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Integrating Possibilistic Programming and Throughput Accounting for Return Optimization of Aggregate Production Planning

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Abstract
This paper presents an integrated approach to aggregate production planning (APP) that combines possibilistic linear programming (PLP) with the throughput accounting system for profit maximization. APP involves making strategic decisions on production levels, inventory management, and resource allocation to meet customer demand while minimizing costs and maximizing profitability. However, the inherent uncertainties and complexities of real-world production environments pose significant challenges to traditional planning models. To address these challenges, this paper proposes the integration of PLP with fuzzy goal programing and the throughput accounting system at the very end, using data received from Rich Pharmaceuticals Ltd, the study's findings were derived using Lingo version 18 software (RPL). The model incorporates possibility distributions of input parameters, allowing decision-makers to consider the uncertainties and imprecisions in demand forecasts, production costs, and capacity constraints. By maximizing profit while considering risk tolerance, it also enables more realistic and reliable production planning decisions

Key Words: Aggregate production planning, fuzzy demands, capacity utilization, Decision maker, throughput accounting

1. INTRODUCTION
Production planning, which aims to effectively organize and coordinate all production processes in such a manner that it meets the objectives of the organizations, is one of the most alluring and crucial topics in manufacturing systems. The key elements of production planning involve figuring out the best output, inventory levels, and other crucial production factors for coping with demand volatility during a specified planning period (Ramezanian, et. Al. 2012).
Aggregate production planning (APP) is a medium-term production decision in a manufacturing organization that establishes the production rate, inventory level, amount of subcontractors, and workforce level in a particular time according to a number of constraints. "Aggregate" refers to the preparation done for two or more manufacturing categories. Determining output levels across all categories to meet current, specific demands is the goal of aggregate production planning. APP governs the best way to meet forecast demand in the intermediate future, often from 6 to 24 months ahead, by adjusting regular and overtime production rates, inventory levels, labor levels, subcontracting and backordering rates, and other controllable variables (Wang et al., 2005). The primary inputs of APP are market demands and the manufacturing plan to meet those expectations. (Leung *et al*., 2003).

2. PRIOR WORKS' LITERATURE
The APP literature has been examined in three primary headings: traditional, uncertainty-based, and multi-objective. Saad (1982) categorizes conventional decision models into six categories for solving APP issues. However, the goals and model inputs when any of these APP models are used generally are assumed to be deterministic/crisp, but the linear programming (LP) method is the most acceptable

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presently. According to Fung et al. (2003), an APP is a strategy for figuring out the necessary levels of labor, inventory, and production to meet all market demands. Junior and Filho (2012) reviewed the works on production planning and control for remanufacturing. Karmarkar and Rajaram (2012) discussed a rivalry version of APP model with capacity constraints. In real-world APP problems, input data or related parameters, such as market demand, available resources and capacity, and germane operating costs, frequently are imprecise/fuzzy owing to some information being inadequate or unobtainable; Thus, the Fuzzy Aggregate Production Planning (FAPP) is enabled.

Fuzzy mathematics programming has since evolved into a number of fuzzy optimization techniques for resolving APP problems. Currently, fuzzy techniques are often efficient in the area of decision making. Essentially every type of decision-making, including multi-objective, multi-person, and multi-stage decision-making, has used fuzzy methodologies (Tamiz,1996). Additionally, applications of fuzzy theory in management, business, and operational research are included in other studies related to fuzzy decision making (Zimmermann, 1991).

In order to tackle multi-product APP choice problems in a fuzzy environment, Wang and Liang (2004a) more recently created a fuzzy multi-objective linear programming model using the piecewise linear membership function. The model can yield an effective compromise solution and the decision maker’s overall levels of satisfaction. Additional research on fuzzy APP problem solving may be found in Wang and Fang (1997), Tang et al. (2000, 2003), Wang and Fang (2001). To optimize profit, minimize repair costs, and maximize machinery usage, Leung and Chan (2009) created a preemptive goal programming approach for the APP problem.

When there are multiple objectives and goals that conflict, decision-makers and production managers must make difficult decisions about which objectives and goals should take precedence. The goal programming (GP) method may be suggested as a workable and useful solution to address this problem. Numerous multi-objective production planning problems have been solved using fuzzy mathematical programming, particularly the fuzzy goal programming (FGP) method.

Management accounting must increasingly rely on advanced analytic tools like technique of goal programing to assist it carry out duties as the operational environment of firms becomes more complicated (ACCA, 2016). Performance of APP models is often measured by revenue, cost, or profit. However according to Goldratt (1990), companies should assess their success by throughput rather than using cost as a metric. The Theory of Constraints is the name of this Goldratt recommendation (TOC). Three appropriate measures—throughput, inventory, and operating expense—are suggested to be used as benchmarks for an organization based on the TOC concept. The main international metrics, such as net profit and return on investment, can be linked to these three metrics. Moreover, they are also capable of being converted into productivity and inventory turnover. These organizational management tools are highly beneficial. As a result, these three metrics are used to create and assess APP models.

Surprisingly, just one study group has documented this novel accounting theory's lower performance when compared to mainstream applications, despite the fact that it has been accepted to be a part of alternative accounting procedures (Lea & Fredendall, 2002; Lea & Min, 2003; Lea, 2007). In fact, Hilmola & Lättilä's (2008) research indicated that profits might potentially rise relative to the initial scenario, although this necessitates a significant degree of cycle time variation together with effort in process buffers in front of resource constraints.

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Vol. 12 Issue 06, June-2023

Neither cost accounting nor TA should be completely abandoned. Throughput accounting (TA) is not always a direct assault on cost accounting. Yet, TA offers a different perspective on accounting metrics, a different way to address problems, and a different way to operate the business at a far greater level of success and profitability. If you will, the accounting standards are updated by TA to better reflect the state of company today.

2.1 Definitions for the Financial Aspects of the Theory of Constraints

There are three main performance measures used by throughput accounting. These measurements are a condensed technique that breaks down accounting into three straightforward measures:

Throughput(TP): The rate at which inventory is changed into sales. If you make lots of products and put them in a warehouse, that is not throughput, *it's inventory.* The products, or services, only count as throughput when they are sold to the customer and new money comes back into the business organization.

Investment/Inventory(IN): the money that the system used to convert inventory to throughput. Formerly known as just inventory, this is now most commonly known as inventory/investment. This broader definition includes buildings, machines, and any other equipment used to produce things that you intend to sell, with the knowledge that any or all of these assets may ultimately be converted into cash.

Operating Expense(OE): the entire sum of money used to produce throughput. All money spent that does not go under one of the other two categories, such as rent, electrical, phone, benefits, and salary, falls under this category. The sum total of all company expenses, excluding totally variable expenses. Expenses usually categorized here are direct and indirect labor, depreciation, supplies, interest payments, and overhead. all costs that are not totally variable are lumped together into the Operating Expenses category.

The Financial Aspects of the Theory of Constraints

In other to cover an aspect of the theory of constraints that deals directly with the work of the accountant, there is an area and it will be referred to as throughput accounting.

The use of profitability analysis at the system level rather than gross margin analysis at the product level is a fundamental idea of throughput accounting. In a conventional cost accounting system, expenses from every stage of manufacturing are tallied and variously assigned to certain goods. This results in a gross margin that is deducted from product pricing and used to assess whether a product is profitable enough to create. At the product level, throughput accounting almost ignores gross margin analysis. The manufacturing process is instead seen as a single system whose total profitability must be optimized.

The amount of money spent on a system to increase its capacity is known as investment, and throughput accounting lays a lot of attention on it. The following formulae are used by throughput accounting in conjunction with throughput, entirely variable costs, and operational expenditures for a variety of accounting decisions:

- Throughput $(TP) =$ Revenue $(R) -$ Totally Variable Expenses(TVE)
- Net Profit(NP) $=$ Throughput(TP) $-$ Operating Expenses(OE)
- Return on Investment (RoI) $=$ Net Profit / Investment
- Productivity(Pr) $=$ Throughput / Operational Expense
- Inventory Turns(IT) $=$ Throughput / Inventory Value

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Goldratt's strategy demanded a shift in emphasis in order to redefine accounting principles. The goal for managers should be to increase throughput while lowering operating costs and inventories. The latter two, however, must be maintained at a certain minimum level to prevent a decrease in throughput, thus there is very little room for reduction in those two areas. These might be viewed as restrictions on the suggested model. The weakest link in the system chain is a constraint (Dettemer, 1997). There are three different kinds of constraints: material, resource, and policy (paradigm) (Woeppel, 2001). Moreover, financial limitations are crucial for real-world issues (Fung, et al., 2003).

3. METHOD AND PROCEDURE

Assumptions and Problem Definition

Following the findings of a real-world case study, the following presumptions are made for the mathematical model of the suggested APP problem.

- Production planning is done in a time horizon of T time periods ($\forall\ t = 1,2, \dots, T$).
- There is a Batch production system capable of producing all kinds of N types of products.
- Market demand can be fulfilled or backordered, however no backorder in the last t is allowed.
- There are two working shifts; Regular time production and Over time production
- A warehouse is allowed for holding final products.
- In advance, the holding cost of inventories are determined and well known.
- The workforce accommodates various skill levels ($k - levels$).
- Workers salary is independent of unit production cost.
- At each period T, Production quantity is considered more of the safety stock for finished products.
- Hiring and firing of Manpower based on product demand is eligible and there is an allowable limit.
- In each period T, the shortage of production is recovered by overtime production in each shift.
- In each period T, the nominal and actual capacity of production machines is not the same due to unforeseen failures. So, the actual capacity of production is usually reduced by a fixed failure percentage.
- If an unforeseen failure occurs during a shift the repair process is completed in the next. This may stop, reduce, or decrease the production rate during maintenance actions
- The impreciseness and uncertainty of real-world problem and confliction of different objectives are modeled using fuzzy goals.
- Linear membership functions are defined for fuzzy goals.
- FGP used to solve the problem.

3.1 Parameters, Indices, Decision Variables and Notations

They are as stated in Tables 1 to 3

Table 1: Set of indices

t	Number of periods in the planning horizon; $t = 1,2, \dots, T$
i	Number of product types; $i = 1,2, \dots, I$
m	Raw material type; $m = 1,2, \dots, M$
q	Types of shifts; $q \in 1,2$
w	Types of warehouse; $w = 1,2, \dots, W$
k	Skill levels of workers; $k = 1,2, \dots, K$
j	Number of objective Functions; $j = 1,2,3$

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Table 2: Notation for parameters

Parameter	Definition
Pw_i	Fraction of the Product i wasted during production in period t
Iw_i	Fraction of the Product i wasting in inventory in period t
CoO_{iq}	Cost of Overhead(fixed) Production; for product i in shift q
DoP_{it}	Demand of product i in period t
CoB_{it}	Cost of Backordering; for product i in period t
SRe_i	Sales Revenue for product i (₦/unit)
E_t	cumulative investment in tools and equipment in period t (currency unit)
PrT_t	Process time of product i in period t
BUL_t	The Budget upper limit in period t
AsP_{it}	Allowable shortage of product i in period t
$\overline{AMW_t}$	Available Maximum workforce in period t
$\underline{AMW_t}$	Available Minimum workforce in period t
WaO	workforce that are available for overtime (in percentage)
CoW_{kt}	Cost of workforce of level k in period t
CoH_{kt}	Cost of Hiring workforce of level k in period t
CoF_{kt}	Cost of firing workforce of level k in period t
CoM_{mtw}	Cost for raw material type m in period t in warehouse w
CoR_{mtw}	Holding cost for raw material type m in period t in warehouse w
$CohP_{itw}$	Holding cost of unit of product i in period t
FoW_t	fraction of the workforce variation in period t
MH_{it}	Machine hours needed to produce unit of product i in period t
MCi_t	Machine capacity that is lost due to **interruption** in period t (in percentage)
MCr_t	Machine capacity that is lost due to **repairs** in period t (in percentage)
MmC_{qt}	The maximum of machine capacity that is available in shift q in period t
MCo	The machine capacity that is available for overtime (in percentage)
ArT_{it}	Available Regular time in both shifts in period t
uMR_{im}	The units of type m raw material required to produce unit of product i
SSP_i	product i safety stock
SSR_m	Raw material type m safety stock
$\overline{M}SW_m$	The maximum available space of warehouse w
$WhCR_{wmt}$	The capacity of warehouse w for storage of raw-material type m in period t
$WhCP_{wit}$	The capacity of warehouse w for storage of finished-product i in period t
$\mathcal{D}d_i$	The Due date of product i
$\mathcal{B}_i$	Batch size of product i
DrF_i	Finished product i Defect rate
PC	Production Capacity

Table 3: **Decision variable** Notation

Decision variable	Definition
X_{iqt}	Number of product i produced in shift q of period t
$X\beta_{iqt}$	Number batches of product i produced in shift q of period t
B_{it}	Backorder level of product i in period t
XW_{kt}	Number of available workers of level k in period t
XH_{kt}	Number of hired workers of level k in period t
XF_{kt}	Number of fired workers of level k in period t
XR_{mtw}	Inventory level of raw material type m at the end of period t in warehouse w
XP_{itw}	Inventory level of finished-product i in period t in warehouse w

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Vol. 12 Issue 06, June-2023

3.2 Model Formulation

Total income less the cost of the materials you purchased is your throughput (TP). Equation (1) can be used to numerically express the throughput (TP).

$$TP = \sum_{i=1}^{I}\sum_{t=1}^{T} SRe_i DoP_{it} - \sum_{i=1}^{I}\sum_{t=1}^{T} SRe_i B_{it} - \sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T} CoM_{mwt} X_{iqt} \tag{1}$$

The first two terms reflect total sales revenue based on total demands and lost sales at the conclusion of the planned horizon. The last term denotes the cost of materials, which includes the cost of materials needed for both regular and overtime production.

The definition of inventory is "the entire money the system invests," which includes the money spent on all assets (such as structures, machinery, and fixtures) as well as on raw materials and parts (Woeppel, 2001). TOC inventory differs from traditional inventory in that it encompasses all assets in addition to raw materials, work-in-progress, and finished goods.

$$IN = \frac{1}{T}\left[\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T} CoR_{mwt} XR_{mwt} + \sum_{t=1}^{T} E_t\right] \tag{2}$$

The APP can take assets like small machines, material handling equipment and other instruments into account. Strategic or long-range planning takes into account structures and huge machineries.
The capacity of a machine or system can be increased and a bottleneck reduced by investing in tools and equipment. Equation (2) represents the typical inventory investment (IN) in terms of TOC. Whereas the second term indicates the investment in tools and equipment, the first term represents the investment in raw materials.

$$\begin{aligned} \mathrm{OE} = &\sum_{k=1}^{K}\sum_{t=1}^{T} CoW_{kt} XW_{kt} + \sum_{k=1}^{K}\sum_{t=1}^{T} CoH_{kt} XH_{kt} + \sum_{k=1}^{K}\sum_{t=1}^{T} CoF_{kt} XF_{kt} + \sum_{i=1}^{I}\sum_{w=1}^{W}\sum_{t=1}^{T} CohP_{iwt} XP_{iwt} \\ &+ \sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T} CoR_{mwt} XR_{mwt} + \sum_{i=1}^{I}\sum_{t=1}^{T} CoB_{it} B_{it} + \sum_{i=1}^{I}\sum_{q\in\{1,2\}}\sum_{t=1}^{T} CoO_{iq} X_{iqt} \end{aligned} \tag{3}$$

The entire amount of money needed to convert inventory into throughput is referred to as operating expenses. All direct and indirect payroll expenses, purchases, overhead and time related expenses are involved. Equation (3) represents operating expense (OE). It covers all labour, overtime, holding expenses for inventory, backordering and fixed overhead costs.

3.3 Aggregate Production Planning Considering Throughput Accounting

Often, the objective function of APP problems is chosen to be the revenue, cost, or profit function. The profit function is the most desirable of these objective functions (Phruksaphanrat et al., 2006). Thus, the objective function of the suggested APP model is the Net Profit (NP). Throughput (TP) minus Operational expenses(OE) equals Net Profit (NP). The profit function includes two TOC metrics. Inventory is the final factor, which should also be taken into account. According to TOC, inventory refers to all financial investments made by the system, including those made in tools and equipment. It is incorporated into the model as constraints.

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 06, June-2023

Maximize Net Profit (NP)

$$Z = \sum_{i=1}^{I}\sum_{t=1}^{T} SRe_i DoP_{it} - \sum_{i=1}^{I}\sum_{t=1}^{T} SRe_i B_{it} - \sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T} CoM_{mwt} X_{iqt} - \left[\sum_{k=1}^{K}\sum_{t=1}^{T} CoW_{kt} XW_{kt} + \sum_{k=1}^{K}\sum_{t=1}^{T} CoH_{kt} XH_{kt} + \sum_{k=1}^{K}\sum_{t=1}^{T} CoF_{kt} XF_{kt} + \sum_{i=1}^{I}\sum_{w=1}^{W}\sum_{t=1}^{T} CohP_{iwt} XP_{iwt} + \sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T} CoR_{mwt} XR_{mwt} + \sum_{i=1}^{I}\sum_{t=1}^{T} CoB_{it} B_{lt} + \sum_{i=1}^{I}\sum_{q\in\{1,2\}}\sum_{t=1}^{T} CoO_{iq} X_{iqt}\right] \quad (4)$$

Constraints

The Labor-force Constraints are considered as follows:

$$\sum_{k=1}^{K} XW_{kt} \le \overline{AMW}_t, \qquad \forall t \quad (5)$$

$$\sum_{k=1}^{K} XW_{kt} \ge \underline{AMW}_t, \qquad \forall t \quad (6)$$

$$XW_{kt} = XW_{k(t-1)} + XH_{kt} - XF_{kt}, \quad \forall k, \forall t, t > 1 \quad (7)$$

$$XW_{kt} - XW_{k(t-1)} \le FoW_t * XW_{kt}, \quad \forall k, \forall t, t > 1 \quad (8)$$

Constraints (5) attests that the total labor utilized during period t does not exceed the total workforce that is available. In a similar vein, (6) guarantees that in period t, the employed workforce exceeds the available minimum workforce. Set of Constraints (7) is a workforce level balance equation that assures that the workforce with skill level k available during a given period is equal to the workforce with the same skill level k during the previous period plus the change in workforce level during the current period. The change in workforce level in each planning period cannot be greater than a benchmark number of workers in the present period, according to constraint number seven.

Time Constraints

$$\sum_{i=1}^{I} PrT_{it} * X_{iqt} \le \sum_{k=1}^{K} ArT_{qt} * XW_{Kt}, \qquad \forall t, \; q = 1 \quad (9)$$

$$\sum_{i=1}^{I} PrT_{it} * X_{iqt} \le \sum_{k=1}^{K} ArT_{qt} * WaO * XW_{Kt}, \qquad \forall t, \; q = 2 \quad (10)$$

The relationships mentioned above make sure that each working shift's necessary production time is less than or equal to the available regular production time and overtime.

Inventory Constraints

$$XP_{iwt} = XP_{iw(t-1)} + \sum_{q\in\{1,2\}} X_{iqt} - B_{it} - DoP_{it}, \quad \forall i, \forall w, \quad t > 1 \quad (11)$$

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International Journal of Engineering Research & Technology (IJERT)
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Vol. 12 Issue 06, June-2023

$$XR_{mwt} = XR_{mw(t-1)} + \sum_{q\in\{1,2\}} X_{iq(t-1)} - uRM_{im}, \quad \forall i, \forall w, \quad t > 1 \tag{12}$$

$$SSR_m \leq \sum_{w\in W} XR_{mwt}, \quad \forall m, \forall t, \tag{13}$$

Constraints (11) ensures that the amount of finished product type I in period t in warehouse w is equal to the amount of finished product type I in period $t-1$ in warehouse w plus the quantity of produced finished goods type I in period t in both working shifts, less the amount of product type I in period t that is on backorder and the quantity of produced finished goods type I in period t in both working shifts. A set of limitations (12) assures that there is a balance between raw materials, and (13) guarantees that the safety stock of raw materials in warehouses is satisfied.

Production Constraint

$$SSP_i \leq \sum_{q\in\{1,2\}} X_{iqt}, \quad \forall i, \forall t, \tag{14}$$

$$DoP_{it} \leq \left(1 - \frac{DrF_i}{\beta_i}\right) * \sum_{q\in\{1,2\}} X_{iqt} + XP_{i(t-1)}, \quad \forall i, \forall t, \quad t > 1 \tag{15}$$

Set of constraints (14), which is written for all product types and all periods of planning, guarantee the satisfaction of safety stock of finished-products in working shifts. Set of constraints (15) represents the total production of non-defected final products plus the inventory of finished-product in previous period should be greater than or equal to demand of the finished-product in current period.

Machine capacity Constraints

$$\sum_{i=1}^{I} MH_{it} * X_{iqt} \leq \overline{M}mC_{qt} - MCi_t * \overline{M}mC_{qt}, \qquad \forall t, \ q = 1 \tag{16}$$

$$\sum_{i=1}^{I} MH_{it} * X_{iqt} \leq MCo * \overline{M}mC_{qt} - MCr_t * MCo * \overline{M}mC_{qt}, \qquad \forall t, \ q = 2 \tag{17}$$

Constraints (16) and (17) pledge that in regular time and overtime, the machine capacity is assured.

Warehouse Capacity Constraint

$$\sum_{w=1}^{W} XP_{iwt} \leq \sum_{w=1}^{W} WhcP_{wit}, \ \forall i, \forall t, \tag{18}$$

$$\sum_{m=1.}^{M} \sum_{w=1}^{W} XR_{mwt} \leq \sum_{w=1}^{W} \sum_{m=1}^{M} WhcR_{mwt}, \quad \forall t, \tag{19}$$

$$\sum_{w=1}^{W} WhcP_{wit} + \sum_{w=1}^{W} WhcR_{mwt} \leq \overline{M}SWh_m, \ \forall i, \forall t, \tag{20}$$

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ISSN: 2278-0181
Vol. 12 Issue 06, June-2023

The first two constraints (18) and (19) gives the restrictions of actual inventories of finished products and raw materials. While (20) guarantees that each warehouse at each period will not be able to allow storage capacity of products an raw materials beyond its maximum warehouse available space.

Backorder, Budget limit and Non-negativity Constraints

There is backorder obeying the following;

$$\sum_{w=1}^{W} B_{it} \leq \sum_{w=1}^{W} AsP_{it} * DoP_{it} \quad \forall i, \quad t \neq T \tag{21}$$

$$B_{iT} = 0, \qquad \forall i \tag{22}$$

$$OE \leq \sum_{t=1}^{T} BUL_t \tag{23}$$

$$X_{iqt}, X\beta_{iqt}, B_{it}, XR_{mtw}, XP_{iwt} \geq 0, \qquad \forall i, \forall q, \forall t, \forall m, \forall w \tag{24}$$

$$XL_{kt}, XH_{kt}, XF_{kt} \quad \geq 0, \qquad \forall t, \forall k, \forall l \tag{25}$$

Constraints (21) represent the backorder level at the end of period t cannot exceed the certain percentage of the demand which determines the upper limit of shortage. While (22) assure that there is no possibility for backordering at the end of time horizon or last period. A restriction on the available budget for each planning period is shown using (23), which ensures that the operating Cost (i.e., Eq. (3)) cannot go beyond the predetermined budget for the time horizon. (24) and (25) both present non-negativity requirements on decision variables.

3.4 Possibilistic Programming on APP Problem with Imprecise Costs

The Net-Profit APP decision problem that has already been looked at may be summarized as follows. Suppose that over a planning horizon of T, a corporation produces N various products to satisfy market demand. On a medium time horizon, the environmental coefficients and associated parameters are often uncertain. As a result, across the planning horizon, related operational expenses and labor are imprecise. When dealing with such ambiguous APP decision problems, assigning a set of precise values for the environmental coefficients and associated parameters is problematic. The Net Profit APP objective function (4) can be restated as:

$$\begin{aligned} Z = &\sum_{i=1}^{I}\sum_{t=1}^{T} SRe_i DoP_{it} - \sum_{i=1}^{I}\sum_{t=1}^{T} SRe_i B_{it} - \sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T} \widetilde{CoM}_{mwt} X_{iqt} - \Bigg[\sum_{k=1}^{K}\sum_{t=1}^{T} \widetilde{CoW}_{kt} XW_{kt} \\ &+ \sum_{k=1}^{K}\sum_{t=1}^{T} \widetilde{CoH}_{kt} XH_{kt} + \sum_{k=1}^{K}\sum_{t=1}^{T} \widetilde{CoF}_{kt} XF_{kt} + \sum_{i=1}^{I}\sum_{w=1}^{W}\sum_{t=1}^{T} \widetilde{CohP}_{iwt} XP_{iwt} + \\ &\sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T} \widetilde{CoR}_{mwt} XR_{mwt} + \sum_{i=1}^{I}\sum_{t=1}^{T} \widetilde{CoB}_{it} B_{lt} + \sum_{i=1}^{I}\sum_{q\in\{1,2\}}\sum_{t=1}^{T} \widetilde{CoO}_{iq} X_{iqt}\Bigg] \end{aligned} \tag{26}$$

This work uses Wang and Liang's (2005) Possibility Linear Programing (PLP) technique to solve the APP problem with uncertainty. Fortunately, possibility distribution offers a useful substitute for dealing with underlying confusing phenomena when assessing environmental coefficients and associated factors (Zadeh, 1978; Inuiguchi and Sakawa, 1996; Hsu and Wang, 2001). This is by adopting the triangular Fuzzy number (TFN) to the APP problem under Fuzzy operational expenses.

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 06, June-2023

TFNs are used in this study to represent cost-related fuzzy data. Assuming the TFN of cost is $\widetilde{Co_i} = (Co_i^p, Co_i^m, Co_i^o)$, in which Co_i^m is the most possible value that certainly belongs to the set of available data (with a membership value of 1 after it is normalized). The lower bound value Co_i^p is the most pessimistic value that has a small likelihood to belong to the set of available data (with a membership value of zero if normalized) and the upper bound value Co_i^o is the most optimistic value with a small likelihood to belong to the set of available values (with a membership value of zero if normalized). Let $\mu(\widetilde{Co_i})$ represent the arbitrary measurement of fuzzy cost in view of the Decision-maker, i.e. membership function, that defines the degree of x in the fuzzy space $\widetilde{Co_i}$ and figure 1 depicts the relationships of this function.

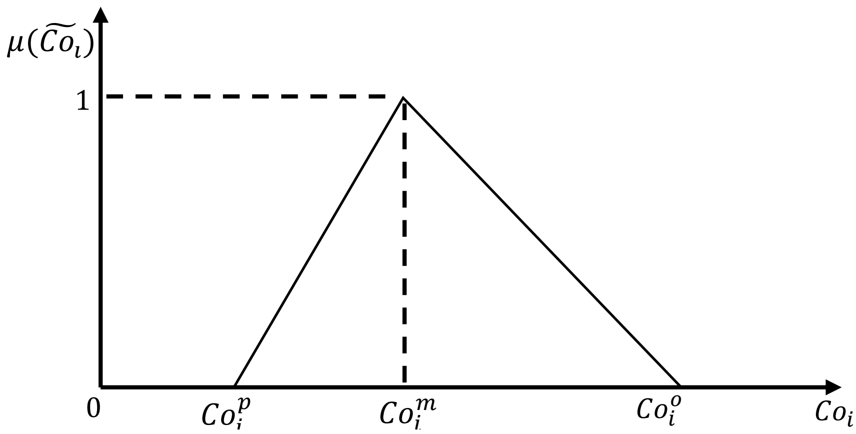

Fig. 1. A *Triangular distribution of the fuzzy Cost.*

Triangular possibility distributions may thus be used to model the imprecise data for the prior APP model, as seen below:

$$\widetilde{CoM}_{mwt} = \left(CoM_{mwt}^p, CoM_{mwt}^m, CoM_{mwt}^o\right) \quad \forall m, \forall w, \forall t$$

$$\widetilde{CoW}_{kt} = \left(CoW_{kt}^p, CoW_{kt}^m, CoW_{kt}^o\right) \quad \forall k, \forall t$$

$$\widetilde{CoH}_{kt} = \left(CoH_{kt}^p, CoH_{kt}^m, CoH_{kt}^o\right) \quad \forall k, \forall t$$

$$\widetilde{CoF}_{kt} = \left(CoF_{kt}^p, CoF_{kt}^m, CoF_{kt}^o\right) \quad \forall k, \forall t$$

$$\widetilde{CohP}_{iwt} = \left(CohP_{iwt}^p, CohP_{iwt}^m, CohP_{iwt}^o\right) \quad \forall i, \forall w, \forall t$$

$$\widetilde{CoB}_{it} = \left(CoB_{it}^p, CoB_{it}^m, CoB_{it}^o\right) \quad \forall i, \forall t$$

$$\widetilde{CoO}_{iq} = \left(CoP_{iq}^p, CoP_{iq}^m, CoP_{iq}^o\right) \quad \forall i, \forall q$$

$$\widetilde{CohR}_{iwt} = \left(CohR_{iwt}^p, CohR_{iwt}^m, CohR_{iwt}^o\right) \quad \forall i, \forall w, \forall t$$

3.4 Approach to Resolving the Imprecise Objective Function

The imprecise objective function of the Net-Profit Possibility APP programing model in the preceding section has a triangular possibility distribution. Geometrically, this imprecise objective is fully defined by three corner points: $(Z^p, 0), (Z^m, 1)$ and $(Z^o, 0)$. The imprecise objective can be maximized by pushing the three corner points towards the right. Because of the vertical coordinates of the critical points being fixed at either 1 or 0, the three horizontal coordinates are the only considerations. The new problem will be to solve;

$$\text{Maximize } (Z^p, Z^m, Z^o) \qquad (27),$$

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 06, June-2023

where (Z^p, Z^m, Z^o) is the vector of the objective functions Z^p, Z^m and Z^o. It is important to make a minor change in order to maintain the possibility distribution's triangular shape (normal and convex). Instead of concurrently maximizing these three objectives, the new approach will maximize Z^m, minimize $(Z^m - Z^p)$ and maximize $(Z^o - Z^m)$, where the first objective function Z^m, is the basis of the last two objective functions, which are actually relative measures from it (see Figure 2). The three new objectives also support the earlier claim that doing so would shift the triangular possibility distribution towards the right.

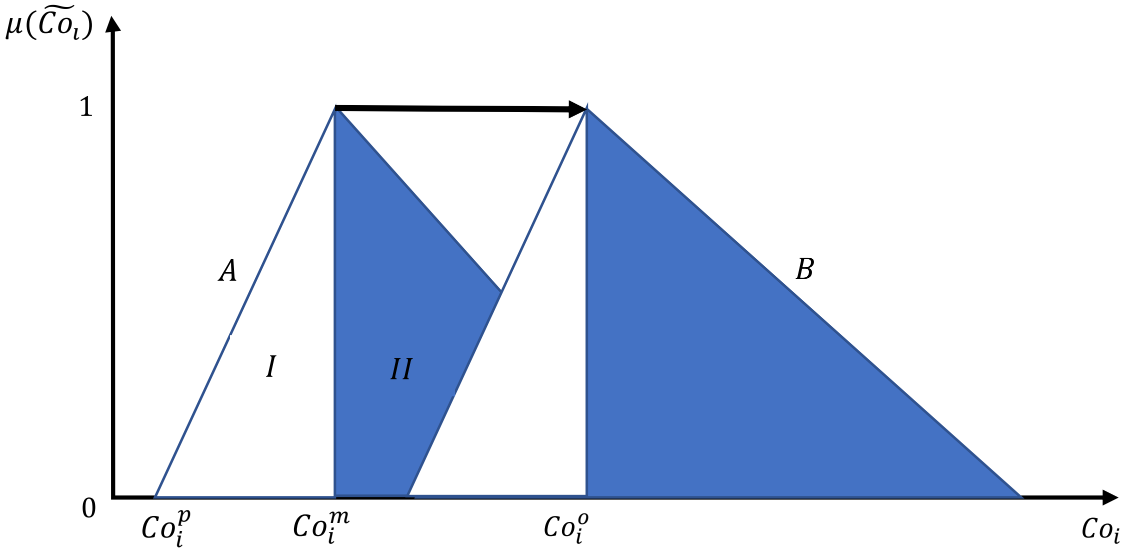

Fig. 2: The Approach to Maximize the Net Profit

This suggested approach equates to maximizing the most possible value of the imprecise profit (at the point of possibility degree = 1). At the same time, it has minimized the inferior side of the possibility distribution. This means minimizing the region (I), which in the perspective is similar to "the danger of receiving reduced profit." Also, this has increased "the chance of generating larger profit," which is similar to area (II) of the probability distribution. Similar to Figure 2, it would be preferred to have the possibility distribution of B against that of A. thus the auxiliary problem of equation (27) then result to three brand-new, precise objective functions as shown below;

$$Max\ Z_1 = Z^m$$

$$= \sum_{i=1}^{I}\sum_{t=1}^{T} SRe_i DoP_{it} - \sum_{i=1}^{I}\sum_{t=1}^{T} SRe_i B_{it} - \sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T} CoM_{mwt}^m X_{iqt} - \Bigg[\sum_{k=1}^{K}\sum_{t=1}^{T} CoW_{kt}^m XW_{kt} + \sum_{k=1}^{K}\sum_{t=1}^{T} CoH_{kt}^m XH_{kt} + \sum_{k=1}^{K}\sum_{t=1}^{T} CoF_{kt}^m XF_{kt} + \sum_{i=1}^{I}\sum_{w=1}^{W}\sum_{t=1}^{T} CohP_{iwt}^m XP_{iwt} + \sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T} CohR_{iwt}^m XR_{mwt} + \sum_{i=1}^{I}\sum_{t=1}^{T} CoB_{it}^m B_{it} + \sum_{i=1}^{I}\sum_{q\in\{1,2\}}\sum_{t=1}^{T} CoO_{iq}^m X_{iqt}\Bigg] \quad (28)$$

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 06, June-2023

$$Min\ Z_2 = (Z^m - Z^p)$$
$$= \sum_{i=1}^{I}\sum_{t=1}^{T} SRe_i DoP_{it} - \sum_{i=1}^{I}\sum_{t=1}^{T} SRe_i B_{it} - \sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T}(CoM_{mwt}^{m} - CoM_{mwt}^{p})X_{iqt} - \Bigg[\sum_{k=1}^{K}\sum_{t=1}^{T}(CoW_{kt}^{m} - CoW_{kt}^{p})XW_{kt} + \sum_{k=1}^{K}\sum_{t=1}^{T}(CoH_{kt}^{m} - CoH_{kt}^{p})XH_{kt} + \sum_{k=1}^{K}\sum_{t=1}^{T}(CoF_{kt}^{m} - CoF_{kt}^{p})XF_{kt} + \sum_{i=1}^{I}\sum_{w=1}^{W}\sum_{t=1}^{T}(CohP_{iwt}^{m} - CohP_{iwt}^{p})XP_{iwt} + \sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T}(CohR_{iwt}^{m} - CohR_{iwt}^{p})XR_{mwt} + \sum_{i=1}^{I}\sum_{t=1}^{T}(CoB_{it}^{m} - CohR_{iwt}^{p})B_{lt} + \sum_{i=1}^{I}\sum_{q\in\{1,2\}}\sum_{t=1}^{T}(CoP_{iq}^{m} - CoO_{iq}^{p})X_{iqt}\Bigg] \quad (29)$$

$$Max\ Z_3 = (Z^o - Z^m)$$
$$= \sum_{i=1}^{I}\sum_{t=1}^{T} SRe_i DoP_{it} - \sum_{i=1}^{I}\sum_{t=1}^{T} SRe_i B_{it} - \sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T}(CoM_{mwt}^{o} - CoM_{mwt}^{m})X_{iqt} - \Bigg[\sum_{k=1}^{K}\sum_{t=1}^{T}(CoW_{kt}^{o} - CoW_{kt}^{m})XW_{kt} + \sum_{k=1}^{K}\sum_{t=1}^{T}(CoH_{kt}^{o} - CoH_{kt}^{m})XH_{kt} + \sum_{k=1}^{K}\sum_{t=1}^{T}(CoF_{kt}^{o} - CoF_{kt}^{m})XF_{kt} + \sum_{i=1}^{I}\sum_{w=1}^{W}\sum_{t=1}^{T}(CohP_{iwt}^{o} - CohP_{iwt}^{m})XP_{iwt} + \sum_{m=1}^{M}\sum_{w=1}^{W}\sum_{t=1}^{T}(CohR_{iwt}^{o} - CohR_{iwt}^{m})XR_{mwt} + \sum_{i=1}^{I}\sum_{t=1}^{T}(CohR_{iwt}^{o} - CoB_{it}^{m})B_{lt} + \sum_{i=1}^{I}\sum_{q\in\{1,2\}}\sum_{t=1}^{T}(CoP_{iq}^{o} - CoO_{iq}^{m})X_{iqt}\Bigg] \quad (30)$$

Also, the fuzzy decision-making of Bellman and Zadeh (1970) and Zimmermann's fuzzy programming (1978) approach may be used to transform the auxiliary MOLP issue into an analogous single-goal LP problem. The three objective functions' Positive Ideal Solutions (PIS) and Negative Ideal Solutions (NIS) can be correspondingly described as follows.

$$Z_1^{PIS} = MaxZ^m;\ Z_1^{NIS} = MinZ^m$$
$$Z_2^{PIS} = Min(Z^m - Z^p);\ Z_2^{NIS} = Max(Z^m - Z^p)(v_j^*)$$
$$Z_3^{PIS} = Max(Z^o - Z^m);\ Z_3^{NIS} = Min(Z^o - Z^m)$$

The corresponding linear membership function for each objective function is defined (see figure 3) by;

$$\mu(Z_1(x)) = \begin{cases} 1 & Z_1(x) \le Z_1^{PIS}, \\ \dfrac{Z_1 - Z_1^{NIS}}{Z_1^{PIS} - Z_1^{NIS}} & Z_1^{NIS} \le Z_1(x) \le Z_1^{NIS}, \\ 0 & Z_1(x) \ge Z_1^{NIS}, \end{cases} \quad (31)$$

$$\mu(Z_2(x)) = \begin{cases} 1 & Z_2(x) \le Z_2^{PIS}, \\ \dfrac{Z_2^{NIS} - Z_2}{Z_2^{NIS} - Z_2^{PIS}} & Z_2^{PIS} \le Z_2(x) \le Z_2^{NIS}, \\ 0 & Z_2(x) \ge Z_2^{NIS}, \end{cases} \quad (32)$$

and $\mu(Z_1(x))$ and $\mu(Z_3(x))$ are similar.

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 06, June-2023

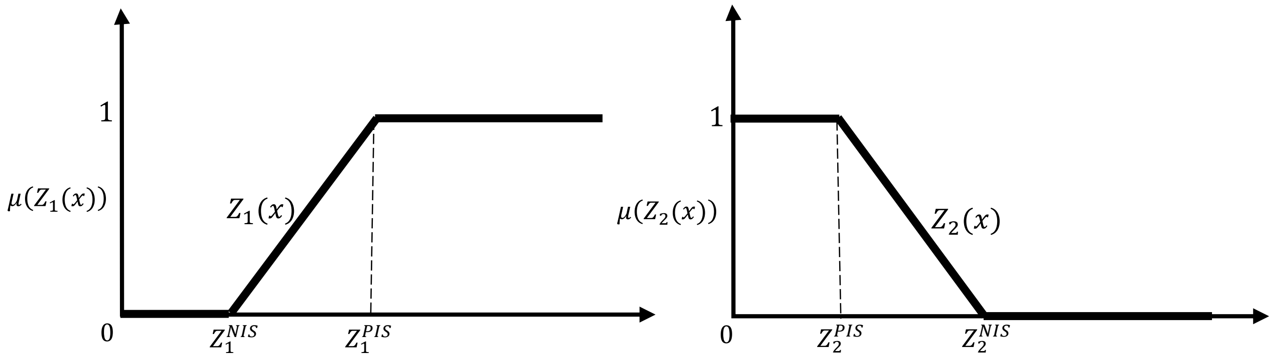

Figure 3: Linear Membership form

Lastly, the APP is solved following equivalent single-objective linear programming model. Hence, the associated FGP model with fuzzy cost for the Net-Profit APP problem (1)-(25) is formulate as follows:

$$\begin{gathered} \text{find} \quad x \\ Maximize \quad \mu(Z_k(x)) \\ \text{to satisfy;} \\ \mu(Z_1(x)) = \frac{Z_1 - Z_1^{NIS}}{Z_1^{PIS} - Z_1^{NIS}} \\ \mu(Z_2(x)) = \frac{Z_2^{NIS} - Z_2}{Z_2^{NIS} - Z_2^{PIS}} \\ \mu(Z_3(x)) = \frac{Z_3 - Z_3^{NIS}}{Z_3^{PIS} - Z_3^{NIS}} \\ \mu\left(Z_j(x)\right) \in [0,1], \;\; j = 1,2,3 \\ Constraints \; (5 \text{ to } 25) \\ x_i \geq 0, i = 1 \ldots\ldots n; j = 1,2,3 \end{gathered} \tag{33}$$

4. Model implementation

Case description

The case study of Rich Pharmaceuticals Limited(RPL) was utilized to show how useful the suggested methodology is. RPL is one of the leading producers of pharmaceuticals in Nigeria. RPL's goods are mostly sold in Southern and Middle belt of Nigeria, some parts of West and East Africa, they have recently experienced strong demand. RPL must monitor financial data and assess performance if it is to expand its company. The company's net profit margin is one statistic they have to pay attention to. RPL's business APP approach is to keep a stable labor force level over the planning horizon, allowing for the flexible meeting of demand through the use of inventories, overtime, and backorders. Due to the shortcomings of the graphical method, in which evaluation comparisons are only available for specific plans under specified conditions and indication for the optimal plan is ambiguous, RPL has been unable to reach the performance initially predicted.

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ISSN: 2278-0181
Vol. 12 Issue 06, June-2023

Alternately, the DM can use a mathematical programming technique to create an aggregate production schedule for RPL factory. Based on company reports, the planning horizon spans for six months, May to October. The model includes two types of standard products. Production expenses for overtime are capped at 30% of production expenses for regular hours. Additionally, it is assumed that each product has no beginning inventory and no backorders at the last period. The inventory's maximum allowed storage area is $3000m^3$. In a day, there are two working shifts. 8 hours are allotted for regular production per shift, while 3 hours allotted for overtime production. To produce these products, 10 types of raw materials are required. Repairs are done just in shift 2 (i.e., overtime) and the overall operating cost is as stated on Table 4 below. When demand for a certain period exceeds production capacity during regular hours and inventory levels are likewise insufficient to meet this demand, production is continued during overtime.

The purpose of the APP decision issue for the industrial instance that is addressed here is to develop a multiple fuzzy goals programming model for determining the optimal approach to adjust output rates, hiring and firing, inventory levels, overtime, and backorders in order to meet the targeted maximum profit using the Throughput accounting process. This APP choice is expected to reduce overall manufacturing costs, shorten the process, and increase sales and profit.

Table 4: Related operating cost data

Period	$\widetilde{CoM}$(₦ /unit)	$\widetilde{CoW}$(₦ /unit)	$\widetilde{CoH}$(₦ /unit)	$\widetilde{CoF}$(₦ /unit)	$\widetilde{CohP}$(₦ /unit)	$\widetilde{CohR}$(₦/unit)	$\widetilde{CoB}$(₦ /unit)	$\widetilde{CoO}$(₦ /unit)
1	45, 80, 140	35, 64, 100	10, 30, 55	15, 40, 60	0.5, 2, 4	800, 1400, 1600	1.5, 2, 4.5	5, 7, 11
2	45, 80, 135	35, 64, 100	10, 30, 55	15, 40, 60	0.5, 2, 4	850, 1400, 1600	1.5, 2, 4.5	5, 7, 10
3	48, 80, 140	35, 64, 100	10, 30, 55	15, 40, 60	0.5, 2, 4	800, 1400, 1500	1, 2, 4.5	5.5, 7, 10
4	47, 80, 140	35, 64, 100	10, 30, 55	15, 40, 60	0.5, 2, 4	850, 1400, 1500	1, 2, 4.5	5.5, 7, 11
5	47, 80, 145	35, 64, 100	10, 30, 55	15, 40, 60	0.5, 2, 4	850, 1400, 1500	1.5, 2, 4.5	5, 7, 11
6	47, 80, 140	35, 64, 100	10, 30, 55	15, 40, 60	0.5, 2, 4	800, 1400, 1600	1.5, 2, 4.5	5, 7, 10

4.1 Results of the Study

The following is a description of the RPL case's solution process using the suggested APP-PP technique:
First Stage: Create the PP model for the APP choice issue in accordance with Equations (4) to (25).
Second Stage: Triangular possibility distributions are used to model the imprecise data as shown in Tables 4.
Third Stage: According to Equations (28) to (30) of the supplementary MOLP problem, create three new precise objective functions. In order to get the initial solutions for each of the objective functions, the original issue is solved using the standard single-objective LP method under the presumption that the DM provided the most likely value of the triangular distribution of each Fuzzy number as the precise value. LINGO 18.0 solver is used to solve the model. The objective values of the initial solutions using the model are $Max\ Z_1 = 2403267, Min\ Z_2 = 1291303$ and $Max\ Z_2 = 2773881$
Fourth Stage: The PIS and NIS of the three new objective functions $(Z_1^{PIS}, Z_1^{NIS}) = (2403267, 898202)$ $(Z_2^{PIS}, Z_2^{NIS}) = (1291303\ , 1977990)$ and $(Z_3^{PIS}, Z_3^{NIS}) = (2773881, 1262890)$. The fuzzy aspiration levels can be quantified using the linear and continuous membership function. According to Eq. (31) and (32), the relevant linear membership functions can be defined as shown below.

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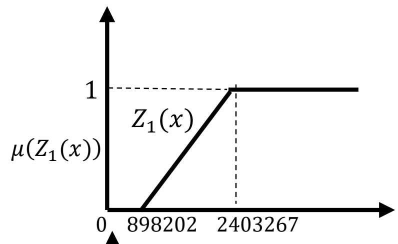
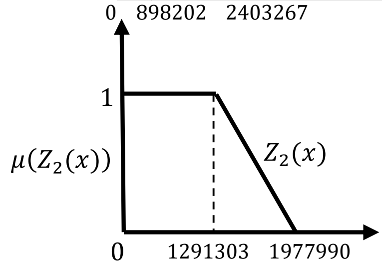
International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 06, June-2023

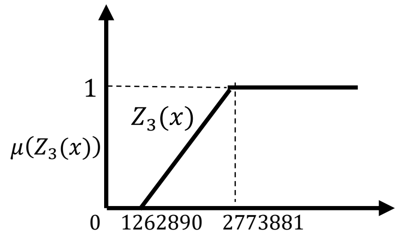
$$\mu(Z_1(x)) = \begin{cases} 1 & Z_1(x) \geq 898202 \\ \frac{Z_1(x)-898202}{2403267-898202} & 898202 \leq Z_1(x) \leq 2403267 \\ 0 & Z_1(x) \leq 2403267 \end{cases}$$



$$\mu(Z_1(x)) = \begin{cases} 1 & Z_2(x) \leq 1291303 \\ \frac{1977990 - Z_2(x)}{1977990 - 1291303} & 1291303 \leq Z_2(x) \leq 1977990 \\ 0 & Z_2(x) \geq 1977990 \end{cases}$$



$$\mu(Z_3(x)) = \begin{cases} 1 & Z_3(x) \geq 1262890 \\ \frac{Z_3(x) - 1262890}{2773881 - 1262890} & 1262890 \leq Z_3(x) \leq 1262890 \\ 0 & Z_3(x) \leq 1262890 \end{cases}$$



Equation (33), in addition, may be used to create the full equivalent single-objective LP model for the RPL situation.

Fifth Stage: Applying the FGP-APP gives the compromise solution a $Z1 = 1721542$, $Z2 = 1604372$, $Z3 = 2085002$s. As will be determined by the triangular possibility distribution, (₦117170, ₦1721542, ₦3806544) is present in the improved profit as a result, and the overall degree of DM satisfaction is 0.5440876.

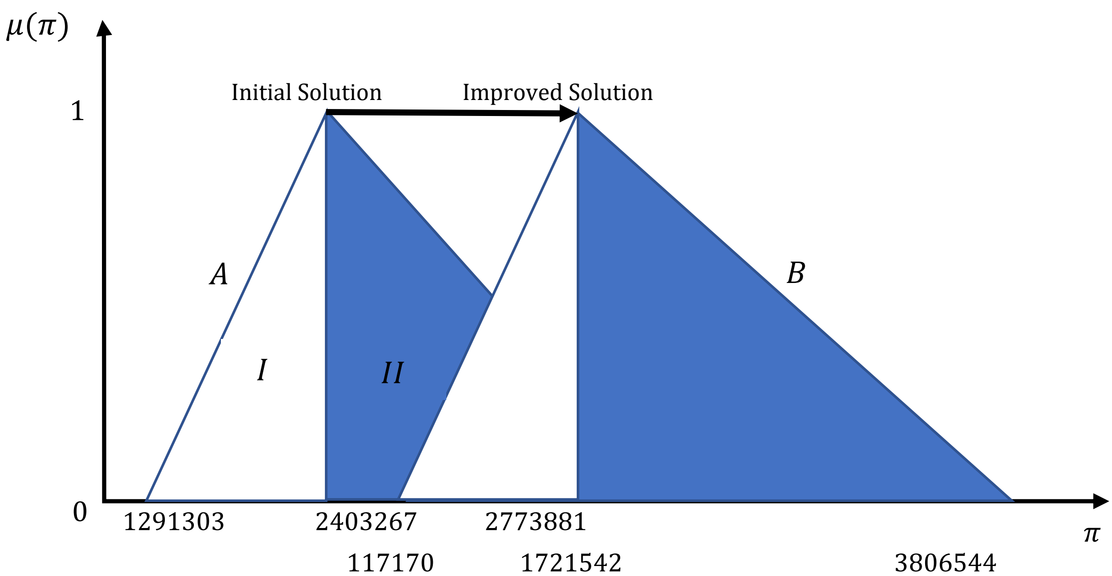


Fig. 2: The Approach to Maximize the Net Profit

The following are important managerial ramifications for using the suggested PLP method in practise. First off, the suggested PLP method produces a productive compromise solution.

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The crisp ordinary LP model was used to resolve the APP choice problem that was posed in the RPL instance. This study made the assumption that the DM had defined the most likely value of each imprecise data's probability distribution as the exact values. As a result, 2403267 was the ideal value while using LP to maximize earnings. The better findings were (117170, 1721542, and 3806544), in contrast to the suggested PLP technique. These numbers suggest that, in comparison to the ideal target value achieved by the LP model, the PLP solutions are an effective compromise option. The new PLP technique is then used in a fuzzy environment with an acceptable level of DM satisfaction to produce an enhanced APP plan. Notably, the objective values utilizing the suggested method should be approximate because the unit cost and associated factors are inherently approximate. On the other hand, the analytical outcomes show that it is irrational to replace the uncertain data with the highest conceivable value or the mean of the probability distribution.
Furthermore, the suggested PLP technique identifies the total level of DM satisfaction under the suggested strategy of maximizing the maximum value, reducing the risk of gaining greater profits, and minimizing the probability of receiving lower profits.

Considering the various fuzzy goal values ($Z_1,\ Z_2\ and\ Z_3$), the suggested model gives the overall levels of DM satisfaction (λ value). Each goal is fully satisfied if the answer is $\lambda\ =\ 1$. If $\lambda =\ 0$, none of the goals are satisfied. If $0 < \lambda < 1$, all of the goals are satisfied at some level. For instance, the initial calculation of the overall DM satisfaction (λ) with the goal values $Z1 = 1721542$, $Z2 = 1604372$, $Z3 = 2085002$ was 0. 5440876. The λ value can be adjusted to look for a set of superior compromise options if the DM did not accept the initial overall degree of this satisfaction value. Furthermore, the λ value can be adjusted to seek a set of better APP compromise solutions since the DM may not accept the initial overall degree of this satisfaction value.

It is quite difficult to apply these types of production/distribution models to actual situations. When the scale of the model is increased, the NP-hard issues that these models defined make it practically difficult to find the best solutions under normal circumstances. More proposed models in this area that are supported by numerical examples and apply the case studies to actual supply chains are offered (Mula et al., 2010).

5. Conclusion

This paper examined the integration of probabilistic linear programming (PLP) and throughput accounting system in the context of aggregate production planning (APP) for profit maximization. Companies may develop a comprehensive strategy for production planning that takes into account system restrictions and profitability by integrating these two techniques.

It is clear from the study done in this paper that PLP offers a strong framework for dealing with the uncertainties and imprecisions present in APP decision-making processes. PLP lets decision-makers to make well-informed decisions that strike a balance between risk and reward by considering probability distributions of input parameters. With the use of this strategy, planning outputs will be more realistic and trustworthy since imprecise and uncertain variables, such as demand projections, production costs, and capacity restrictions, may be modelled.

The throughput accounting system's integration also improves the decision-making process by revealing how production choices affect the system's overall profitability. The throughput accounting method aids in locating production bottlenecks, optimizing resource allocation, and prioritizing tasks that are most important for generating profits by focusing on throughput, operating costs, and

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International Journal of Engineering Research & Technology (IJERT)
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Vol. 12 Issue 06, June-2023

investment. Organizations may better connect their production planning choices with their financial goals thanks to this integration, which ultimately boosts performance and profitability. A proactive and flexible approach to production planning is encouraged by the joint use of PLP and the throughput accounting system. Companies can efficiently adjust to shifting market circumstances, consumer needs, and resource availability by taking into account both the uncertainties of the external environment and the internal limits of the system. With this strategy, capacity planning, production scheduling, and inventory management can all be done more precisely, which lowers costs, boosts customer satisfaction, and boosts overall profitability.

The difficulties in using PLP and the throughput accounting system in aggregate production planning, however, must be recognized. The availability of precise and trustworthy data and the computational difficulty of solving PLP models are important problems that require careful consideration. Additionally, a thorough comprehension of the system's limitations, precise cost allocation, and the capacity to recognize and measure throughput drivers properly are necessary for the effective integration of the throughput accounting system.

In conclusion, a strong framework for planning aggregate output that attempts to maximize profit is provided by the combination of probabilistic linear programming and the throughput accounting system. Utilizing the advantages of these approaches, businesses may examine production choices in a more thorough and accurate manner, improving their financial performance and competitiveness. By enabling proactive and profit-focused production planning, the combination of PLP and the throughput accounting system gives a strategic edge as businesses negotiate increasingly complicated and uncertain business situations.

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