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Optimization of Material Flow in Manufacturing Plant for Improved Productivity and Cost Reduction

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Abstract

Manufacturing plants must continuously improve material flow, production planning, and resource utilization to remain competitive. This paper presents an optimization-based production-planning framework for an aluminium non-stick bowl manufacturing plant, formulated as a constrained profit-maximization problem with three decision variables representing small, medium, and large bowl production. The model incorporates raw-material availability, six process-capacity constraints (blanking, drawing, trimming, polishing, coating, and curing), labour, production time, total plant capacity, and customer-demand bounds. Linear Programming (LP) is solved in MATLAB to obtain a benchmark optimum, and a Genetic Algorithm (GA) is implemented as an integer-constrained alternative search method. The LP benchmark yields 5,000 small, 4,500 medium, and 2,500 large bowls per month with a monthly profit of ₹885,000, while the GA converges to a near-optimal plan of 5,007/4,494/2,499 units and ₹884,805 profit — approximately 99.98% of the LP benchmark. Resource-utilization analysis shows the curing oven is the most heavily loaded operation (75.8%) and trimming the least (26.3%), with average machine utilization of 50.1% and labour utilization of only 11.8%. The results demonstrate that optimization-based planning can improve material utilization and productivity without exceeding available plant resources.

Keywords—*material flow, production planning, linear programming, genetic algorithm, resource utilization, manufacturing optimization.*

I. Introduction

Supply chain and material-flow management are essential components of modern manufacturing systems. Physical flows begin with suppliers and continue through purchasing, transportation, manufacturing, warehousing, and distribution before reaching the final customer. An effective system ensures that required materials and products are available at the right time, quantity, and location while inventory, handling, and operating costs are controlled. Excessive inventory increases holding cost, whereas insufficient inventory interrupts production; an efficient manufacturing system must therefore balance material availability against inventory investment.

Material-flow management is particularly important because continuous production depends on the timely availability of raw materials, components, and tools. Delays in supply cause machine idle time, production interruptions, and delayed deliveries, while unnecessary movement, handling, and storage of material increase operating cost and reduce efficiency. Purchasing and supplier selection further influence total product cost, since raw materials and components represent a significant proportion of manufacturing expenditure; supplier reliability,

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lead time, quality, and capacity must therefore be evaluated together with price.

From an industrial-engineering standpoint, production planning should not treat procurement and manufacturing as independent activities. Material availability, machine capacity, and labour hours are all finite resources, while customer demand fixes the boundaries within which production quantities must fall. Because different products consume different amounts of material, machine time, and labour while generating different revenue, an optimization-based approach is required to allocate limited resources among competing products and to determine not only how much can be produced, but which products should be prioritized.

This paper addresses these issues for Surya Aluminum Manufacturing, a manufacturer of aluminium kitchen and household products established in 1992 and located in Vijayawada, Andhra Pradesh, India. The company produces small, medium, and large aluminium non-stick bowls and has identified productivity improvement, material optimization, and cost reduction as priority areas. The problem addressed is: given fixed raw-material availability, six sequential process capacities, labour hours, production time, overall plant capacity, and customer-demand bounds for three products, what monthly production mix maximizes profit while remaining feasible with respect to every resource constraint?

The aim of this study is to develop and solve a constrained optimization model for material-flow and production planning using Linear Programming (LP) and a Genetic Algorithm (GA), and to compare the two solutions on the basis of profit, production mix, and resource utilization. The specific objectives are: (i) to formulate the production-planning problem as a mathematical optimization model; (ii) to solve the model using LP as a benchmark and GA as an alternative integer-constrained search method in MATLAB; (iii) to evaluate aluminium, labour, and machine utilization for the optimized solution; and (iv) to draw management implications for productivity improvement and cost reduction.

II. Literature Review

Research on production planning and supply-chain optimization has increasingly relied on mathematical programming, simulation, and metaheuristics such as Genetic Algorithms (GA) to solve complex manufacturing problems. Saez-Mas et al. [1] redesigned in-plant supply logistics for an automotive assembly facility, showing that an integrated logistics formulation can substantially reduce internal distribution time. Xu and Song [2] combined production capacity, raw-material ordering, and production planning under time and quantity uncertainty, demonstrating the value of jointly optimizing material decisions with capacity. Gyulai et al. [3] applied network analytics to shop-floor logistics, while Thongkerd and Pornsing [4] used GA for hybrid flow-shop scheduling in steel-plate manufacturing, both confirming that evolutionary and network-based methods improve internal material movement.

Several studies extend production planning to include supplier selection and reliability. Che et al. [5] proposed a multi-objective GA (W-NSGA2) for assembly planning and supplier selection under capacity constraints, and Saputro et al. [6] integrated supplier selection with inventory management under supply disruption using a GA-driven simulation-optimization framework. Liu and Yang [7] and Mahmudy et al. [8] applied local-search-based and improved GA formulations to multi-product aggregate production planning — directly relevant to the present three-product problem. Cullen and Cooper [9] reviewed material flows from a broader sustainability perspective, linking efficient material utilization to reduced resource consumption and environmental performance, while Seifbarghy et al. [10] used Material Flow Cost Accounting to determine appropriate raw-material quality levels.

More recent work has combined simulation with optimization: Gao and Long [11] used digital-twin simulation for assembly-line material flow, Wang and Zhang [12] developed a hybrid Genetic Grey Wolf Optimizer for prefabricated-component scheduling, and Klar et al. [13] applied deep reinforcement learning to multi-objective factory-layout planning with

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embedded material-flow simulation. Dulina et al. [14] presented an industrial case study on material-flow and workplace-layout improvement, and Yiğit and Lazarevska [15] combined Fuzzy AHP with GA for production planning under asymmetric setup times.

Collectively, this literature demonstrates extensive work on supplier selection, scheduling, factory layout, and material-flow optimization considered largely in isolation. Fewer studies directly address a plant-level, multi-product production-mix problem in which raw-material availability, sequential process capacity, labour, production time, total plant capacity, and customer demand are represented simultaneously within a single formulation. This paper addresses that gap using a three-product aluminium bowl manufacturing case, and follows established practice [1]–[15] by using LP to obtain a mathematical-programming benchmark and GA to independently verify the solution through population-based search.

III. Methodology

A. Manufacturing System and Data Collection

The manufacturing system considered converts aluminium raw material into small, medium, and large non-stick bowls through a sequence of casting, rolling, reheating, pressing, blanking, drawing, trimming, polishing, coating, and curing operations (Fig. 1).



Fig. 1. Pressing operation in the aluminium bowl manufacturing process.

Aluminium is well suited to this process because of its low density, good formability, and high thermal conductivity, but each bowl size consumes a different quantity of material, machine time, and labour. Monthly production data — unit profit, aluminium requirement, process-time coefficients, labour hours, plant capacity, and customer-demand bounds — were collected for each product and used to formulate the optimization model.

B. Mathematical Model

The decision variables x_1, x_2, x_3 denote the monthly production quantities of small, medium, and large bowls, respectively (treated as non-negative integers in the GA formulation). Four auxiliary variables y_1–y_4 represent aluminium quantities obtainable from four suppliers and extend the model toward a procurement formulation, though the MATLAB LP/GA implementations optimize x_1–x_3 directly. With unit profits of ₹55, ₹80, and ₹100 for small, medium, and large bowls, the objective is:

$$Maximize\ Z = 55x_1 + 80x_2 + 100x_3 \quad (1)$$

Because MATLAB's linprog performs minimization, (1) is implemented as Minimize $Z' = -55x_1 - 80x_2 - 100x_3$; the GA fitness function is defined identically as the negative of total profit. The model is subject to a raw-material constraint and six sequential process-capacity constraints, each of the linear form $a_1x_1 + a_2x_2 + a_3x_3 \leq b$, together with labour, production-time, plant-capacity, and demand constraints. Table I lists the per-unit resource coefficients and available capacity for each constraint.

The plant-capacity constraint limits total monthly output to 12,000 units ($x_1+x_2+x_3 \leq 12000$), and demand bounds restrict production to 3,500–6,000 small, 2,200–4,500 medium, and 1,200–2,500 large bowls per month. The extended supplier formulation requires Σy_i to equal total aluminium demand ($0.25x_1+0.40x_2+0.60x_3$), subject to individual supplier capacities of 2,500, 3,000, 3,500, and 2,800 kg/month and a procurement-cost function $C = 268y_1+265y_2+272y_3+270y_4$, providing a basis for future supplier-integrated optimization.

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Constraint	Small	Medium	Large	Capacity
Aluminium (kg)	0.25	0.40	0.60	6,000
Blanking	0.30	0.40	0.55	12,000
Drawing	0.80	1.10	1.50	24,000
Trimming	0.25	0.35	0.45	15,000
Polishing	0.40	0.60	0.80	14,000
Coating	0.70	0.90	1.20	18,000
Curing oven	1.50	2.00	2.50	30,000
Labour (hr)	0.05	0.08	0.10	7,280
Prod. time (min)	3.5	4.8	6.5	124,800

Table 1: **Resource Coefficients and Available Capacity**

Table 1 presents the resource coefficients and available capacities for producing small, medium, and large aluminium non-stick bowls. Each coefficient represents the amount of a particular resource required to produce one unit of the respective bowl size. Aluminium consumption is 0.25, 0.40, and 0.60 kg, while the requirements for blanking, drawing, trimming, polishing, coating, and curing oven are specified according to product size. Labour requirements are 0.05, 0.08, and 0.10 hours per unit, and production time requirements are 3.5, 4.8, and 6.5 minutes per unit for small, medium, and large bowls, respectively. The available monthly capacities are 6,000 kg of aluminium, 12,000 blanking units, 24,000 drawing units, 15,000 trimming units, 14,000 polishing units, 18,000 coating units, 30,000 curing-oven units, 7,280 labour hours, and 124,800 production minutes. These resource limits form the main constraints of the optimization model and ensure that the selected production quantities remain within the plant's available resources.

C. LP and GA Implementation in MATLAB

The LP model is solved with linprog using objective vector f = [−55 −80 −100], constraint matrix A and capacity vector b from Table I, and demand bounds as lb/ub. The GA model uses the ga function with an identical constraint set, integer constraints on x_1–x_3 (IntCon = [1 2 3]), and a fitness function equal to the negative of (1). Both implementations report the optimized production plan, monthly profit, aluminium and labour utilization, per-operation utilization for the six manufacturing processes, and production quantity relative to minimum demand (Fig. 2).

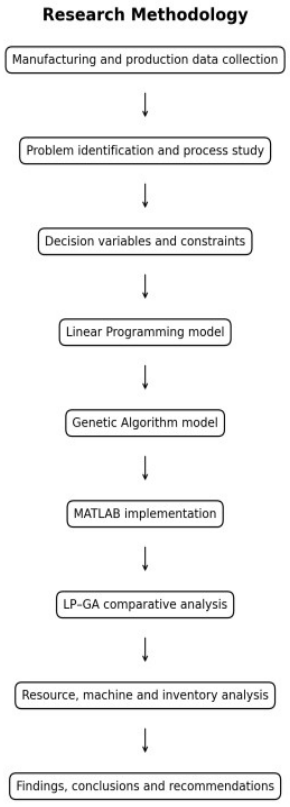


Fig. 2. Research methodology flow used for the LP/GA optimization study.

The manufacturing process flow, as presented in the flow chart above, begins with aluminium scrap and raw-material procurement, followed by casting, rolling and sheet preparation, cutting and circle cutting, pressing and bowl forming, blanking and drawing, trimming and polishing, non-stick coating, curing and quality inspection, and finally dispatch. At each stage, the material is inspected and processed according to the required dimensions and quality standards, while scrap and defective materials are suitably segregated for rework or recycling. This sequential flow ensures proper material movement, minimizes

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wastage and unnecessary handling, and supports efficient production of aluminium non-stick bowls from raw material to finished product.

IV. Results and Discussion

A. LP and GA Solutions

Measure	LP	GA	Δ
Small bowl	5,000	5,007	+7
Medium bowl	4,500	4,494	−6
Large bowl	2,500	2,499	−1
Total (units)	12,000	12,000	0
Profit (₹)	885,000	884,805	−195

TABLE 2: LP vs. GA Production and Profit Comparison

Solving the LP formulation gives a benchmark optimum of 5,000 small, 4,500 medium, and 2,500 large bowls per month — a total of 12,000 units that exactly matches plant capacity — with a monthly profit of ₹885,000. Medium and large bowls are produced at their maximum demand levels, while small-bowl output lies between its bounds. The GA, using an identical constraint set, converges to 5,007 small, 4,494 medium, and 2,499 large bowls (also totalling 12,000 units) and a profit of ₹884,805 — within ₹195, or about 0.022%, of the LP benchmark (99.98% of optimal). This close agreement confirms that the population-based GA search reliably approximates the mathematical-programming optimum for this formulation; the small residual gap is attributable to the stochastic nature of GA selection, crossover, and mutation.

B. Profit Contribution

Bowl Size	Monthly Profit (₹)	Profit Contribution (%)
Small	275,385	31.1
Medium	359,520	40.6
Large	249,900	28.3
Total	884,805	100.0

Table 3. Profit contribution by bowl size based on the GA solution.

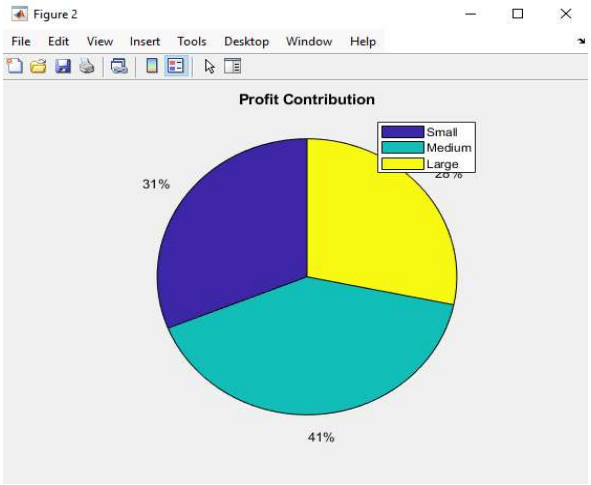


Fig. 3. Profit contribution by bowl size (GA solution).

Based on the GA solution, small bowls contribute ₹275,385 (31.1%), medium bowls ₹359,520 (40.6%), and large bowls ₹249,900 (28.3%) of total monthly profit (Fig. 3). Although the large bowl has the highest per-unit profit, medium bowls contribute the most in absolute terms because their optimized production quantity is considerably higher. This confirms that unit profit alone should not guide production decisions — resource consumption per unit must be weighed jointly with profitability, which is precisely what the constrained optimization model achieves.

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C. Resource and Machine Utilization

Resource / Capacity	Available per Month	GA Solution Consumption	Utilization (%)	Remaining Capacity
Aluminium	6,000 kg	4,548.75 kg	75.8	1,451.25 kg
Labour	7,280 h	859.77 h	11.8	6,420.23 h
Production Capacity	12,000 units	12,000 units	100.0	0 units

Table 4. Resource and machine utilization based on the GA solution.

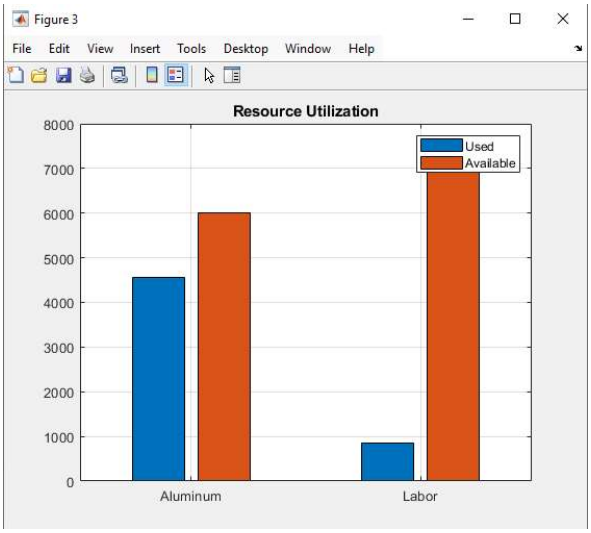


Fig. 4. Aluminium and labour resource utilization (GA solution).

Under the GA solution, aluminium consumption is 4,548.75 kg of the available 6,000 kg/month (75.8% utilization), and labour consumption is 859.77 of 7,280 available hours (11.8% utilization) (Fig. 4). The large gap between material and labour utilization indicates that aluminium availability, not labour, is the more influential resource constraint, though full plant-capacity utilization (12,000/12,000 units) means production cannot simply be increased without also relaxing demand or process-capacity limits.

Table 5 and Fig. 5 report utilization for the six sequential manufacturing operations. The curing oven is the most heavily loaded operation at 75.8%, making it the closest potential bottleneck, while trimming has the lowest utilization at 26.3%. Average utilization across the six operations is 50.1%, indicating that, on average, roughly half of installed process capacity is used under the current demand and resource assumptions, with load distributed unevenly across the process sequence.

Operation	Utilization
Blanking	39.0%
Drawing	52.9%
Trimming	26.3%
Polishing	47.8%
Coating	58.6%
Curing oven	75.8%

TABLE 5: Machine / Process Utilization (GA Solution)

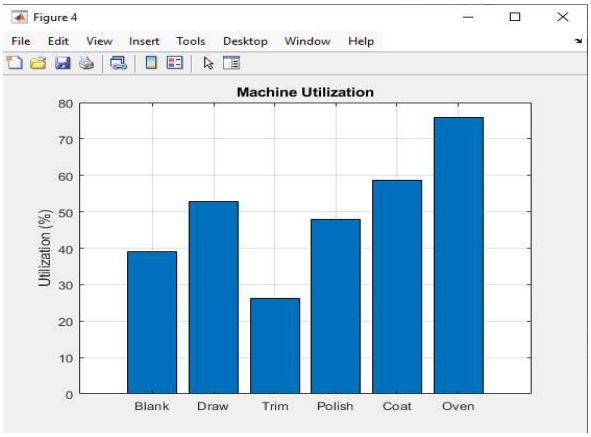


Fig. 5. Machine utilization for the GA production plan.

D. Combined Optimization Summary and Discussion

Fig. 6 summarizes the GA optimization output, combining production quantities, profit contribution, resource utilization, machine loading, and inventory-above-minimum-demand in a single view. Production above minimum demand totals 5,100 units across the three bowl sizes; this should be interpreted as headroom relative to the modeled minimum-demand bound rather than confirmed unsold stock. The uneven machine loading — particularly the gap between the curing oven (75.8%) and trimming (26.3%) — suggests that upstream operations could

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accumulate work-in-process if scaled without regard to curing-oven throughput, underscoring the value of analyzing production planning and internal material flow together rather than in isolation.

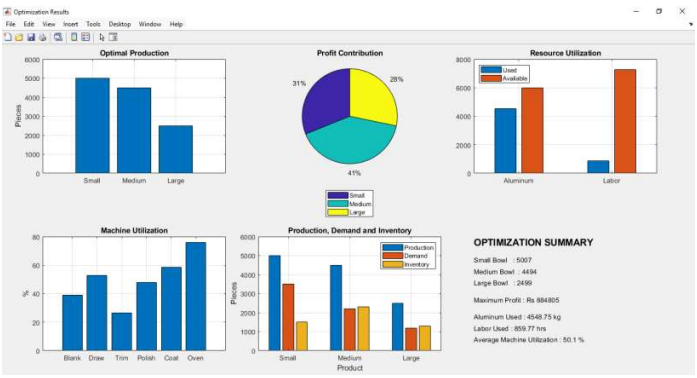


Fig. 6. Combined GA optimization summary: production, profit, resource and machine utilization, and inventory.

From a management perspective, four implications follow directly from the results. First, the curing oven should be prioritized for preventive maintenance and scheduling attention, as it is the closest process bottleneck. Second, the substantial idle labour capacity (88.2% unused) could be redirected toward quality inspection, maintenance, or material handling rather than treated as a hard constraint. Third, customer-demand bounds used in the model should be refreshed regularly, since production quantities above minimum demand only represent modeled headroom, not guaranteed sales. Fourth, because aluminium utilization is already at 75.8%, improved scrap recovery and recycling of trimming and shearing waste could further reduce material cost. More broadly, the LP and GA models together form a reusable decision-support tool: as demand, material availability, or capacity change, the models can be re-solved to obtain an updated, resource-feasible production plan.

V. Conclusion

This paper developed and solved a constrained production-planning optimization model for an aluminium non-stick bowl manufacturing plant, integrating raw-material availability, six sequential process capacities, labour, production time, plant capacity, and customer demand. The LP benchmark achieves a monthly profit of ₹885,000 with a 5,000/4,500/2,500 unit production mix, while the GA independently converges to a near-identical 5,007/4,494/2,499 mix at ₹884,805 — 99.98% of the LP optimum — validating the model and demonstrating that population-based search is a viable alternative for integer-constrained production planning. Resource-utilization analysis identifies the curing oven as the primary bottleneck (75.8% utilization) and confirms that labour (11.8%) and aluminium (75.8%, below its 6,000 kg limit) are not simultaneously binding, while full plant-capacity utilization shows the plant already operates at its stated production ceiling. These results demonstrate that optimization-based production planning can improve material-flow efficiency, productivity, and profitability without violating any operational constraint, and that the LP/GA framework can serve as a reusable decision-support tool for ongoing production planning. Future work may extend the model to jointly optimize supplier allocation and procurement cost (y_1–y_4), incorporate multi-objective criteria such as energy use and material waste, integrate real-time production data, and benchmark GA against other metaheuristics such as Particle Swarm or Ant Colony Optimization.

VI Future Scope

The future scope of the study can be extended by incorporating supplier quantities (y_1–y_4) as additional decision variables in the MATLAB optimization model to simultaneously optimize production planning and procurement costs. Supplier selection can further consider transportation cost, delivery time, material quality, reliability, and warranty. A multi-objective optimization model can also be developed by simultaneously considering profit, production time, material waste, energy consumption, and inventory cost. In addition, real-time production data, machine availability, and changing customer demand can be integrated into a dynamic optimization framework for improved decision-making. Finally, simulation and digital-twin techniques can be used to validate the optimized material flow and evaluate its performance before industrial implementation.

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