; introduction of variables to measure deviations from target values; assigning of weights to goals to reflect their importance; and defining the objective function to minimize a weighted sum of deviation variables.

There are many advantages that the GP approach offers: It handles multiple objectives and consists of flexible weighting scheme. It is easy to interpret the results it provides and can incorporate constraints. Areas of applications of GP include production planning, resource allocation, financial planning, supply chain management, and maintenance scheduling. Among the software tools used in solving GP problems are the Excel Solver, LINGO, MATLAB, LINDO, and Python libraries (e.g., PuLP, Pyomo).

The application of Goal Programming enables decision-makers to find optimal solutions that balance multiple objectives. This fit makes the application of GP a powerful approach to complex decision-making.

LITERATURE REVIEW

Overview of Optimization Techniques in Production and Inventory Management

Production and inventory management optimization techniques aim to minimize costs, maximize efficiency, and improve decision-making. Production optimization techniques include Linear Programming (LP), Integer Programming (IP), Dynamic Programming (DP), Heuristics, and Simulation Optimization (SO). Inventory optimization techniques include Economic Order Quantity (EOQ), Just-in-Time (JIT), Inventory Control Theory, Stochastic Inventory Control, and Multi-Echelon Inventory Optimization. Integrated Optimization techniques include Supply Chain Optimization, Production-Inventory-Distribution Optimization, and Multi-Objective Optimization. There also are the advanced techniques of optimization which include Machine Learning, Genetic Algorithms, Simulated Annealing, and Ant Colony Optimization,

These optimization techniques help organizations to make better decisions, reduce costs, and improve efficiency in production and inventory management.

Goal Programming Approach in Tissue Paper Production

Goal programming method can be applied to issue paper production to optimize production planning, resource allocation, and inventory management. The goals in the application are: to minimize production costs, environmental impacts, and inventory levels. It is also used to maximize quality and to meet demand. Decision variables in the GP approach include production levels for each product, resource allocation, and inventory levels for finished goods and raw materials. The constraints considered in GP methodology include production capacity limits, resource availability, quality standards, demand satisfaction, and inventory storage capacity.

The objective function of a GP problem seeks to minimize a weighted sum of deviations from target values for each goal. The weights are the production costs, the quality, the environmental impact, demand satisfaction, and the inventory levels. These weights can also serve as the targets with set values.

Applying the GP model in solving tissue paper production problems is a very good method of optimizing its processes, as it enables production planning, resource allocation, and inventory management to achieve a balance between competing goals and objectives.

Empirical Works on Optimization – An Overview

Several authors have done a lot of work in the field of operations research; especially in developing solutions to optimization problems. For instance, in the area of Multi-Objective Optimization, Charnes and Cooper (1961), introduced Goal Programming, a multi-objective optimization technique, Lee (1972), developed the first interactive method for multi-objective optimization, while Steuer (1986), reviewed multi-objective linear programming methods. Dantzig (1959), introduced the simplex method for integer programming, and Gomory (1960), developed the cutting plane method for integer programming. Balas (1965), introduced the additive algorithm for integer programming.

In the area of stochastic optimization, Dantzig (1955), introduced stochastic linear programming, Charnes and Cooper (1959), developed chance-constrained programming, and Birge and Louveaux (1997), made a review of stochastic programming. Meanwhile, Kirkpatrick et al. (1983), Glover (1986), and Holland (1975), were not left out in the scholarly contributions made by these other authors. As such, Kirkpatrick et al. (1983), are known to have introduced simulated annealing. Glover's (1986) contribution was the introduction of tabu search, while Holland (1975), introduced genetic algorithms.

Okpala, Okonkwo, and Ezeanyim (2018), posited that optimization augments and modernizes the business methods of a company; this is because it is performed to transform design specifications into manufacturing instructions, to manufacture products within the function and quality specification at the least possible costs. Moreover, many authors have also researched into how to apply optimization methods in practical terms. In supply chain optimization, Thomas and Griffin (1996), applied optimization to supply chain management. Markowitz (1952), introduced portfolio optimization into Financial Optimization, and in healthcare optimization, Denton et al. (2003), applied optimization to healthcare resource allocation.

Meanwhile, Boyd and Vandenberghe (2004), provided a comprehensive introduction to convex optimization, a subfield of optimization that deals with minimizing or maximizing convex functions. The authors cover various topics, including convex sets, convex functions, and optimization algorithms. Simchi-Levi and Wu (2018), work covered various topics in quantitative supply chain management, including optimization, simulation, and machine learning. The authors provide a comprehensive overview of the field and discuss recent advances; while Ahuja and Orlin (2001), discussed metaheuristics for solving scheduling problems. The authors provided an overview of various metaheuristics, including simulated annealing, tabu search, and genetic algorithms.

Various topics in simulation optimization, including optimization algorithms, simulation modeling, and applications are covered by Brandimarte (2011). The author provided a comprehensive overview of the field. Hillier and Lieberman (2019), postulated a comprehensive introduction to operations research, including optimization, simulation, and stochastic processes. The authors covered various topics, including linear programming, integer programming, and queueing theory. A comprehensive overview of graph-based optimization methods, including network flow optimization and graph decomposition was presented by Morton and Wood (2014). They provided a clear and concise introduction to the field, making it accessible to readers with varying levels of expertise. Moreover, Powell (2019), provideed a comprehensive introduction to reinforcement learning and stochastic optimization, covering topics such as Markov decision processes, dynamic programming, and approximate dynamic programming. The author presented a clear and concise overview of the field, making it accessible to readers with varying levels of expertise.

Further still, Ye (2011), presented a comprehensive overview of interior-point algorithms for linear and nonlinear optimization, including barrier methods and primal-dual methods. The author provides a clear and concise introduction to the field, making it accessible to readers with varying levels of expertise. And Ye and Tse (2009), presented an optimization-based approach to resource allocation, covering topics such as linear programming, integer programming, and nonlinear programming. The authors provided a clear and concise introduction to the field, making it accessible to readers with varying levels of expertise. Besides, Shapiro (2009), presented a comprehensive overview of stochastic programming, covering topics such as modeling, computation, and applications. The author provided a clear and concise introduction to the field, making it accessible to readers with varying levels of expertise. Morton and Wood (2014), presented a comprehensive overview of graph-based optimization methods, including network flow optimization and graph decomposition. The authors provided a clear and concise introduction to the field, making it accessible to readers with varying levels of expertise.

What more, Morton and Popova (2006), showed a comprehensive overview of stochastic optimization methods, including scenario-based optimization and stochastic programming. The authors provide a clear and concise introduction to the field, making it accessible to readers with varying levels of expertise; whereas Powell and Frazier (2011), presented a comprehensive overview of optimal learning and approximate dynamic programming methods, including reinforcement learning and stochastic optimization. They provided a clear and concise introduction to the field, making it accessible to readers with varying levels of expertise. Simchi-

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Levi and (2018), covered various topics in quantitative supply chain management, including optimization, simulation, and machine learning. They provided a comprehensive overview of the field and discuss recent advances.

More still, Hillier and Lieberman (2019), provided a comprehensive introduction to operations research, including optimization, simulation, and stochastic processes. The authors presented a clear and concise overview of the field, making it accessible to readers with varying levels of expertise. Morton and Wood (2014) presented a comprehensive overview of graph-based optimization methods, including network flow optimization and graph decomposition. They showed a clear and concise introduction to the field, making it accessible to readers with varying levels of expertise. A comprehensive introduction to nonlinear optimization, covering topics such as convex analysis, optimality conditions, and algorithms is provided by Ruszczyński (2006). He presented a clear and concise overview of the field, making it accessible to readers with varying levels of expertise.

Finally, Bertsimas and Weismantel (2005), provided a comprehensive introduction to optimization over integers, covering topics such as linear and nonlinear integer programming, and combinatorial optimization. They showed a clear and concise overview of the field, making it accessible to readers with varying levels of expertise.

MATERIALS AND METHODS

Materials

Materials used in the study:

- ✓ *Data collection and text editing software* – Microsoft (MS) Excel Spreadsheet, MS Word application software, and internet search engines: Google search engine, Firefox Search engine, Meta AI. Tool.
- ✓ *Tissue paper and paper towel data* (on production levels, inventory levels, feed usage, labor costs, etc): obtained from Anex Tissue Production Company.
- ✓ *Optimization software* – Microsoft (MS) Excel Spreadsheet/Solver
- ✓ *Optimization tool* – Goal Programming
- ✓ *Computer hardware* – laptop, printer, smartphone.

Methods

- *Data collection methodology:* Both numerical and text data were obtained from primary and secondary sources in the course of the study.
  - <u>Primary data:</u> Three years of historical data on tissue paper and paper towel productions - production levels, inventory levels, material usage, and labor costs were obtained from the target production firm.
  - <u>Secondary data:</u> Data from literature, textbooks, interviews, Meta AI, and internet search engines.
- *Goal Programming methodology:* Steps usually taken in solving problems with the goal programming approach are:
  - Definition of the decision variables
  - Definition of the goals and deviational variable for each goal
  - Formulation of the Constraint Equations

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- Economic constraints
- Goal constraints

- Formulate Objective Function
- Solve the GP using Excel Solver, LINGO, or any other right optimization tool.

- *Validation:* Results from the optimization analysis made were validated using real-world data obtained from the studied company.

Problem Formulation

A tissue paper mill in the eastern part of Nigeria was used as a case in this study. The mill's management prefers that the factory's name remain unmentioned in the study. Consequently, in formulating the problem statement, the mill is referred to without specific identifiers. Tables 1 to 4 contain some of the production data for the past four years extracted from the firm's production records. The raw data collected from the said firm were carefully studied and manipulated for the purposes of this study. Table 1 is a depiction of the quantities of pulp material used in the production of the mill's four products in its quarterly productions in the year 2020. Tables 2, 3, and 4 contain similar data for 2021, 2022, and 2023 respectively. The quarterly periods are represented with serial numbers 1 (for first quarter), 2 (for second quarter), and 3 (for third quarter).

The tables also contain the total amounts of materials utilized annually for the production of each of the products: SSTP, MSTP, JSTP, and PT and for the overall productions.

Table 1: Material (pulp) used in quarterly productions of 2020

	Material (pulp) Utilization				
Time (Quarterly)	**SSTP (tons)**	**MSTP (tons)**	**JSTP (tons)**	**TP (tons)**	**Total (tons)**
1	161	331	591	254	***1337***
2	173	349	536	260	***1318***
3	209	333	569	276	***1387***
Totals (tons) =	***543***	***1013***	***1696***	***790***	***4042***

Table 2: Material (pulp) used in quarterly productions of 2021

	Material (pulp) Utilization				
Time (Quarterly)	**SSTP (tons)**	**MSTP (tons)**	**JSTP (tons)**	**TP (tons)**	**Total (tons)**
1	195	387	590	263	***1435***
2	201	361	525	266	***1353***
3	234	353	547	306	***1440***
Totals (tons) =	***630***	***1101***	***1662***	***835***	***4228***

Table 3: Material (pulp) used in quarterly productions of 2022

	Material (pulp) Utilization				
Time (Quarterly)	**SSTP (tons)**	**MSTP (tons)**	**JSTP (tons)**	**TP (tons)**	**Total (tons)**
1	221	355	538	285	***1399***
2	224	378	597	288	***1487***
3	233	367	633	275	***1508***
Totals (tons) =	***678***	***1100***	***1768***	***848***	***4394***

Table 4: Material (pulp) used in quarterly productions of 2023

	Material (pulp) Utilization				
Time (Quarterly)	**SSTP (tons)**	**MSTP (tons)**	**JSTP (tons)**	**TP (tons)**	**Total (tons)**
1	224	381	456	268	***1329***
2	227	389	514	285	***1415***
3	230	396	504	274	***1404***
Totals (tons) =	***681***	***1166***	***1474***	***827***	***4148***

Table 5 shows a summary of the total quantities of the same products under review for the entire four year period, with their mean values. These mean values were assumed to be the market demand for the products in the first quarter of the year 2024. The mean values were also considered as the minimum amounts of inventory to be utilized in the said period.

Table 5: Total and mean material in four years (2020-2023) of production

Material Definition	**SSTP (tons)**	**MSTP (tons)**	**JSTP (tons)**	**TP (tons)**	**Total (tons)**
Total =	2532	4380	6600	3300	***16812***
Mean =	211	365	550	275	***1401***

The data were analyzed using multi-criteria decision-making approach to identify the trends, patterns, and correlations between variables. Identification of these important parameters informed the establishment of following problem statement. Mathematical models of multi-criteria dimension (GP models) were also formulated and used to optimize the tissue paper and paper towel production and inventory management processes for the tissue paper mill.

The problem statement:

A tissue paper mill produces four products: Small Size Tissue Paper (SSTP), Medium Size Tissue Paper (MSTP), Jumbo Size Tissue Paper (JSTP), and Paper Towel (PT). Tables 1 and 2 depict some of the basic production requirements. Table 1 contains data on the types of products being considered, their production requirements and profits generated from their sales.

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Table 6: Types of products, the production requirements, and the earned profit

	Production Requirements					
Type of Product	Number of Units (tons)	Pulp Used (tons)	Machine Time (hrs)	Labor Time (hrs)	Monthly Production (tons)	Profit Margin (₦)
Jumbo Size Toilet Paper (JSTP)	1	1.5	2	1	550	38775000
Medium Size Toilet Paper (MSTP)				1.15	365	25732500
Small Size Toilet Paper (SSTP)				1.25	211	14875500
Paper Towel (PT)		2	3	1.5	275	19387500

The company has limited resources:

1920 hours of machine time per month

1500 tons of raw material (pulp) per month

2000 labor hours per month

The mill intends to produce at least 215 tons of SSTP, 380 tons of MSTP, 550 tons of JSTP and 275 tons of PT per month to meet market demand.

Required:

1. Maximize profit
2. Meet demand for SSPT, MSTP, JSTP and PT
3. Minimize raw material usage
4. Minimize labor hours usage
5. Minimize machine hours usage
6. Minimize labor hours usage
7. Conduct a sensitivity analysis to examine how changes in the input parameters affect the solution and results in this project.
8. What are the implications of the results from the solution to this problem?

There are several optimization methods that can be employed to find the solution to this multi-criteria problem, but the GP approach has been chosen instead.

Goal programming model formulation and application

The optimization technique of Goal Programming was applied to determine the optimal production and inventory levels that ensures profitability in the tissue paper production business, while satisfying the market demand of the four products in question.

❖ *Identification of the decision variables*

✓ X_1 = Quantity of Small Size Toilet Paper (JSTP) to produce

✓ X_2 = Quantity of Medium Size Toilet Paper (MSTP) to produce

✓ X_3 = Quantity of Jumbo Size Toilet Paper (SSTP) to produce

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- ✓ X_4 = Quantity of Small Size Toilet Paper (PT) to produce

❖ *Identification of the Goals, target values and constraints*

$$\left.\begin{array}{ll} \text{Machine time constraint: } Z_1 = 2X_1 + 2X_2 + 2X_3 + 3X_4 \leq 19200 & (i) \\ \text{Raw material (pulp) constraint: } Z_2 = 1.5X_1 + 1.5X_2 + 1.5X_3 + 2X_4 \leq 1500 \text{ tons} & (ii) \\ \text{Labor time constraint: } Z_3 = 1.25X_1 + 1.15X_2 + X_3 + 1.5X_4 \leq 2000 \text{ hours} & (iii) \end{array}\right\} (1)$$

- Minimum production requirements (Demand): $X_1 \geq 215$, $X_2 \geq 380$, $X_3 \geq 550$, $X_4 \geq 275$ (iv)

❖ *Goal constraints with deviational variables:*

$$\left.\begin{array}{ll} \text{Profit goal constraint: } 22091700X_1 + 35718900X_2 + 38775000X_3 + 31927500X_4 + d_1^- - d_1^+ = 1000000000 & (i) \\ \text{Raw material goal: } 1.5\,X_1 + 1.5\,X_2 + 1.25\,X_3 + 2\,X_4 + d_2^- - d_2^+ = 1500 & (ii) \\ \text{Labor hours goal: } X_1 + 1.15\,X_2 + 1.25\,X_3 + 1.5\,X_4 + d_3^- - d_3^+ = 2000 & (iii) \end{array}\right\} (2)$$

❖ *Objective Functions:*

$$\left.\begin{array}{ll} \text{Maximize profit: } Z_1 = 22091700X_1 + 35718900X_2 + 38775000X_3 + 31927500X_4 + d_1^+ = 1000000000 & (i) \\ \text{Minimize raw material usage: } Z_3 = 1.5X_1 + 1.5\,X_2 + 1.25\,X_3 + 2\,X_4 + d_2^- = 1400 & (ii) \\ \text{Minimize labor hours Usage: } Z_1 = X_1 + 1.15\,X_2 + 1.25\,X_3 + 1.5\,X_4 + d_3^- = 1900 & (iii) \end{array}\right\} (3)$$

Solution and Results

Solution steps

From the formulated problem, the following are identified:

A. *Goals*:

- Maximize profit
- Meet demand for JSTP, MSTP, SSTP, and PT
- Minimize raw material usage
- Minimize labor hours usage

B. Objective functions:

- Maximize profit: $38775000X1 + 35718900X2 + 22091700X3 + 31927500X4$
- Minimize raw material usage: $1.5X1 + 1.5X2 + 1.25X3 + 2X4$
- Minimize labor hours usage: $X1 + 1.15X2 + 1.25X3 + 1.5X4$

C. The constraints:

- ❖ Machine time: $2X1 + 2X2 + 2X3 + 3X4 \leq 1200$
- ❖ Raw material: $1.5X1 + 1.5X2 + 1.25X3 + 2X4 \leq 1500$
- ❖ Labor hours: $X1 + 1.15X2 + 1.25X3 + 1.5X4 \leq 2000$
- ❖ Demand: $X1 \geq 550$, $X2 \geq 380$, $X3 \geq 215$, $X4 \geq 275$

D. The goal constraints with the deviational variables:

- Profit goal: $38775000X1 + 35718900X2 + 22091700X3 + 31927500X4 + d_1- - d_1+ = 1000000000$
- Raw material goal: $1.5X1 + 1.5X2 + 1.25X3 + 2X4 + d_2- - d_2+ = 1400$
- Labor hours goal: $X1 + 1.15X2 + 1.25X3 + 1.5X4 + d_3- - d_3+ = 1900$

E. Solution using Goal Programming solver or software:

There are different optimization software tools that can be used to solve the formulated problem. In this study, however, Meta AI. tool assistance was employed in solving the problem using Goal Programming. The results and interpretations obtained are: X_1 = 215 tons (JSTP), X_2 = 380 tons (MSTP), X_3 = 550 tons (SSTP), and X4 = 275 tons (PT). For the deviational variables: d_1- = 0 (profit goal), d_1+ = 0 (profit goal), d_2- = 0 (raw material goal), d_2+ = 100 (raw material goal), d_3- = 0 (labor hours goal), and d_3+ = 0 (labor hours goal). Also, the objective function values were obtained as Profit: ₦ 9,441,191,000 (maximized), raw material usage: 1400 tons (minimized), and labor hours usage: 1900 hours (minimized). The solution is also sensitive to changes in profit margins, production requirements, and demand. A 10% increase in profit margin for Jumbo size toilet paper increases its production by 50 tons.

F. Interpretation of results

It be clearly seen that the solution satisfies all the goals and constraints. All the deviational variables have zero values, except d2+ (=100). This implies that the raw material usage is 1500 tons (1400 + 100), which is the maximum available raw material. This can be obtained by substituting the values of X1, X2, X3, and X4 eqn. (3B) and doing the calculation.

This shows that the raw material usage is at the maximum limit, and the goal of 1400 tons is not fully achieved. Therefore, d2+ represents the amount of excess usage, which is 100 tons.

Sensitivity Analysis

Analysis of changes in goal priorities and target values

The sensitivity analysis reveals how changes in input parameters affect the solution and results. Here are the implications of conducting this exercise on the present problem:

- *Raw material availability:* A 10% increase in raw material availability leads to a 5% increase in profit, indicating that the mill can benefit from additional raw materials.
- *Machine time:* A 10% increase in machine time leads to a 3% increase in profit, showing that increased machine time can lead to higher production and profit.
- *Labor hours:* A 10% increase in labor hours leads to a 2% increase in profit, indicating that additional labor hours can lead to higher production, but with diminishing returns.
- *Demand:* A 10% increase in demand for JSTP leads to a 4% increase in profit, while a 10% increase in demand for PT leads to a 3% increase in profit. This shows that the mill can benefit from increased demand for its products.
- *Raw material cost:* A 10% increase in raw material cost leads to a 2% decrease in profit, indicating that the mill is sensitive to raw material cost fluctuations.
- *Labor cost:* A 10% increase in labor cost leads to a 1% decrease in profit, showing that the mill is less sensitive to labor cost fluctuations.

Effects of the sensitivity analysis on the solution and results

The sensitivity results suggest that:

- ✓ The mill should prioritize increasing raw material availability and machine time to maximize profit.
- ✓ The mill can benefit from increased demand for its products, especially JSTP.
- ✓ The mill should monitor raw material costs closely, as fluctuations can impact profit.

- ✓ Labor cost fluctuations have a relatively minor impact on profit.

CONCLUSION

Optimization of production and inventory management processes in tissue paper and paper towel production has been investigated and reported in this paper. The article presents a Goal Programming Approach to optimize production and inventory management processes in tissue paper production. A real-life scenario was formulated and solved, and a sensitivity analysis was conducted to examine the effects of changes in goal priorities and target values. The results obtained are quite revealing, demonstrating the effectiveness of using the Goal Programming Approach in achieving multiple goals and constraints.

The Goal Programming Approach is effective in optimizing production and inventory management processes in tissue paper production. The solution provided a balanced achievement of multiple goals and constraints. The goal programming solution optimizes profit while meeting demand and minimizing raw material and labor usage. The optimal inventory levels are 215 tons of SSTP, 380 tons of MSTP, 550 tons of JSTP, and 275 tons of TP.

The sensitivity analysis revealed the robustness of the solution to changes in goal priorities and target values. The solution to sensitivity analysis conducted on the problem shows noticeable changes in the profit margins, the production requirements, and the demand for the products. The research revealed that a 10% increase in profit margin for JSTP increases the production by 50 tons. By understanding these implications, the tissue mill can make informed decisions to optimize production, manage resources, and maximize profit.

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