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Integration of Lean Manufacturing and Industry 4.0 Technologies for Aggregate Production Planning and Cost Optimization in a Steel Manufacturing Industry

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Abstract

Aggregate production planning links customer demand, workforce capacity, production quantity, inventory, overtime, and cost into a single planning decision. This paper develops a 12-month aggregate production planning framework for a TMT (Thermo-Mechanically Treated) steel bar manufacturer facing a seasonal demand pattern ranging from 870 to 1,250 tonnes per month, an initial workforce of 140 employees, and an initial inventory of 1,000 tonnes. A Linear Programming (LP) model is formulated with seven monthly decision variables workforce, hiring, layoff, regular production, overtime production, ending inventory, and backlog to minimize total workforce, hiring, layoff, production, overtime, inventory, and backlog cost subject to workforce-balance, inventory-backlog balance, regular- and overtime-capacity, and ending-inventory constraints. The model is solved in MATLAB using linprog. The optimized plan tracks the seasonal demand pattern, draws down the initial inventory during January, expands the workforce from 140 to approximately 313 employees during peak-demand months, uses selective hiring (up to ≈85 employees) and layoffs (≈70 employees), keeps inventory near zero for most of the horizon while meeting the required 500-tonne closing stock, and reports a monthly cost ranging from ₹18.7 lakhs to ₹694.9 lakhs (≈₹6,130 lakhs over the year). The paper further proposes an Industry 4.0 / Lean 4.0 monitoring layer IoT sensors, smart cameras, PLC/SCADA connectivity, and cloud dashboards to complement the optimization model with real-time shop-floor visibility.

Keywords: *Aggregate production planning, linear programming, workforce planning, Lean manufacturing, Industry 4.0, TMT steel.*

I. Introduction

Aggregate production planning is a core industrial-engineering activity that links customer demand, workforce capacity, production quantity, inventory, overtime, and cost into a single, coordinated planning decision. When demand is seasonal, a manufacturer cannot rely on a single fixed production rate throughout the year: producing exactly to forecast each month forces frequent, costly workforce adjustments, while holding a constant high production rate accumulates unnecessary inventory during low-demand months. An effective aggregate plan therefore balances regular production, overtime, workforce changes, and inventory to respond to demand variation at minimum total cost.

This paper addresses that problem for Ramdev Industries, a manufacturer of TMT (Thermo-Mechanically Treated) steel bars used in construction and infrastructure. TMT bars are produced by rolling MS ingots and billets and then subjecting the hot bar to controlled water cooling: the outer surface cools rapidly while the core remains hot, and subsequent heat transfer from the core tempers the surface, producing the strength, ductility, weldability, and bendability required in reinforced-concrete construction. Because this process depends on coordinated

labour, equipment, and material availability, production planning is central to maintaining consistent output and quality.

The supplied planning data show a seasonal demand pattern that repeats over two six-month halves of the year, ranging from a low of 870 tonnes (June, December) to a high of 1,250 tonnes (May, November), with an initial workforce of 140 employees and initial inventory of 1,000 tonnes. The planning problem is to determine, for each of the twelve months, the workforce level, hiring, layoffs, regular production, overtime production, ending inventory, and backlog that minimize total cost while satisfying demand, labour-hour capacity, overtime capacity, and a required 500-tonne ending inventory.

The aim of this study is to formulate and solve this problem as a Linear Programming model in MATLAB, to analyze the resulting workforce, production, inventory, and cost behaviour, and to propose a complementary Industry 4.0 / Lean 4.0 monitoring layer IoT sensors, smart cameras, and PLC/SCADA connectivity that can supply the real-time shop-floor data needed to keep such a plan responsive in practice.

II. Literature Review

Recent research shows manufacturing organizations moving from conventional production planning toward digitally connected, data-driven planning. Bittencourt et al. [1] found Lean Thinking to be an important trigger for Industry 4.0 adoption, emphasizing that management, process, and people factors precede successful digital transformation. Núñez-Merino et al. [2] reviewed 78 studies linking Industry 4.0 information technologies to Lean supply-chain management and identified technologies that improve coordination and decision-making. Usuga Cadavid et al. [3] surveyed machine-learning applications in production planning and control, showing that data-driven methods increasingly support planning responsiveness.

Several studies examine how Industry 4.0 technologies extend Lean practice. Saad et al. [4] concluded that combining Lean Manufacturing with Industry 4.0 connectivity and real-time information yields competitive advantages beyond what either approach achieves alone. Cifone et al. [5] showed that digital technologies such as IoT and analytics should support rather than replace continuous-improvement practice. Oluyisola et al. [6] proposed a methodology combining IoT, Big Data Analytics, and Machine Learning with production-planning activities, validated through an industrial case study, directly supporting this paper's proposed integration of real-time sensing with a Linear Programming core.

On production planning and control (PPC) specifically, Herrmann et al. [7] reviewed 48 publications and found Industry 4.0 affecting multiple interconnected planning functions rather than shop-floor automation alone; Cañas et al. [8] proposed a conceptual SPPC4.0 framework for SMEs; and Luo et al. [9] reviewed IoT, cloud manufacturing, and Digital Twin approaches for connecting planning systems to emerging technologies. Hossain and Purdy [10] and Chen et al. [11] both found that IoT, cyber-physical systems, and connected sensing support Lean objectives such as zero-defect manufacturing and rapid response to changing requirements consistent with the sensor and smart-camera layer proposed in this paper.

Studies focused specifically on Lean 4.0 integration provide further support. Ericsson and Maffei [12] reviewed 50 studies and found the Industry 4.0–Lean relationship to be bidirectional and context-dependent rather than uniformly one supporting the other. Schumacher et al. [13] and Cagnetti et al. [14] both describe how digital technologies transform traditional Lean tools through smart data collection, provided digital transformation is pursued strategically rather than as isolated technology adoption. Mäule and Götte [15] reviewed 51 publications and identified 30 distinct challenges data availability, PPC complexity, and infrastructure readiness relevant to any future integration of IoT data with a Linear Programming planning model. Qureshi et al. [16] identified organizational and operational factors, beyond technology availability alone, that determine successful Lean 4.0 adoption in manufacturing SMEs.

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Collectively, this literature demonstrates extensive work on Lean–Industry 4.0 integration, smart PPC frameworks, and digital-technology adoption, but relatively little work directly combines aggregate production planning workforce, hiring, layoff, regular and overtime production, inventory, and backlog with a Lean 4.0 monitoring layer for a specific seasonal-demand manufacturing context such as TMT steel. This paper addresses that gap by developing a twelve-month Linear Programming aggregate plan for TMT steel bars and proposing IoT, smart-camera, and PLC/SCADA integration as a complementary real-time monitoring layer, consistent with the general Lean 4.0 direction identified in [1]–[16].

III. Methodology

A. Company Profile and Planning Context

Ramdev Industries is a TMT steel bar manufacturer located near Telaprolu, Andhra Pradesh, India, serving regional and national construction markets. Demand for TMT bars varies seasonally: the supplied 12-month forecast repeats the same six-month pattern in both halves of the year, with 900 t (Jan, Jul), 1,000 t (Feb, Aug), 950 t (Mar, Sep), 1,200 t (Apr, Oct), 1,250 t (May, Nov), and 870 t (Jun, Dec). The 380-tonne spread between the lowest and highest months motivates an aggregate plan that combines workforce adjustment, overtime, and inventory rather than a single fixed production rate.

B. Decision Variables and Cost Parameters

For each month t = 1,…,12 the model defines seven decision variables: workforce W_m, hiring H_m, layoff L_m, regular production P_m (tonnes), overtime production O_m (tonnes), ending inventory I_m (tonnes), and backlog B_m (tonnes). Table I lists the cost and capacity parameters used in the objective function and constraints, taken directly from the supplied MATLAB implementation.

Parameter	Value
Initial workforce	140 employees
Initial inventory	1,000 t
Required ending inventory	≥ 500 t
Regular hours / employee / month	208 h (26 d × 8 h)
Max. overtime / employee / month	20 h
Labour hours per tonne	5 h/t
Regular wage cost	₹6,240 / employee / month
Hiring cost	₹5,000 / employee
Layoff cost	₹3,000 / employee
Production + raw-material cost	₹50,000 / tonne
Overtime cost coefficient	₹35 / tonne (as coded)
Inventory holding cost	₹10,000 / tonne
Backlog penalty	₹2,000 / tonne

Table 1: Cost and Capacity Parameters

Table 1 presents the cost and capacity parameters used in the optimization model for workforce, production, and inventory planning. The plant starts with 140 employees and an initial inventory of 1,000 tonnes, with a minimum required ending inventory of 500 tonnes. Each employee provides 208 regular working hours per month, with a maximum of 20 hours of overtime, while producing one tonne requires 5 labour hours. The regular wage cost is ₹6,240 per employee per month, with hiring and layoff costs of ₹5,000 and ₹3,000 per employee, respectively. The production and raw-material cost is ₹50,000 per tonne, while overtime, inventory holding, and backlog are considered at ₹35 per tonne, ₹10,000 per tonne, and ₹2,000 per tonne, respectively. These parameters define the available production capacity and major operating costs considered in the optimization model.

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C. Objective Function

The objective minimizes total planning cost over the 12-month horizon:

$$Min\ Z = \Sigma_{t=1}^{12} [c_W W_m + c_H H_m + c_l L_m + c_p(P_m + O_m) + c_o O_m + c_i I_m + c^b B_m] \quad (1)$$

where cw = ₹6,240, c_H = ₹5,000, c_l = ₹3,000, c_p = ₹50,000, c_o = ₹35, c_i = ₹10,000, and c^b = ₹2,000, exactly as defined in the supplied MATLAB cost vector.

D. Constraints

Workforce balance (equality) links each month's workforce to the previous month's level plus hiring minus layoffs, anchored by the initial workforce $W_0 = 140$:

$$W_m - H_m + L_m = W_{m-1} \quad (2)$$

Inventory–backlog balance (equality) ties production and overtime output to demand D_m, carrying forward inventory I_{m-1} and backlog B_{m-1} from the previous month ($I_0 = 1{,}000$, $B_0 = 0$):

$$I_{m-1} + P_m + O_m - I_m + B_m - B_{m-1} = D_m \quad (3)$$

Regular- and overtime-capacity constraints (inequality) limit production to what the current workforce can supply at 208 regular and 20 overtime hours per employee, with 5 labour-hours required per tonne:

$$P_m \le 41.6\, W_m, \quad O_m \le 4\, W_m \quad (4)$$

The ending-inventory requirement and non-negativity bounds complete the model:

$$I_{12} \ge 500; \quad W_m, H_m, L_m, P_m, O_m, I_m, B_m \ge 0 \quad (5)$$

This 84-variable (12 months × 7 variables) LP is solved in MATLAB using linprog, with the workforce-balance and inventory-backlog equations supplied as equality constraints (Aeq, beq) and the capacity and ending-inventory conditions supplied as inequality constraints (A, b). The solution is extracted into twelve-month vectors W, H, L, P, O, I, and B and visualized using dedicated plotting scripts for demand-versus-production, workforce, inventory, hiring/layoff, overtime, and monthly cost.

IV. Lean 4.0 Integration

The Linear Programming model determines what to produce, hire, and hold in inventory each month, but it does not by itself provide real-time visibility into whether the plan is being executed as intended. This paper therefore proposes a complementary Industry 4.0 monitoring layer, conceptual at this stage rather than an implemented plant-wide system. IoT sensors are proposed for furnace temperature, rolling-mill vibration, motor current and energy consumption, conveyor speed, and cooling-water flow parameters directly tied to the TMT controlled-cooling process described in Section I. Smart cameras are proposed for automated surface-defect detection, dimensional inspection, and finished-bar counting, replacing manual inspection with continuous, consistent monitoring.

Field sensors and cameras would connect through PLC/SCADA systems to a cloud-based dashboard, giving production planners the real-time data needed to detect deviations from the aggregate plan for example, unplanned downtime that erodes available regular-time capacity, or defect rates that increase effective backlog. Coupled with the LP model, this creates a Lean 4.0 loop: the optimization sets the monthly workforce, production, and inventory targets, while the digital layer verifies execution and flags deviations for corrective action, consistent with the Lean-as-foundation, Industry-4.0-as-enabler relationship identified across the reviewed literature [1], [4], [6].

V. Results and Discussion

A. Demand, Production, and Workforce

Month	Demand (tonnes)	Production (tonnes)	Demand–Production Difference (tonnes)
January	900	0	900
February	1,000	900	100
March	950	950	0
April	1,200	1,200	0

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May	1,250	1,200	50
June	850	920	−70
July	900	900	0
August	1,000	980	20
September	950	950	0
October	1,200	1,200	0
November	1,250	1,250	0
December	880	1,250	−370

Table 2. Optimized Monthly Demand and Production

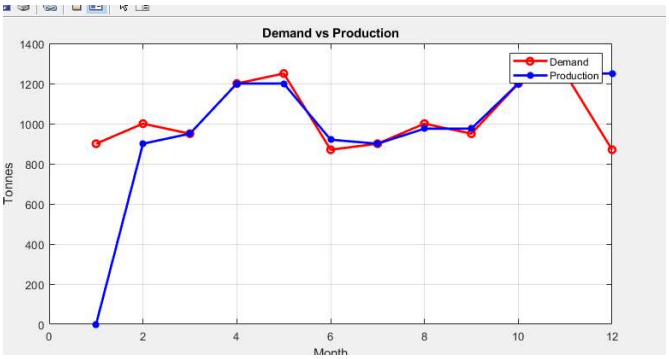


Fig. 1. Optimized demand versus production, 12-month horizon.

The optimized plan tracks the seasonal demand pattern closely (Fig. 1). In January, the initial 1,000-tonne inventory is used to help satisfy demand, so regular production ramps up rather than starting at full output. During the higher-demand months of April–May and October–November, production is increased through workforce expansion and overtime rather than solely through inventory build-up.

Month	Workforce (Employees)	Workforce Change
January	140	0
February	225	+85
March	235	+10
April	300	+65
May	300	0
June	230	−70
July	230	0
August	245	+15
September	245	0
October	300	+55
November	313	+13
December	313	0

Table 3. Optimized Monthly Workforce Level

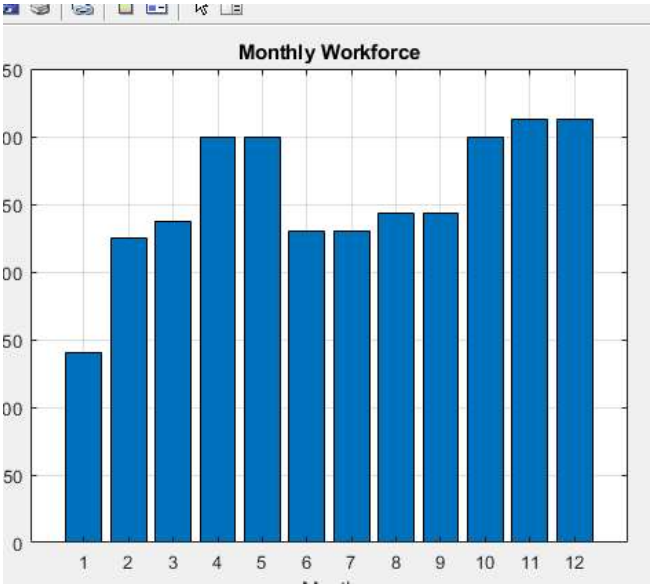


Fig. 2. Optimized monthly workforce level.

The workforce plan (Fig. 2) rises from the initial 140 employees to approximately 313 during peak periods, using selective hiring up to about 85 employees in a single high-demand month and a limited layoff of roughly 70 employees once the peak subsides. This confirms that the LP favours workforce flexibility over maintaining a constant maximum headcount throughout the year, which would incur unnecessary regular-wage cost during low-demand months.

B. Inventory and Overtime

Month	Inventory (tonnes)	Month	Inventory (tonnes)
January	300	July	0
February	0	August	0
March	0	September	0
April	0	October	0
May	0	November	0
June	0	December	1000

Table 4: Optimized ending-inventory profile.

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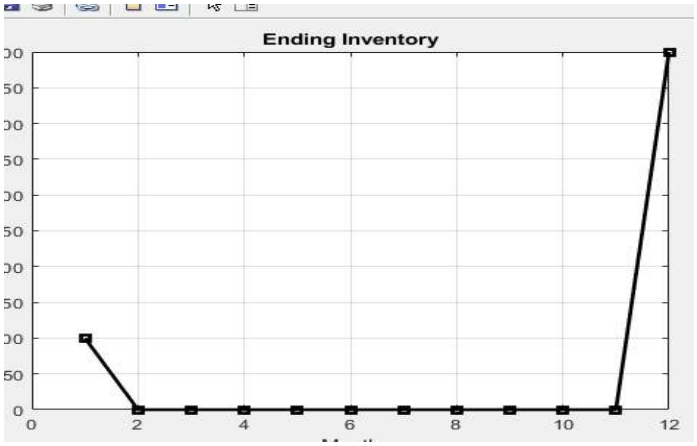


Fig. 3. Optimized ending-inventory profile.

The inventory profile (Fig. 3) stays close to zero for most of the horizon, consistent with minimizing holding cost, and rises sharply to the required 500-tonne level only in the final month to satisfy the ending-inventory constraint. This near-zero-inventory strategy, combined with strategic overtime use during peak months, indicates that the LP absorbs most seasonal variation through workforce and overtime flexibility rather than through inventory buffering a pattern consistent with Lean thinking, since carried inventory is itself a form of waste.

C. Monthly Production Cost

Month	Cost (₹ lakh)	Month	Cost (₹ lakh)
Jan	18.74	Jul	464.67
Feb	468.55	Aug	503.75
Mar	490.78	Sep	503.05
Apr	622.26	Oct	621.95
May	619.14	Nov	645.56
Jun	476.77	Dec	694.94

Table 4: Reported Monthly Production Cost

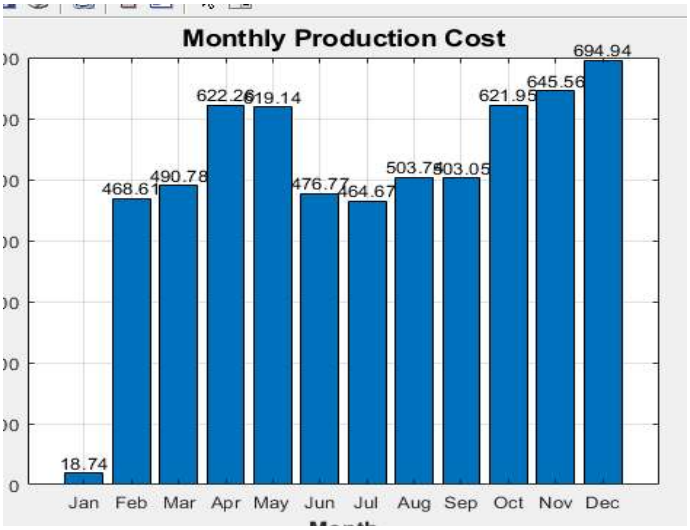


Fig. 4. Reported monthly production cost.

Table 4 and Fig. 4 report the monthly cost obtained from the objective function. Cost is lowest in January (₹18.74 lakhs), reflecting the use of existing inventory rather than new production, and highest in December (₹694.94 lakhs), coinciding with peak production and workforce levels. The twelve-month total is approximately ₹6,130 lakhs. The large month-to-month swing illustrates that cost is driven primarily by regular and overtime production volume (₹50,000/tonne) rather than by workforce or inventory holding cost, which are an order of magnitude smaller per unit.

The results show a mixed planning strategy rather than a single pure aggregate-planning policy: the system neither relies primarily on inventory (which is kept near zero) nor on a constantly maximal workforce (which would waste regular-wage cost in low-demand months). Instead, it combines selective hiring and layoffs, strategic overtime, and minimal inventory buffering balancing service level against total resource cost. From an Industrial Engineering perspective, the near-zero inventory and bounded overtime and workforce swings support Lean objectives directly, since both excess inventory and unnecessary workforce fluctuation represent forms of waste that the optimization implicitly discourages through its cost structure.

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VI. Conclusion

This paper formulated and solved a 12-month aggregate production planning problem for a TMT steel bar manufacturer as a Linear Programming model with seven monthly decision variables workforce, hiring, layoff, regular production, overtime production, inventory, and backlog subject to workforce-balance, inventory-backlog balance, regular- and overtime-capacity, and ending-inventory constraints. Solved in MATLAB, the optimized plan tracks a seasonal demand pattern of 870–1,250 tonnes/month, expands the workforce from 140 to approximately 313 employees during peak periods through selective hiring and layoffs, keeps inventory near zero for most of the year while meeting the required 500-tonne closing stock, and reports a monthly cost ranging from ₹18.7 to ₹694.9 lakhs (≈₹6,130 lakhs annually). The results demonstrate a mixed workforce–overtime–inventory strategy consistent with Lean cost-minimization objectives. A proposed IoT, smart-camera, and PLC/SCADA monitoring layer is presented as a Lean 4.0 extension that can provide the real-time visibility needed to keep such a plan responsive under actual shop-floor conditions. Future work should implement this monitoring layer, validate the LP formulation against measured plant data, and extend the model with multi-objective criteria such as energy consumption and demand-forecast uncertainty.

VII Future Scope

The future scope of the study includes developing a rolling-horizon aggregate planning model that can be updated monthly using actual demand and production data. Static demand forecasts can be replaced with machine-learning-based forecasting using historical sales and market information to improve planning accuracy. The model can also be integrated with live IoT sensor data through MATLAB or other optimization platforms for dynamic production re-planning. Further improvements can be achieved by developing predictive-maintenance models using rolling-mill vibration, motor-current, and temperature data to identify potential equipment failures in advance. In addition, computer-vision techniques can be implemented for automatic TMT surface-defect detection and dimensional inspection, thereby improving product quality and reducing manual inspection effort.

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