

A Mixed-Integer Linear Programming Model for Minimizing Production Costs with Soft Constraints: A Case Study of the Fast-Moving Consumer Goods Industry

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Abstract

High midstream supply chain costs related to production, by which financial liquidity is directly affected, are addressed in this research. An optimization model for monthly aggregate production planning was developed to reduce costs in the fast-moving consumer goods industry using linear programming (LP). Initially, the model (Minimize Z1) was presented to the factory and at a conference. Knowledge was integrated so that the efficiency of the production plan could be improved for the lowest cost. Based on industry feedback, the study was expanded to daily production scheduling. Outputs from Minimize Z1 were used as constraints in the daily model, and variables for the on-off status of production lines were added so that actual working conditions could be matched. It was shown by the evaluation results that traditional factory methods were outperformed by the developed models in every year. Average inventory costs were reduced by 99.98%, average raw material costs by 8.46%, and total average costs by 85.8 million baht (approximately 2.6 million USD) by the LP model (Minimize Z1). Furthermore, regular and overtime working hours were efficiently allocated by applying mixed-integer linear programming (MILP) in the second model (Minimize Z2). As a result, average daily costs were decreased, and the management of operational resources was emphasized. When regular and overtime costs were compared, it was found that costs were further reduced by Minimize Z2 by a total of 8,270,382 baht (about 255,000 USD) from the previous results. An important contribution to knowledge was made by this finding. Also, a p-value of less than 0.05 was found through a statistical test using 72 months of data. It was shown by this test that costs were significantly reduced by the Minimize Z2 model.

Keywords: mixed-integer linear programming, minimizing production costs, soft constraints, fast-moving consumer goods, midstream of supply chain

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1. INTRODUCTION

The fast-moving consumer goods (FMCG) industry is characterized by high-volume production, and products are sold on shelves at various prices based on brands. However, for popular brands, products are quickly sold out, so shelves must be restocked consistently. For this reason, large quantities are produced to meet daily consumer demand. Gradual and continuous growth of these products is observed in the ASEAN region. It is stated in a report by the Siam Commercial Bank Economic Intelligence Center (SCB EIC., 2025) that necessary consumer goods and services are continuously expanded and recovered. At the same time, however, the company's order volumes have not been significantly increased. Therefore, annual order volumes have been kept relatively stable over the past several years. Because the products are driven by seasonal demand, the required volumes can be clearly forecasted, as shown in Figure 1, where demand-driven production is indicated.

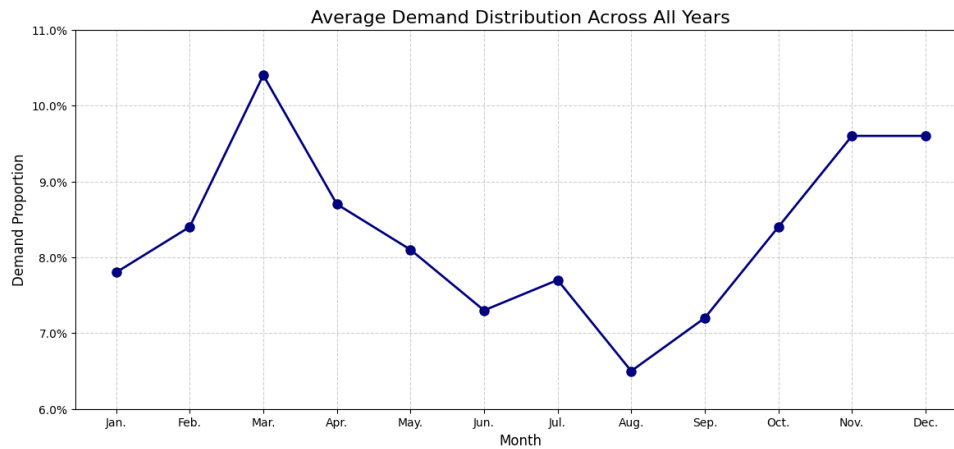


Figure 1 Average Seasonal Demand

Seasonal demand is reflected in Figure 1. Consequently, production resources throughout the supply chain are required to be managed, as illustrated in Figure 2. However, only the midstream supply chain is focused on in this research. Raw material costs and inventory costs are evaluated, and both factors are considered as the main decision variables.

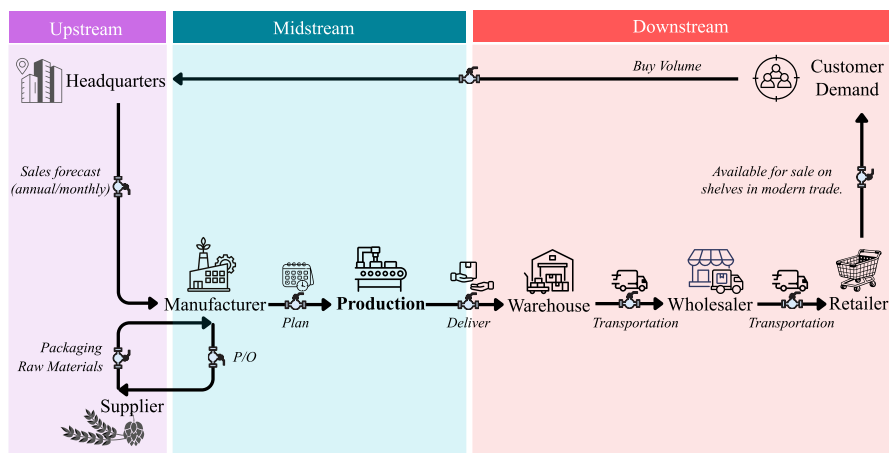


Figure 2 Supply Chain of Company Case Study

As shown in Figure 2, the production planning process is focused on in this research. Decisions regarding midstream regular and overtime costs are covered, along with decisions on upstream raw material costs and downstream inventory costs. Consequently, an optimal production plan is created, and overall costs are reduced for parallel continuous production lines. To align with customer demand, related workstation conditions must be carefully considered so that the open or closed status of the production lines can be determined, as illustrated in Figure 3.

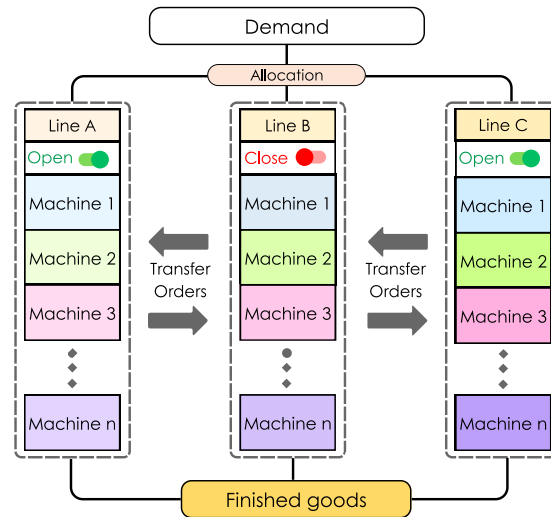


Figure 3 Parallel Production Line

As shown in Figure 3, after the constraints of determining the production line status to fulfill orders are considered, production resources must be planned to align with the operating time. Especially when high production targets are set, the first and second regular shifts must be managed, and additional overtime hours must be decided upon, as illustrated in Figure 4.

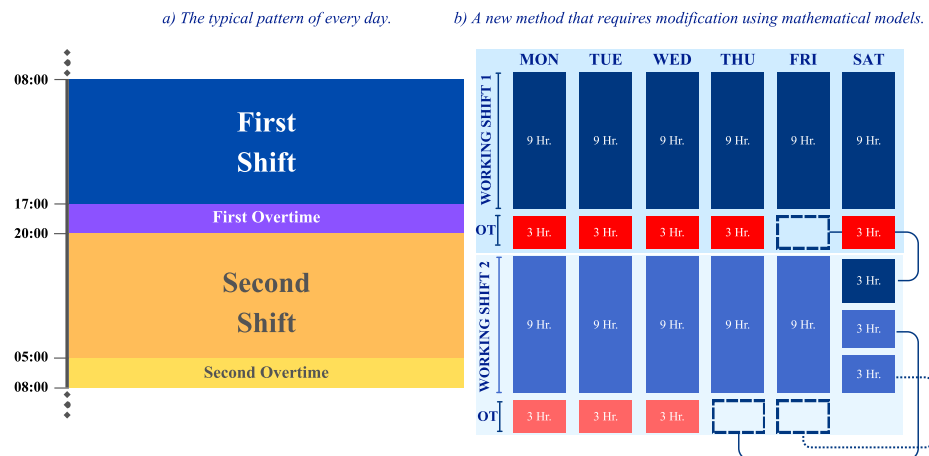


Figure 4 Characteristic of production line hours

As shown in Figure 4, total production costs are directly affected by the management of regular and overtime working hours. To find the optimal solution for integrated decisions regarding production lines and working shifts, traditional planning cannot be only relied upon to reduce costs. Instead, knowledge of mixed-integer mathematical models must be applied. Hard constraints are frequently used by many studies in mixed-integer linear programming models. However, answers from the linear program are used as constraints in this research. When these constraints are combined with minor daily routines, complex results are produced. Furthermore, conflicts are caused between these constraints and calendar days. Therefore, soft constraints must be applied so that the model is made flexible for actual factory use, as will be detailed in the literature review section.

2. LITERATURE REVIEW

2.1 Mathematical Models for Production Planning

Integrated decision-making problems are solved by considering production line management, working shifts, and overtime simultaneously so that actual situations can be supported. Moreover, it is realized by recent research that traditional mathematical models might be insufficient when uncertain data is faced. Therefore, cross-disciplinary knowledge is integrated, such as robust optimization models being combined with aggregate planning so that demand fluctuations are handled (Özel & Yılmaz, 2025). Advanced evolutionary algorithms, such as Genetic Algorithms (GA) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II), are widely used so that solutions in problems with complex constraints can be found (Mirzapour et al., 2011; Tirkolaee et al., 2023). It is reflected that modern models are not only used to create production schedules but are also functioned as the main simulation systems of organizations (Jurczak et al., 2022; Rafique & Cui, 2026). When the development of mathematical models over the past three decades is reviewed, a significant transition from isolated linear problem-solving to complex integrated models that support uncertainty is found. In the early stages, linear programming was focused on by researchers to manage basic lot-sizing and delivery scheduling problems (Aghezzaf, 2000). Later, it was found that industrial complexity was not limited to machines but was also expanded to labor and time. Thus, Mixed-Integer Linear Programming (MILP) models were utilized so that situations could be simulated more realistically. For example, overtime at the workstation level was reduced (Rinyarat, 2017); agricultural labor was allocated despite being less complex than the industrial sector but containing high hidden costs (Pantong & Chansombut, 2025); and packaging types were minimized using Binary Integer Linear Programming (BILP) because high costs were caused by unit diversity in the industry (Teeradech et al., 2018). Furthermore, specific operational constraints, such as cleaning-in-process (CIP), must be included so that mathematical models can be practically used in the fast-moving consumer goods (FMCG) industry. Flexible constraints are recommended by research so that a balance is created between strict capacity limits and changing production targets. Also, inventory holding constraints are often added so that excess stock is limited (Tirkolaee et al., 2019).

2.2 Production Cost Optimization

In the past, objective function equations were focused on minimizing direct costs, and overtime was often considered as an excess that must be eliminated (Rinyarat, 2017). Subsequently, cost structures were considered based on strategic trade-off principles. Certain costs were allowed to occur so that waste could be prevented. For instance, subcontracting and overtime were elevated as mechanisms by which capacity flexibility is created (Mokhtari et al., 2012). When idle capacity penalties are calculated alongside shift change and overtime costs, it is required by the models to weigh whether allowing idle time, producing in advance for inventory, or allowing backorders will result in the most optimal financial balance (Özel & Yılmaz, 2025). The dimension of finding optimal costs has been expanded to sustainable cost evaluations at the supply chain level. It is realized that minimizing costs may not only be a financial dimension but

must also cover impact costs. An obvious example is that goals for reducing negative environmental impacts are included as one of the equations along with total cost reduction. This reflects a new research perspective where it is recognized that the true cost of production is balancing the organization's financial survival with resource stability and social-environmental responsibility (Tirkolaee et al., 2023; Pinchat et al., 2023).

3. METHODOLOGY

Integrated mathematical models are applied in this research. Linear programming, by which total production costs are reflected, is combined with mixed-integer linear programming. The mixed-integer method is chosen because the calculated results from the aggregate plan are used so that a production schedule can be created. Through this schedule, resources are allocated to align with the forecasted demand, as illustrated by the research methodology in Figure 5.

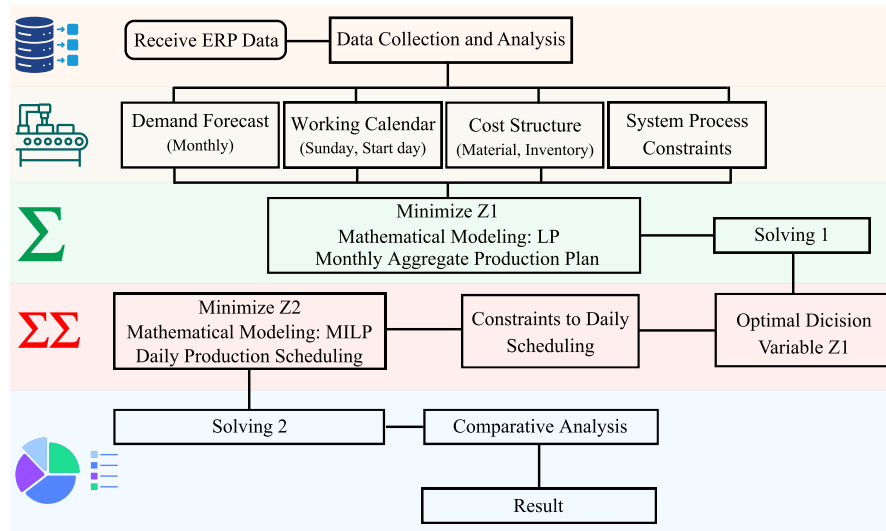


Figure 5 Research Methodology

As shown in Figure 5, data is received from the enterprise resource planning system to begin the research process. Then, the data is analyzed, filtered, and divided into four main groups: 1) six years of demand forecast data from 2021 to 2026, which are used for optimization processing; 2) working day data, including the allocated annual working calendar; 3) collected cost structure data; and 4) various constraints found in the production process. Once all data is collected, a monthly mathematical model (Minimize Z_1) is created, and it is optimized using Microsoft Excel Solver. After the optimal results for regular and overtime hours are obtained, they are allocated to production lines A, B, and C in the next step. This is done so that production dates, the open or closed status of the lines, or order adjustments can be determined. For this purpose, a second mathematical model (Minimize Z_2) is created so that the problem can be solved using mixed-integer linear programming. Finally, after the results for each year are processed, the mathematical model outputs are compared with traditional planning methods, and the research findings are concluded.

3.1 Mathematical Model

Mathematical models are created in this research so that actual production conditions are reflected, and the results can be practically implemented in business. The foundational monthly optimization model, represented by the first mathematical model (Minimize Z_1), adapts and extends the linear programming framework previously proposed by Charungsin et al. (2026). The monthly optimization model is represented by the first mathematical model (Minimize Z_1). Then, the optimized results from the first model

are used so that the second mathematical model (Minimize Z_2) is developed. These optimal results are allocated to production lines A, B, and C by applying soft constraints. Fundamental assumptions are made for the aggregate plan model (Minimize Z_1) and the master plan model (Minimize Z_2) to define the research problem. Monthly product demand is known in advance because forecasts are provided by headquarters. Unexpected machine variance is not considered since an emergency allowance is included in the production lines. Line efficiency is based on a manual agreed upon by management. Raw materials and packaging are assumed to be unlimited and always available. Finally, setup costs and times are kept constant for each line, and the production sequence is not considered. Because the problem is classified as NP-Hard, infeasible solutions are caused by some added sub-conditions. For example, conflicts with other equations are created when major cleaning cycles are moved to Sundays. Also, because regular and overtime hours must be aligned with the first model (Minimize Z_1), errors from decimal placements are generated, so finding exact solutions is made infeasible. Therefore, when the aggregate plan model (Minimize Z_1) is transferred to the master plan model (Minimize Z_2), regular and overtime cost factors are included, as shown in Table 1.

Table 1 Cost per hour from core and combined production (Baht)

Symbol	Line A	Line B	Line C	Total Cost per Hour
α	1819.50	1819.50	2114.50	5753.50
β	2729.25	2729.25	3171.75	8630.25
ϑ	1200	1100	1000	3300

Note: The average exchange rate is 1 USD = 33 THB in 2025 (Source: Bank of Thailand).

The hourly costs incurred by each production line are shown in Table 1. In the aggregate mathematical model (Minimize Z_1), all three lines are considered to be running simultaneously. However, in the master plan mathematical model (Minimize Z_2), all lines are not required to run at the same time, as the production lines can be turned on or off.

3.2 Aggregate Mathematical Modeling

Indices and sets

t The month is represented by index t , $t = \{1, 2, 3, \dots, 12\}$

Define Parameters

C_r The regular time cost per hour (5,753.50 THB)
 C_o The overtime time cost per hour (8,630.25 THB)
 C_h The inventory holding cost per unit (1.08 THB)
 C_m The raw material cost per unit (10 THB)
 C The production capacity per hour
 S_t The number of line startup hours in month t
 A_t The number of allowance hours in month t
 CIP_t The number of major cleaning-in-process hours in month t
 D_t The product demand in month t
 N_t The number of working days in month t

Define Decision Variables

P_t The production quantity in month t
 I_t The inventory at the end of month t
 O_t The number of overtime working hours in month t
 R_t The number of regular working hours in month t

3.3 Master Mathematical Modeling

Indices and sets

- l The set of production lines, where $l, l \in \{A, B, C\}$
 d The set of production days, where $d, d \in \{1, 2, \dots, N_t\}$
 k The dummy index for calendar days, where $k, k \in \{1, 2, \dots, M_t\}$

Define Parameters

- α_i The regular time cost for production line i
 β_i The overtime cost for production line i
 ϑ_i The setup cost for production line i
 φ_i The production capacity units per hour of line i
 P_t The production quantity from the aggregate mathematical model in month t
 O_t The number of overtime hours from the aggregate mathematical model in month t
 CIP_t The number of major cleaning-in-process hours in month t
 C The total production capacity from the aggregate mathematical mode
 γ The line setup time hour
 ∂ The allowance or clearance time hours
 S_{sun} The number of Sundays in that month
 N_t The net number of working days in month t
 M_t The total number of calendar days in month t

Penalty Parameter

- ρ_{demand} The penalty cost per unit of product shortage (10,000 THB)
 ρ_{OT} The penalty cost per hour of overtime deviation (5,000 THB)
 ρ_{CIP} The penalty cost per hour of incomplete CIP (20,000 THB)

Define Decision Variables

Slack Variables

- S_{demand} The number of product units failing to meet the target
 S_{OT}^- The amount of overtime below the target
 S_{OT}^+ The amount of overtime exceeding the target
 S_{CIP} The number of periodic major cleaning-in-process hours failing to meet the target

Continuous Variables

- $r_{i,d}$ The regular working hours of production line i on day d
 $o_{i,d}$ The overtime working hours of production line i on day d

Binary Variables

- $y_{i,d}$ The production status

$$y_{i,d} = \begin{cases} 1 & \text{Open Production Line in day } d \\ 0 & \text{Close Production Line in day } d \end{cases}$$

 $\delta_{i,d}$ The setup status for starting the production line

$$\delta_{i,d} = \begin{cases} 1 & \text{have activity Setup in day } d \\ 0 & \text{have no activity Setup in day } d \end{cases}$$

 u_d The periodic major cleaning status

$$u_d = \begin{cases} 1 & \text{have activity CIP in day } d \\ 0 & \text{have no activity CIP in day } d \end{cases}$$

3.4 Mathematical model of the aggregate production plan

Objective Function:

$$\text{Minimize } Z_1 = \sum_t C_r R_t + \sum_t C_o O_t + \sum_t C_h I_t + \sum_t C_m P_t \quad (1)$$

Subject to:

$$C \times (R_t + O_t - A_t - CIP_t) - P_t \geq 0 \quad \forall t \quad (2)$$

$$R_t + O_t - A_t - CIP_t \geq 0 \quad \forall t \quad (3)$$

$$P_t + I_{t-1} - I_t - D_t \geq 0 \quad \forall t \quad (4)$$

$$\frac{I_t}{D_t} \leq 0.02 \quad \forall t \quad (5)$$

$$\frac{O_t}{N_t} \leq 6 \quad \forall t \quad (6)$$

$$\frac{R_t + O_t}{N_t} \leq 24 \quad \forall t \quad (7)$$

$$A_t - S_t - 4N_t = 0 \quad \forall t \quad (8)$$

$$\frac{CIP_t}{N_t} = 1.1 \quad \forall t \quad (9)$$

$$\frac{R_t}{N_t} \leq 18 \quad \forall t \quad (10)$$

$$P_t, O_t, I_t, R_t \geq 0 \quad \forall t \quad (11)$$

3.5 Mathematical model of the master production scheduling

Objective Function:

$$\begin{aligned} \text{Minimize } Z_2 = & \sum_d^{N_t} (\alpha_A \cdot r_{A,d}) + \sum_d^{N_t} (\beta_A \cdot o_{A,d}) + \sum_d^{N_t} (\vartheta_A \cdot \delta_{A,d}) + \sum_d^{N_t} (\alpha_B \cdot r_{B,d}) + \sum_d^{N_t} (\beta_B \cdot o_{B,d}) \\ & + \sum_d^{N_t} (\vartheta_B \cdot \delta_{B,d}) + \sum_d^{N_t} (\alpha_C \cdot r_{C,d}) + \sum_d^{N_t} (\beta_C \cdot o_{C,d}) + \sum_d^{N_t} (\vartheta_C \cdot \delta_{C,d}) \\ & + (\rho_{demand} \cdot S_{demand}) + \rho_{OT} \cdot (S_{OT}^- + S_{OT}^+) + (\rho_{CIP} \cdot S_{CIP}) \end{aligned} \quad (12)$$

Subject to:

$$\sum_d (\varphi_A r_{A,d} + \varphi_B r_{B,d} + \varphi_C r_{C,d} + \varphi_A o_{A,d} + \varphi_B o_{B,d} + \varphi_C o_{C,d}) + S_{demand} \geq P_t \quad \forall t \quad (13)$$

$$\sum_d (\varphi_A o_{A,d} + \varphi_B o_{B,d} + \varphi_C o_{C,d}) + S_{OT}^- - S_{OT}^+ = C \cdot O_t \quad \forall t \quad (14)$$

$$\delta_{A,d} \geq y_{A,d} - \frac{O_{A,d-1}}{6} \quad \forall d > 1 \quad (15)$$

$$\delta_{B,d} \geq y_{B,d} - \frac{o_{B,d-1}}{6} \quad \forall d > 1 \quad (16)$$

$$\delta_{C,d} \geq y_{C,d} - \frac{o_{C,d-1}}{6} \quad \forall d > 1 \quad (17)$$

$$r_{A,d} \leq 18 \quad \forall d \quad (18)$$

$$r_{B,d} \leq 18 \quad \forall d \quad (19)$$

$$r_{C,d} \leq 18 \quad \forall d \quad (20)$$

$$o_{A,d} \leq 6 \quad \forall d \quad (21)$$

$$o_{B,d} \leq 6 \quad \forall d \quad (22)$$

$$o_{C,d} \leq 6 \quad \forall d \quad (23)$$

$$r_{CIP,d} = 5.5 \times u_d \quad \forall d \quad (24)$$

$$\sum_d r_{CIP,d} + S_{CIP} \geq CIP_t \quad \forall t \quad (25)$$

$$r_{A,d} + o_{A,d} + r_{CIP,d} + \gamma \cdot \delta_{A,d} + \partial \cdot y_{A,d} \leq 24 \cdot y_{A,d} \quad \forall d \quad (26)$$

$$r_{B,d} + o_{B,d} + r_{CIP,d} + \gamma \cdot \delta_{B,d} + \partial \cdot y_{B,d} \leq 24 \cdot y_{B,d} \quad \forall d \quad (27)$$

$$r_{C,d} + o_{C,d} + r_{CIP,d} + \gamma \cdot \delta_{C,d} + \partial \cdot y_{C,d} \leq 24 \cdot y_{C,d} \quad \forall d \quad (28)$$

$$y_{i,d} = 0 \quad \forall i \in \{A, B, C\}, \forall d \in \{S_{sun}\} \quad (29)$$

$$\sum_{k=d}^{d+5} u_k \leq 1 \quad \forall d \in \{1, 2, 3, 4, 5, \dots, M_t - 5\} \quad (30)$$

$$r_{A,d}, r_{B,d}, r_{C,d}, o_{A,d}, o_{B,d}, o_{C,d} \geq 0 \quad \forall d \quad (31)$$

3.6 Explain the meaning of limit equations

The objective function of the aggregate plan model (Minimize Z1) is represented by Equation (1). The lowest total monthly cost is targeted, which is calculated from the sum of regular working time costs, overtime costs, inventory holding costs, and raw material costs. Production capacity from working hours (regular and overtime minus allowance and major cleaning times) is required to be sufficient for the target production quantity by Equations (2) and (3), and the total allocated working hours must not be negative. Inventory balance is maintained by Equation (4). The production volume combined with the inventory carried over from the previous period, after deducting the ending inventory, is required to be equal to or greater than the customer demand for that month. The monthly inventory level is restricted to not exceed 2% of the product demand by Equation (5). The average daily overtime is limited to a maximum of 6 hours by Equation (6). The sum of average daily regular and overtime hours is limited to a maximum of 24 hours by Equation (7). The allowance time will be obtained by deducting the time required for activities in the production line, Equation (8). The monthly cleaning-in-process (CIP) time will be 1.1 times the number of working days in month, Equation (9). The average daily regular working hours are limited to a maximum of 18 hours by Equation (10). Decision variables, including production quantity, overtime, inventory, and regular working time, are constrained to be non-negative by Equation (11). The objective function of the daily master plan model (Minimize Z2) is represented by Equation (12). The lowest daily production scheduling cost is targeted. Regular and overtime costs for each production line (A, B, and C) are covered, and penalty costs from soft constraints are also added to the equation. These include penalties for unmet

production targets, overtime deviations from the aggregate plan, and incomplete major cleaning (CIP) target hours. A soft constraint for the production target is defined by Equation (13). The total production volume generated from regular and overtime hours across all lines (multiplied by the capacity ϕ_i), combined with the slack variable for unmet production (S_{demand}), is required to reflect the target product demand. Through this, the mathematical model is allowed to find a solution without an infeasible error, even if the production schedule cannot exactly meet the target. A soft constraint for overtime management and total capacity is established by Equation (14). Production from all overtime hours, evaluated against the maximum total capacity of C units (viewing all 3 lines as the factory's total capacity), is controlled to be as close to the master plan's overtime target as possible. Flexibility is permitted through two slack variables: actual overtime below the target and actual overtime exceeding the target. The daily setup status for production lines A, B, and C is required to be related to the open status and overtime hours of the previous day by Equations (15), (16), and (17). Regular working hours for production lines A, B, and C are limited to a maximum of 18 hours per day by Equations (18), (19), and (20). Overtime hours for production lines A, B, and C are limited to a maximum of 6 hours per day by Equations (21), (22), and (23). This indicates that if the binary decision variable on that day were to perform a CIP (Cleaning-in-Process) operation, it would take 5.5 hours, according to Equation (24). During that month, all CIP activities must be completed according to the first mathematical model using Equation (25). The sum of all daily operating times for lines A, B, and C which consists of regular working time, overtime, major cleaning (CIP) time, setup time, and clearance time is restricted to not exceed 24 hours by Equations (26), (27), and (28). All production lines are required to be closed on Sundays by Equation (29). Major cleaning (CIP) activities are limited to be performed no more than once within a consecutive 5-day period by Equation (30). Regular and overtime working hour variables for all production lines are constrained to be non-negative by Equation (31).

3.7 Optimization solver tools

Microsoft Excel Solver is utilized to optimize the aggregate mathematical model (Minimize Z_1) because the decision variables are maintained at a level that can be calculated by the program. Meanwhile, the Google OR-Tools library is used to find optimal results because processing limitations are found in the Excel add-in. When the constraints in the master plan mathematical model (Minimize Z_2) are considered, such as Equations (15) to (17) and Equations (26) to (30), it is found that binary decision variables are used. For instance, $y_{i,d}$ is used for the open-close status of the production lines, $\delta_{i,d}$ for the setup status, and u_d for the cleaning status. These variables are operated alongside continuous variables on every working day for all three production lines. Consequently, the model is characterized as mixed-integer linear programming. This is classified as a highly complex problem, where the number of variables and constraints is expanded beyond the processing capacity of basic tools. Therefore, these complex variables can be successfully managed by applying Google OR-Tools.

4. RESULTS AND DISCUSSION

Total costs were found to be reduced by the aggregate mathematical model (Minimize Z_1). Regular and overtime working costs were decreased compared to traditional planning methods. This baseline cost reduction achieved by the aggregate model is consistent with the preliminary findings presented in Charungsin et al. (2026). This is illustrated in Figure 6, where the results of the aggregate mathematical model (Minimize Z_1) are compared with the traditional factory plan.

4.1 Computational Characteristics and Solver Performance

The datasets used to calculate cost reduction results were collected from the enterprise resource planning (ERP) system. Demand forecasts from 2021 to 2026 were included to be used as inputs for the mathematical models. Production reports were utilized to evaluate outputs and costs, while traditional production plans were used for comparison. Working calendars were assessed to determine regular time,

overtime, production days, and holidays. Next, financial statements were reviewed so that the business impact of this research could be evaluated. Finally, process blueprints were used to formulate both monthly and daily constraint equations. The continuous flow of the three identical production lines and the shared order volumes were detailed by these blueprints.

Problem complexity and processing efficiency are summarized in Table 2. The monthly model was solved by Microsoft Excel Solver because a small number of decision variables was contained, and less processing time was required. However, binary decision variables, such as $y_{i,d}$, $\delta_{i,d}$, and u_d were required by the daily model. Because the limit of Microsoft Excel Solver was exceeded by these variables, the Google OR-Tools library was used to calculate the daily results.

Table 2: Problem size and computation execution time

Mathematical model	Solver tool	Continuous variables	Binary variables	Constraints	Average execution time (seconds)
Minimize Z_1 (Monthly Aggregate)	Microsoft Excel Solver	4	-	9	12.14
Minimize Z_2 (Daily Master Plan)	Google OR-Tools	186	186	375	124.90

Note: The execution time recorded on a laptop with an AMD Ryzen 5 7520U with Radeon Graphics and 16 GB of RAM

Average execution times over 72 months (six years) are shown in Table 2. Less than one minute is needed to optimize the aggregate model because fewer decision variables are used. In contrast, a longer average time of over one minute is required by the master plan model because many continuous and binary variables are included. Each execution was processed and timed month by month. Satisfactory results were produced, which are displayed as figure in Section 4.2: Model Comparison Results.

4.2 Model Comparison Results

The results of the monthly cost optimization from the aggregate model (Minimize Z_1) compared to traditional planning are shown in Figure 6. It is demonstrated that better planning results are produced by the mathematical model than by traditional factory methods. Also, the knowledge contribution from extending the Minimize Z_1 model to the Minimize Z_2 model is presented. Suitable results were generated, which will be shown next.

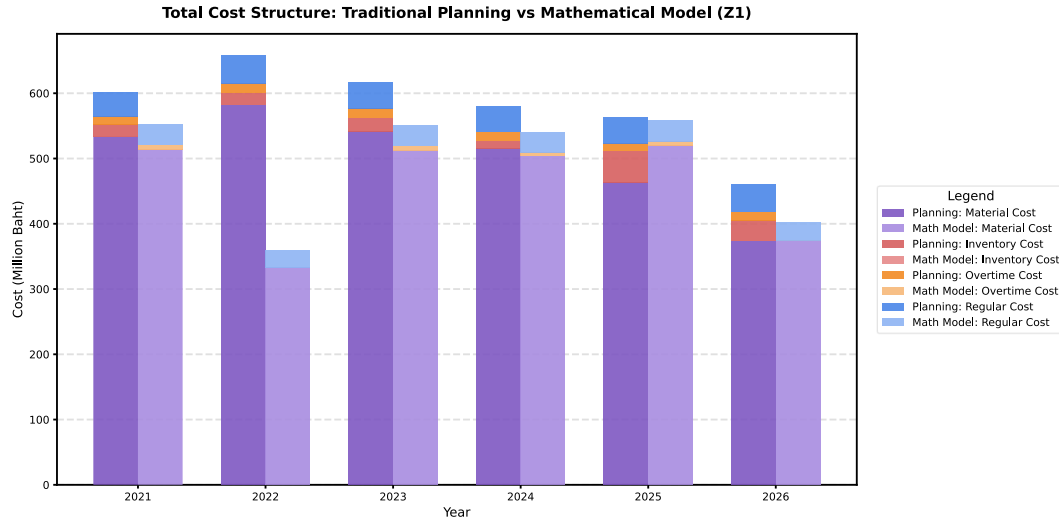


Figure 6 Result of aggregate mathematical model

As shown in Figure 6, it is demonstrated that traditional production planning is outperformed by the mathematical model across all decision variables. Very low inventory levels are maintained. Regular and overtime working hours are allocated based on actual demand. Furthermore, when regular and overtime costs are reduced, overproduction for inventory is not required, and raw materials are utilized appropriately. However, although raw material costs are high and prominent in the graph, regular and overtime working hour costs are the decision variables considered in the master plan model (Minimize Z_2). This is illustrated in Figure 7, where regular and overtime working hours are compared with the traditional production plan.

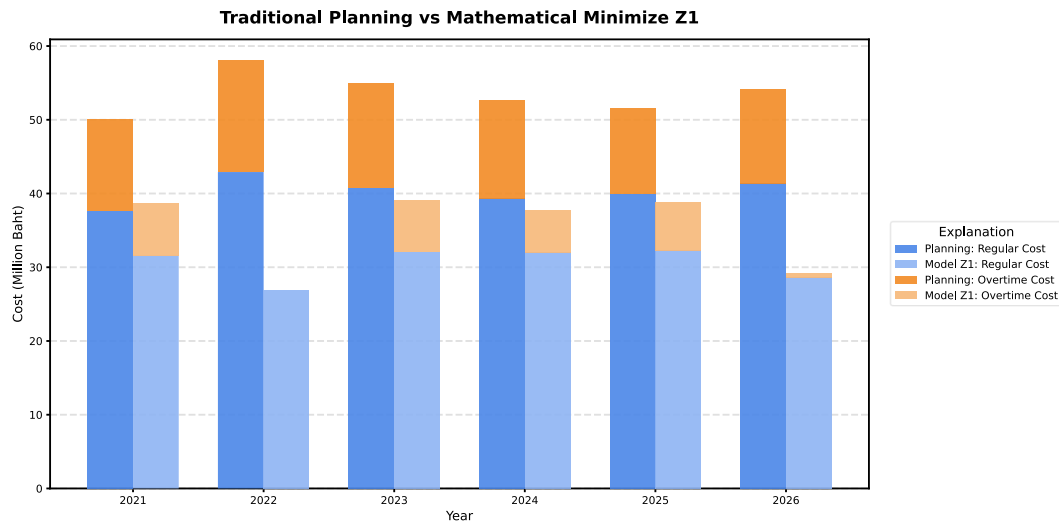


Figure 7 The cost per hour (regular hours and overtime)

As shown in Figure 7, when regular and overtime costs are compared, the aggregate mathematical model is found to be more efficient than traditional factory planning methods in every year. However, a macroscopic perspective is maintained by the aggregate model because all three production lines are considered as a single line. Consequently, in this aggregate view, all three lines are opened and closed simultaneously, and major cleaning (CIP) cycles are performed at the same time. For this reason, the efficiency of distributing production volume to each line must be appropriately optimized by the master

plan mathematical model (Minimize Z_2). In practice, even though all lines operate simultaneously, regular and overtime costs for the three lines are not equal. When evaluated in the master plan model (Minimize Z_2), Line C is found to have higher operating costs than Lines A and B, yet Line C has the lowest setup cost. Therefore, this can be defined as a production distribution problem. To enable the mathematical model to find an optimal solution, setup penalties are added. Additionally, optimal results from the aggregate model (Minimize Z_1) including regular working time (R_t), overtime (O_t), and major cleaning activities (CIP_t) are applied as constraints in the master plan model (Minimize Z_2) due to their correlation. The optimal results generated by the master plan model (Minimize Z_2) are presented in Table 2, where reduced regular and overtime schedules are demonstrated. This occurs when Lines A and B are primarily selected by the model, while partial setup costs are accepted in certain periods. As a result, production line statuses or order adjustments must be processed by the algorithm, which reflects its decision-making behavior in creating the production schedule. When the results from the master plan model (Minimize Z_2) are evaluated, it is revealed that transferring from a macroscopic to a microscopic model leads to cost reductions. This is achieved because flexible line switching, on/off statuses, and workload adjustments are allowed, reflecting further cost reductions as illustrated in Figure 8. An example of the 2025 results is presented in Table 3.

Table 3 Year's production results table 2025

Month	Production	Overtime hours			Regular time hours			Number of times the line was set up	Number of CIP times
		Line A	Line B	Line C	Line A	Line B	Line C		
Jan.	7.10%	0	0	0	463.5	463.5	78.0	60	15
Feb.	7.89%	114	102	0	333.5	342.5	225.0	27	15
Mar.	10.42%	156	156	156	336.0	336.0	335.8	18	12
Apr.	10.01%	156	153	114	331.5	334.5	329.4	15	15
May	8.54%	106	71	0	391.0	419.0	223.1	41	18
Jun.	7.34%	70	17	0	387.5	427.5	138.1	49	15
Jul.	7.48%	15	15	0	463.5	463.5	102.2	61	15
Aug.	6.82%	0	0	0	445.5	445.5	75.4	58	15
Sep.	6.98%	0	0	0	445.5	445.5	97.8	59	15
Oct.	8.81%	132	84	0	375.5	411.5	245.3	34	15
Nov.	9.65%	146	145	120	321.5	322.5	312.2	14	15
Dec.	8.95%	121	106	10	379.0	390.8	261.0	33	18
Total	100%	1016	849.23	399.77	4673.5	4802.27	2423.15	469	183

When the 2025 data from Table 3 is analyzed, the highest production proportion is found to be concentrated in March. An increased rate of workload balancing into the regular working hours of lines A and B is observed. For 2026, low forecast volumes were provided by the headquarters. Consequently, minimal overtime was required, so it is not presented in the table. Furthermore, the comparison between regular and overtime costs is illustrated in Figure 8.

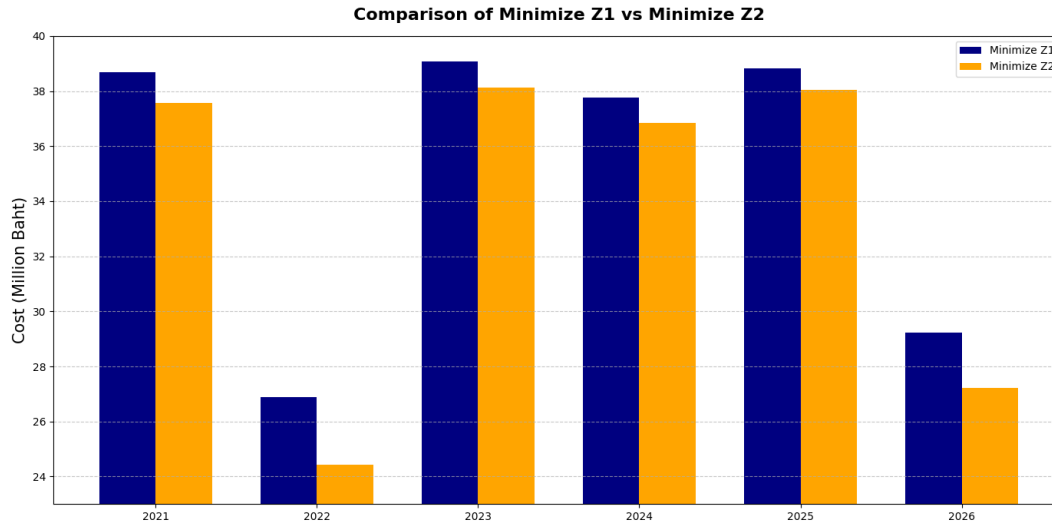


Figure 8 Compare the costs of regular working hours and overtime.

As shown in Figure 8, the sum of regular and overtime working costs is compared. Because a macroscopic perspective of total production is maintained by the aggregate mathematical model (Minimize Z_1), production lines are required to be operated simultaneously by the factory. However, in actual production, workloads can be shifted from Line C to Lines A and B. Alternatively, Line C can be operated during periods of heavy orders, and lower setup costs are accepted as a cost-effective choice. For these decisions, results are processed by the algorithm (Solver), including whether to produce, which lines to select, how to adjust workloads, and when to schedule overtime. When optimal results from the aggregate model (Minimize Z_1) are used so that a production schedule can be created for the master plan model (Minimize Z_2), the problem is considered at a microscopic level. Because workloads can be adjusted and each line can be opened or closed independently, more efficient results are generated. This evaluation effectively builds upon the first model (Minimize Z_1), where only the macroscopic level was considered. When this is developed as a contribution to knowledge, improved efficiency is achieved, and the results can be effectively applied by the factory at the operational level. It is found that the total regular and overtime costs of the master plan model (Minimize Z_2) are reduced compared to the aggregate model (Minimize Z_1). This reduction is caused by microscopic factors. Even though optimal results from the aggregate model are applied, minor details must be evaluated, such as unequal costs among production lines. If operations are not continuous, production lines must be restarted, and additional setup costs are incurred. Because of these factors, production line statuses and workload adjustments are required to be processed by the algorithm.

4.3 Result Validation and Statistical Analysis

A statistical analysis was conducted using a paired two-sample t-test so that the solution quality and the model efficiency could be confirmed. Total monthly regular and overtime costs from the aggregate linear programming model (Minimize Z_1) and the master mixed-integer linear programming model (Minimize Z_2) were compared. Seventy-two paired monthly data points from 2021 to 2026 were included in the dataset. The cost reduction achieved by changing from the macroscopic plan level (Minimize Z_1) to the microscopic scheduling level (Minimize Z_2) was evaluated to determine if it was statistically significant. A summary of the t-test results is shown in Table 4.

Table 4 Paired Two-Sample t-Test for Solution Quality Comparison

	<i>LP – Minimize Z_1</i>	<i>MILP – Minimize Z_2</i>
Mean	2923588	2808721
Variance	3.7×10^{11}	4.5×10^{11}
Observations	72	72
Pearson Correlation	0.998	
Hypothesized Mean Difference	0	
Degree of Freedom	71	
t Stat	13.5	
P(T ≤ t) one-tail	1.5×10^{-21}	
t Critical one-tail	1.7	
P(T ≤ t) two-tail	3.1×10^{-21}	
t Critical two-tail	2.0	

As shown in Table 4, a lower average monthly cost of 2,808,721 THB is produced by the mixed-integer linear programming (MILP) model, compared to 2,923,588 THB by the linear programming (LP) model. Because the p-value is much lower than the standard 0.05 significance level, the null hypothesis is rejected. It is confirmed by this statistical evidence that a significantly better solution quality is provided by the master production scheduling model (Minimize Z_2). Through this, reliable and consistent cost reduction is ensured throughout the entire planning period.

5. CONCLUSION

5.1 Summary of Findings

Total costs in the midstream supply chain of the fast-moving consumer goods industry were successfully reduced by applying linear programming (LP) for monthly planning in the aggregate plan model (Minimize Z_1). Average inventory costs were reduced by 99.98%, average raw material costs by 8.46%, and total average costs by 85.8 million baht per year. Furthermore, when the results from the aggregate plan were used to create a daily production schedule using mixed-integer linear programming (MILP) in the master plan model (Minimize Z_2), regular and overtime working hours were efficiently allocated. Consequently, operational costs were further reduced compared to the linear programming method in every tested year by a total of 3.93%, and an additional 8,270,382 Thai baht was saved.

5.2 Discussion and analysis of results

Overproduction for inventory is focused on by traditional factory planning methods, whereas production quantities are adjusted by mathematical models to align with actual demand. Consequently, unnecessary raw material usage is reduced, and inventory is managed according to corporate policies. Customer service levels are not affected by reducing factory inventory levels to no more than 2%, because demand fluctuation risks are already managed by the headquarters. Although efficient results are provided by the aggregate plan model (Minimize Z_1), limitations are found in its macroscopic perspective, where all three production lines are integrated as a single unit. These limitations are resolved by the master plan model (Minimize Z_2) by processing the differences in labor and setup costs of each production line. Therefore, lower-cost production lines, such as Lines A and B, are selected by the algorithm, and setup costs are accepted in some situations so that maximum overall cost-effectiveness is achieved. Finally, the model's results can be utilized by management to evaluate the trade-off between approving overtime, opening high-cost production lines, or accepting the risk of product shortages, so that cash flow is managed with maximum efficiency.

Furthermore, the proposed mathematical models, especially the master scheduling model (Minimize Z_2), are not limited to the fast-moving consumer goods industry. Parallel production lines are efficiently managed, and regular and overtime shifts are dynamically allocated by the core logic. Also, state-dependent setup and cleaning-in-process (CIP) constraints are included. Therefore, this logic can be adapted to other continuous or semi-continuous manufacturing sectors. For example, identical constraint behaviors are shared by strict hygiene processes and mandatory CIP cycles between product batches in the pharmaceutical, chemical, and cosmetics industries. Moreover, flexibility is provided by penalty-weighted soft constraints. Through this, the model can be easily customized to be used in other contexts.

REFERENCES

- Aghezzaf, E.-H. (2000). Lot-sizing problem with setup times in labor-based capacity production systems. *International Journal of Production Economics*, 64(1-3), 1-19. [https://doi.org/10.1016/s0925-5273\(99\)00029-8](https://doi.org/10.1016/s0925-5273(99)00029-8)
- Chantaros, P., Klaychey, R., & Limpianchob, C. (2023). Efficiency improvement of sustainable supply chain planning system for Namwa banana production using mixed integer linear programming model. *Thai Journal of Operations Research*, 11(1), 21-31.
- Charungsin, W., Sirivongpaisal, N., & Suwatcharachaitiwong, S. (2026). Demand-driven aggregate production planning in fast-moving consumer goods manufacturing: A linear programming framework. In *National Operations Research Network Conference 2026*. (pp. 298-308). Kasetsart University: Bangkok.
- Hirunthornjiraphat, R. (2017). *Production planning to reduce overtime: A case study of an electronic parts manufacturing plant*. (Master's thesis). Bangkok: King Mongkut's Institute of Technology Ladkrabang.
- Jacobs, F. R., Chase, R. B., & Lummus, R. R. (2011). *Operations and supply chain management*. McGraw-Hill Irwin: New York.
- Jurczak, M., Miebs, G., & Bachorz, R. A. (2022). Multi-criteria human resources planning optimisation using genetic algorithms enhanced with MCDA. *Operations Research and Decisions*, 32(4), 57-74. <https://doi.org/10.37190/ord220404>
- Laisupanwong, T., Intiyot, B., & Tipwiwatpotjana, P. (2018). Integer linear programming models for reduction of number of types of packing boxes. *Thai Journal of Operations Research*, 6(2), 22-31.
- Mirzapour Al-e-hashem, S. M. J., Malekly, H., & Aryanezhad, M. B. (2011). A multi-objective robust optimization model for multi-product multi-site aggregate production planning in a supply chain under uncertainty. *International Journal of Production Economics*, 134(2), 28-42. <https://doi.org/10.1016/j.ijpe.2011.01.027>
- Mokhtari, H., Nakhai Kamal Abadi, I., & Amin-Naseri, M. R. (2012). Production scheduling with outsourcing scenarios: a mixed integer programming and efficient solution procedure. *International Journal of Production Research*, 50(19), 5372-5395. <https://doi.org/10.1080/00207543.2011.627687>
- Özel, Ö., & Yılmaz, G. (2025). Flexible production planning MILP model including shift and overtime decisions. *IFAC PapersOnLine*, 59(10), 1695-1699. Izmir University of Economics: İzmir. <https://doi.org/10.1016/j.ifacol.2025.09.285>

- Pantong, A., & Chansombut, S. (2025). Mixed-integer linear programming model for production planning and labor allocation in the melon farm. *Kasem Bundit Engineering Journal*, 15(2), 126-141.
- Rafique, F., & Cui, H. (2026). Balancing exploration and exploitation in genetic algorithm with a novel selection operator. *Operations Research and Decisions*, 36(1), 53-73. <https://doi.org/10.37190/ord/211420>
- Siam Commercial Bank Economic Intelligence Center. (2025). *Navigating the economic storm: 2026 business trends amidst economic storms and all-around risks*. <https://www.scbeic.com/th/detail/product/9990>
- Tirkolaei, E. B., Aydin, N. S., & Mahdavi, I. (2023). A bi-level decision-making system to optimize a robust-resilient-sustainable aggregate production planning problem. *Expert Systems With Applications*, 228, 120476. <https://doi.org/10.1016/j.eswa.2023.120476>
- Tirkolaei, E. B., Goli, A., & Weber, G. W. (2019). Multi-objective Aggregate Production Planning Model Considering Overtime and Outsourcing Options Under Fuzzy Seasonal Demand. In *Advances in Manufacturing II-Volume 2* (pp. 81-96). Springer. https://doi.org/10.1007/978-3-030-18789-7_8