International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V72I6P126

Volume 72 Issue 6, 273-286, June 2024
© 2024 Seventh Sense Research Group®

Original Article

A Clearing Function for Multi-Product Production Planning Based on Price and Lead Time Sensitive Demand

Kumara Pinasthika Dharaka[1], Ega Rizkiyah[2]

[1]*Department of Industrial Engineering, Faculty of Engineering, Bina Nusantara University, Jakarta, Indonesia*
[2]*Department of Industrial and Systems Engineering, Faculty of Industrial Technology and Systems Engineering, Institut Teknologi Sepuluh Nopember, Kampus ITS Sukolilo, Surabaya, Indonesia.*

[1]*Corresponding Author : kumara.pinasthika@binus.ac.id*

Received: 25 March 2024 Revised: 17 May 2024 Accepted: 29 May 2024 Published: 29 June 2024

Abstract - *Customers are more likely to pay for a shorter lead time the more sensitive they are to lead time. In three periods, the smoothing for multiple products (P_MCFS) model can meet the same amount of demand. It makes sense that the P_MCFS model's longer lead time would result in a lower demand. When lead time is more important to consumers than price, the model with flexible production for multiple products (P_MCFF) model exhibits a substantial price rise for high utilization levels. Businesses may charge a significantly higher price when there is less demand sensitivity and clients are willing to pay more for a shorter lead time. Businesses are compelled to cut their prices when a market segment is solely price-sensitive, which lowers their profit per unit sold. Consumers who value lead time are prepared to spend more, which means that a larger profit may be made. In this situation, businesses that are unable to complete demand orders within the minimal lead time may suffer penalties. Due to a smoothing constraint, this was demonstrated by a significantly reduced demand and profit loss in the P_MCFS model. The way that customers react to a firm's lead times and price greatly influences the development cycle of that company. Using the same input that is available under the numerical investigation, we run the three models using IBM CPLEX software and conduct a comparison analysis.*

Keywords - *Clearing function, Production planning, Lead time, Sensitive demand, Multi-Product.*

1. Introduction

It is commonly acknowledged that there are two stages of production planning: disaggregate (detailed) at the shop floor or lower managerial planning level and aggregate at the upper managerial planning level. When congestion at the upper planning level is ignored, the disaggregate production plan may become unworkable, leaving shop floor managers with tough decisions to make [1]. At the lower planning level, the widely used production-planning tool MRP assumes that the degree of WIP and throughput have a linear relationship. This presumption causes an overestimation of resource capacity, which results in a production plan that is not realistic. The literature on production planning has recently demonstrated a growing interest in the various methods for calculating the Clearing Function (CF) through analytical or simulation techniques. Nevertheless, the simulation approach has a drawback in that it is hard to apply the resulting CF to situations other than the one Missbauer [2] is considering. Furthermore, the analytical method mainly depends on determining the CF for the machine that is the bottleneck. Regretfully, in re-entrant manufacturing setups with many goods, the product mix itself causes the bottleneck to shift, and this shift occurs from period to period based on the planning run's (typically linear program's) advice. Products in many industries must complete a sequence of production steps, or “route,” in order to be finished. Controlling the production flows becomes challenging when machines are partially flexible, meaning they can process steps of distinct goods or different steps of the same product (reentrant flows) [3]. Variant-specific capabilities can be varied across production lines in high-volume, high-variant production to handle product variance while minimizing required investments [4]. From an operational point of view, the lead time between the start of a manufacturing stage and its execution, or between the procurement of raw materials and the delivery of an order, is another noteworthy issue [5]. The need for improved coordination between marketing and operations has long been recognized by scholars and practitioners, yet managing this "marketing operations interface" remains a difficult undertaking. The opposing goals and tactics of these two functional departments are the cause. Nonetheless, a company's performance may depend on the marketing and operations departments working together well. A company's profitability may suffer from ineffective departmental information sharing, such as when it comes to client demand. Salespeople strive to close as many deals as they can because their pay is based on sales volume, increased utilization, capacity overload, and congestion, and thus, increased manufacturing department costs are the outcomes of this [6].

Since the production and marketing departments divide lead time and price decisions, Hamed et al. [7] recommend that organisations with high utilisation levels pay more attention to the marketing operations interface. In a production system, we will first investigate the impact of congestion or load-dependent lead time. Conversely, we will investigate how lead time sensitivity and pricing affect demand. In the end, we will combine the two ideas to investigate how they affect production scheduling and a company's profit. This entails thinking about how production planning models should take customer preferences into account.

These papers make several contributions to literature. Initially, two Upasani and Uzsoy [8] models incorporating the influence of pressure on a production cycle (P_MCFF) were adapted. This type offers more production flexibility and cleaning functions. Moreover, the P_MCFS model suggests leveling or smoothing this input, allowing performance to be reached in the same amount in a shorter amount of time.

Second, it fills a gap in the literature by discussing how to price and prepare for product development for multiple products over different time periods with capacity constraints to boost sales and draw customers while also communicating lead times and demand expectations through cooperation between the marketing and manufacturing departments. The models also include lead time in addition to a dependent demand element. This paper will examine the production models for a few utilization levels across different lead times. After that, select a significant number of orders that the company plans to fulfill, after which we will release volumes and sustain utilizations at reasonable rates.

Furthermore, in a manufacturing network of several goods, the impact of congestion or load-based lead time should be correlated with the price and lead time sensitivity on demand such that the effects on the benefit and output planning of a business are regarded [9]. This model includes clearing functions and allows the production to be more flexible than the fixed lead time model. The P_MCFS model proposes smoothing or levelling this input and enables performance to be achieved in the same quantity in increasing time only. This model could be compared with the P_MFLT model, which shows the impact of congestion when incorporating load-dependent lead times in production models such as price and demand. In addition, the models have a dependent demand element as well as a lead time. Compared to production models in various lead time scenarios for utilization levels. Then, determine a sufficient number of orders that the firm plans to meet, and release volumes and utilization rates will be maintained at acceptable levels.

2. Related Works

In their more recent work, Upasani and Uzsoy [8] explored the use of clearing functions to create an integrated model to simultaneously plan price and production for a manufacturing firm whose resources were congested. Clearing functions show how a resource's projected output is predicted based on its expected work-in-progress over a specific time period. The results of a numerical analysis utilizing two distinct models—a clearing function (CF model) and a Fixed Lead-Time (FLT) model—are presented in the research. The CF model is the first to demonstrate the impacts of queuing-induced congestion by integrating dynamic pricing and production planning over time.

Several possible clearing functions are shown in Figure 1, where the constant level clearing function—which is primarily utilized for linear programming models—refers to an upper capacity limit. Because processing occurs in the development network independently of work-in-progress, this suggests prompt output without lead time constraints. Munyaka and Yadavalli's [10] review paper provides an in-depth analysis of the role of clearing functions in inventory management, with a specific emphasis on multi-item production scenarios. The study highlights the significance of dynamic clearing functions in adapting to changing demand patterns, improving order fulfillment rates, and mitigating stockouts.

Research by Ardjmand et al. [11] explored a model for multi-product production planning that integrates price and lead time-sensitive demand. The study emphasized the importance of considering these factors in decision-making processes to achieve optimal production levels. By incorporating a clearing function that dynamically adjusts production quantities based on real-time demand changes, This research demonstrated improved efficiency and responsiveness to market fluctuations.

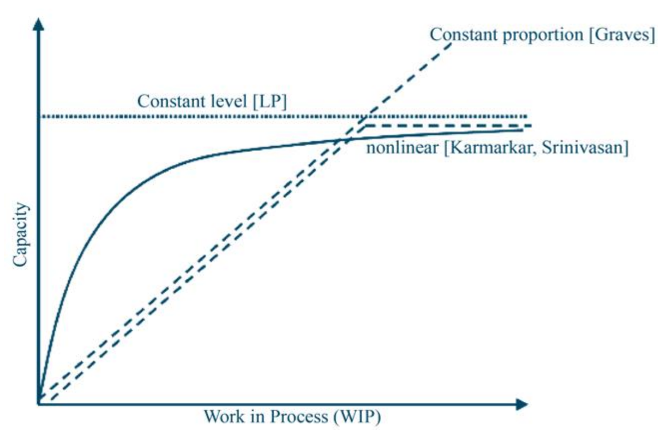

Fig. 1 Clearing function

Furthermore, Li et al. [12] conducted a simulation-based study to analyze the impact of price and lead time sensitivities on production planning outcomes. Their findings highlighted the significance of accurately capturing demand variations influenced by pricing strategies and lead time requirements. By implementing a clearing function that accounts for these dynamics, organizations can enhance their competitiveness and adaptability in dynamic market environments. Research by Dubey et al. [13] focused on the development of dynamic clearing functions that adapt to real-time changes in demand and production conditions. The study emphasized the importance of flexible clearing functions in enabling agile production systems to respond quickly to disruptions and market uncertainties.

Numerous publications are included in the state-of-the-art allocated to the process planning. As a result, these definitions are regarded as the foundation and core of the production systems. Every manufacturing process plan shows a strong correlation between the system's utility and the characteristics of the goods[14]. This implies that it can be thought of as a link between resources and products. Furthermore, in a study by Chi Phan et al. [15], the role of clearing functions in implementing just-in-time (JIT) manufacturing principles was explored. The research highlighted how clearing functions facilitate the synchronization of production activities, minimize inventory waste, and improve responsiveness to market changes in JIT environments.

Production planning can be helpful in manufacturing systems for scheduling, capacity, and output control, as well as production process management. There have been several reviews in this area [16]. When dealing with a reconfigurable environment, the final work's limitations and barriers may be related to product quantity and quality during processing. Several case studies have demonstrated the benefits of implementing an effective clearing function in multi-product production planning. For example, a study by Salah et al. [17] showed that by using a mathematical optimization model to optimize resource allocation, a manufacturing company was able to reduce production costs by 15% while meeting customer demand more effectively.

3. Demand Functions

The consumer's desire, which the development timetable will fulfill, and the resulting discrepancy between supply and demand frequently give rise to a preparedness question. The variable nature of customer-requested demand is the primary factor driving increased inventory rates and decreased productivity. In this chapter, the demand can be delicate. Our demand function is derived from Upasani and Uzsoy's (2014) demand function.

$$D(P,L) = M_j - a_{jt}P_{jt} - b_{jt}L \qquad (1)$$

In Upasani and Uzsoy 's article, M_j represents the demand feature intercept and a_{jt} and b_{jt} respectively, the responsiveness of price and lead time. The issue with this demand feature is that the interest for the price and lead period vary in units. The price will vary from broad values to times specified by L. It refers to a premium potentially having a significantly larger impact on sales than the lead period. The benefit is adjusted by dividing the price and lead time value by a comparative price (p_o) and the lead time (l_o) to examine the effects of income and lead time equally.

$$D(P,L) = M_j - \frac{\alpha_p}{p_o}P_{jt} - \frac{\alpha_l}{l_o}L \qquad (2)$$

With $\alpha = \alpha_p + \alpha_l$

α : demand sensitivity

α_p : demand sensitivity, which is price dependent

α_l : demand sensitivity, which is lead-time dependent

A specific alpha may be set based on the degree of utilization. If the output use is strong (such as U=0.95), if a shortage arises, the demand sensitivity will be smaller, whereas when the utilization becomes small (such as U=0.7), the demand sensitivity will be greater. Lead time determines demand either completely or somewhat. In these circumstances, investigating the scenario in which customers are more likely to accept a maximum lead time or determine that a shorter lead time is more significant than a cheaper price. They may afford to pay the least because their waiting period is shorter. Businesses can concentrate on responding to clients more quickly. According to our model, this means that either there is no price sensitivity at all (α = 0) or there is a situation where $\frac{\alpha_p}{\alpha_l} \leq 1$, meaning that customers are quite sensitive to price changes, but lead time is still the most important factor determining demand.

Demand then shifts to a much more market-based basis. Consumers are highly selective and highly responsive to factors other than short lead times. They are able to remain longer in order to pay less. In order to attract customers, businesses should focus on being cost-effective and offering a low-price plan. In our model, this is associated with either a lead time sensitivity of zero, $\alpha_1 = 0$ (i.e., the sensitive customer scenario), or or $\frac{\alpha_p}{\alpha_l} \geq 1$. Although buyers are more sensitive to lead times, quality is still the most crucial factor.

Not to mention, consumers react to lead time just as much as they do to demand. Businesses would have to ensure that the quality of the goods met customer demand while keeping processing times under control so as not to interfere with shipment dates. Our models have $\alpha_p = \alpha_l$.

4. The Proposed Model

There are two theories on joint price-production planning discussed in Upasani and Uzsoy's (2014) paper: Fixed Lead Time (FLT) model and the Clearing Mechanism (CF) model. The models related to the CF model are discussed in this research. The notation is as follows:

Sets
j :*Set of products = {1,…,J}*
t :*Set of periods = {1,…,T}*
Parameters
a_{jt} : Product cost j and demand sensitivity during time t
b_{jt} : Lead-time product sensitivity to demand in time period t
h_{jt} : Retaining finished goods inventory at cost for product j throughout time t
ω_{jt} : retaining the cost of WIP inventory for product j during time t
ϕ_{jt} : Cost per unit of production for product j during time t
c_{jt} : Cost of order release for product j that is released during time t
v : Maximum quantity that can be sent prior to the deadline over the horizon
K_1 : Optimum Production Capacity in Theoretical
K_2 : Curvature parameter of CF
M_j : Intercept of the demand function, i.e., demand when price = lead time = 0
T : Length of the planning horizon, t = 1,..,T
L_G : Guaranteed delivery time (in periods)
$f(.)$: CF
ξ_{jt} : Amount resources for product j in period t
Decision Variables
R_{jt} : Order released quantity for product *j* at period *t*
X_{jt} : Production quantity for product *j* at period *t*
W_{jt} : Work-in-process inventories for product *j* at the end of period *t*
I_{jt} : Finished goods inventory (FGI) for product *j* at end of period *t*
P_{jt} : Price of product *j* in period *t*
D_{jt} : Sales quantity for product *j* in period *t*
Y_{jt} : Quantity shipped for product *j* in period *t*
Z_{jt} *:* Allocation Factors for product j in period t

4.1. Multi-item Production Clearing Function Model (P_MCF Model)

Firstly, the Upasani and Uzsoy (2014) model of clearing functions is non-linear, which implies that the problem cannot be solved using CPLEX terminology. Thus, the linearized function can be identified below in restriction (8) using ten segments by specifying the feature meaning b_k and the slope a_k. However, this intuitive formulation might provide capacity for one product while holding work in process for another. Consider a system with two products, A and B, whose capacity constraint can be expressed as $X_A + X_B \leq f(W_A + W_B)$. A solution with $X_A > 0, X_B = 0, W_A = 0$, and $W_B > 0$ may exist, even if there is no work in process to produce the product. The most suitable solution to this problem may be to keep high work in process levels of the product for which it is cheapest to do so and use the capacity provided by this device (i.e., the high value of the CF attained by retaining high work in process of the inexpensive product) to store little or no work in process of other goods. In other words, there is no relationship between the periods's WIP mix and productivity.

Asmundsson et al. handled this problem by adding an additional set of variables $Z_{jt} \leq 0$ to allocate the projected throughput indicated by the CF among the different products [18]. Constraints (9) to guarantee that the resource's production throughout the planning period is proportionate with the degree of work in process.

Secondly, as mentioned before, the demand in period t is expressed by the demand function $D(P,L) = M - a_t P_t - b_t(\frac{W_t}{X_t})$. By Little's Law, the expected lead time in period *t* is given by $L = W_t/X_t$, expressed in units of periods. In this way, the L is exogenous and can be found optimal in the following section by using numerical experiments and comparison. As a result, the variable which represents the quantity shipped in a period (Y_t) is no longer important. A new variable is introduced (D_{t-L}) which represents the demand asked by the customer in the previous period $[M(1 - \frac{\alpha_p}{p_0} P_{jt} - \frac{\alpha_l}{l_0} L)]$

The last adjustment is about the demand function discussed in Section 3, which changed from $M_j - a_{jt}P_{jt} - b_{jt}L$ to $[M(1 - \frac{\alpha_p}{p_0} P_{jt} - \frac{\alpha_l}{l_0} L)]$.

4.1.1. P_MCF Model

$$Max \ \sum_{j=1}^{J} \sum_{t=1}^{T} \left[P_{jt} \left(M_j (1 - \frac{\alpha_p}{p_0} P_{jt} - \frac{\alpha_l}{l_0} L) \right) - c_{jt} R_{jt} - \phi_{jt} X_{jt} - h_{jt} I_{jt} - \omega_{jt} W_{jt} \right] \quad (3)$$

$S.t.$

$$W_{jt} = W_{jt-1} - X_{jt} + R_{jt} \quad \forall_{jt} \quad (4)$$

$$I_{jt} = I_{jt-1} + X_{jt} - D_{jt-L} \quad \forall_{jt} \quad (5)$$

$$\xi_{jt} X_{jt} \leq a_k \xi_{jt} W_{jt} + Z_{jt} b_k \quad \forall_{jt}, \forall_k = 1, \ldots, 10 \quad (6)$$

$$\sum_j Z_{jt} = 1 \quad \forall_t \quad (7)$$

$$M_j (1 - \frac{\alpha_p}{p_0} P_{jt} - \frac{\alpha_l}{l_0} L \geq 0 \quad \forall_{jt} \quad (8)$$

$$X_{jt}, P_{jt}, I_{jt}, W_{jt}, R_{jt}, D_{jt-L} \geq 0 \quad \forall_{jt} \quad (9)$$

4.2. Adjusted CF Models: P_MCFF and P_MCFS for Multiple Products

Two modern versions are rendered with something different from the CF model, extending from the two models above. As mentioned earlier, the lead time of the model is endogenous, which means that the lead time in period t (L_t) is specified by the estimated WIP in period t ($\hat{W}_t$) and the production quantity in period t (X_t). Therefore, to convert to an exogenous lead time two new models are defined. The first model sums up the release (up to t-L) and makes it less or equal to the production sum (up to t). The name of the CF model of modular output for several items (P_MCFF) is a configuration that applies this restriction. The second model is by using smoothing, and the lead time has been set multiplied by the production greater or equal to the WIP. Therefore, this new model is called the Smoothing model for multiple products (P_MCFS).

4.2.1. P_MCFF: Model with Flexible Production for Multiple Products

Also, considering the material from the P_MCFF model was added at period t can possibly be produced in period t – L + 1, t – L + 2, t; thus, output can be already available before the time t. Taking into account all mentioned above makes the production planning schedule more flexible.

$$Max\ \sum_{j=1}^{J}\sum_{t=1}^{T}\left[P_{jt}\left(M_j(1-\frac{\alpha_p}{p_0}P_{jt}-\frac{\alpha_l}{l_0}L)\right)-c_{jt}R_{jt}-\phi_{jt}X_{jt}-h_{jt}I_{jt}-\omega_{jt}W_{jt}\right] \quad (10)$$

$S.t.$

$$W_{jt}=W_{jt-1}-X_{jt}+R_{jt} \qquad \forall_{jt} \quad (11)$$

$$I_{jt}=I_{jt-1}+X_{jt}-D_{jt-L} \qquad \forall_{jt} \quad (12)$$

$$\sum_{j=1}^{J}\sum_{1}^{t-L}R_{jt}\le\sum_{j=1}^{J}\sum_{1}^{t}X_{jt} \qquad \forall_{jt} \quad (13)$$

$$\xi_{jt}X_{jt}\le a_k\xi_{jt}W_{jt}+Z_{jt}b_k \qquad \forall_{jt},\forall_k=1,\ldots,10 \quad (14)$$

$$\sum_j Z_{jt}=1 \qquad \forall_t \quad (15)$$

$$M_j(1-\frac{\alpha_p}{p_0}P_{jt}-\frac{\alpha_l}{l_0}L)\ge 0 \qquad \forall_{jt} \quad (16)$$

$$X_{jt},P_{jt},I_{jt},W_{jt},R_{jt},D_{jt-L}\ge 0 \qquad \forall_{jt} \quad (17)$$

4.2.2. P_MCFS: Model with Smoothing for Multiple Products

The second model is the P_MCFS model which all the concepts in slightly the same as the first model; however, in this model, a new capacity constraint called $LX_t\ge(W_{t-1}+R_t)$ is formulated. This constraint makes the model produce quickly, due to high capacity. However, the physical capacity restriction, which is the linearized clearing function, restricts the resource.

As already stated, the clearing function reflects the planned performance as a function of the estimated WIP during that time. High lead times were, therefore, set to satisfy all of the constraints in this model. The distinction between this smoothed model and the standard P_CFF model is that in each period, the number of outputs generated stays limited, whereas, in P_CFF, a specific number of outputs will come out of the method at each time, which means that in t – L + 1, the number of outputs can be more than the number that is produced, e.g. t – L + 2.

$$Max\ \sum_{j=1}^{J}\sum_{t=1}^{T}\left[P_{jt}\left(M_j(1-\frac{\alpha_p}{p_0}P_{jt}-\frac{\alpha_l}{l_0}L)\right)-c_{jt}R_{jt}-\phi_{jt}X_{jt}-h_{jt}I_{jt}-\omega_{jt}W_{jt}\right] \quad (18)$$

$S.t.$

$$W_{jt}=W_{jt-1}-X_{jt}+R_{jt} \qquad \forall_{jt} \quad (19)$$

$$I_{jt}=I_{jt-1}+X_{jt}-D_{jt-L} \qquad \forall_{jt} \quad (20)$$

$$LX_{jt}\ge(W_{jt-1}+R_{jt}) \qquad \forall_{jt} \quad (21)$$

$$\xi_{jt}X_{jt}\le a_k\xi_{jt}W_{jt}+Z_{jt}b_k \qquad \forall_{jt},\forall_k=1,\ldots,10 \quad (22)$$

$$\sum_j Z_{jt}=1 \qquad \forall_t \quad (23)$$

$$M_j(1-\frac{\alpha_p}{p_0}P_{jt}-\frac{\alpha_l}{l_0}L\ge 0 \qquad \forall_{jt} \quad (24)$$

$$X_{jt},P_{jt},I_{jt},W_{jt},R_{jt},D_{jt-L}\ge 0 \qquad \forall_{jt} \quad (25)$$

4.3. Model Analysis

4.3.1. Numerical Experiments

Clarified our numerical feedback in this portion. The numerical analysis has previously performed the same numerical review as the Upasani and Uzsoy papers (2014) to validate the CF pattern. As mentioned above, used the same CF model as in the previously mentioned paper but linearize to use an alternate method to evaluate parameters of responsiveness.

Figure 2 illustrates the process of linearizing the clearing function by approximating ten segment lines to the graph drawing. The resulting ten segment points are depicted in the diagram.

The same duration for the planning period as Upasani and Uzsoy (2014) are used. Set a threshold of 95 percent for high utilization for the utilization rate and 70 percent for low utilization. The values and specifications of the inputs are listed out below. To avoid making numerical study too complex, one value for the costs that come with the production process has been chosen.

Table 1. Slopes and Intercepts Clearing Function

Slope (a_k)	Value of the function (b_k)
0.5	0
0.069	136
0.036	154.8
0.03	160
0.028	173.6
0.023	181.3
0.018	189.7
0.014	193.4
0.01	196.9
0.08	199.6

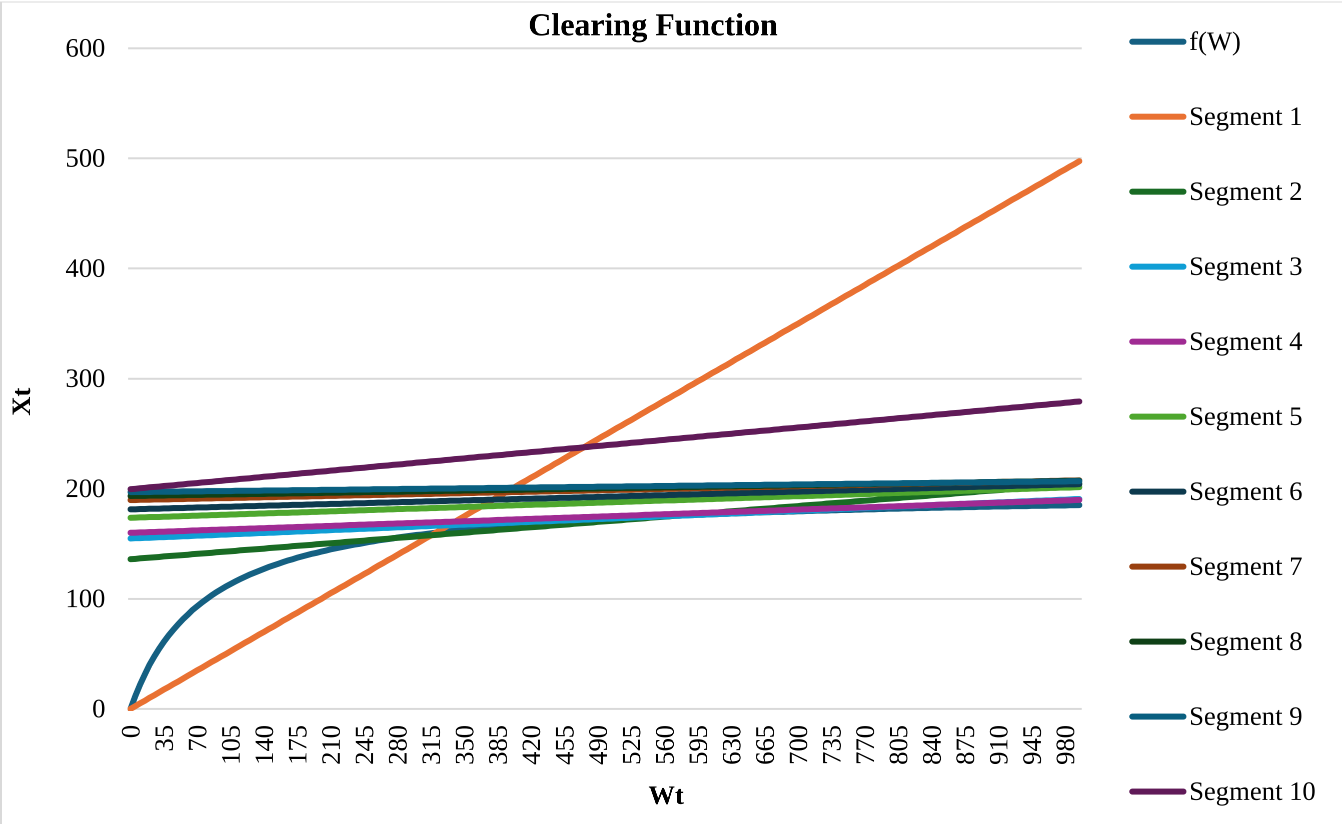

Fig. 2 Clearing function graphic

Table 2. Price and lead time sensitivities for all products

Period Span	**Price Sensitivity (α_t)**	**Lead-time Sensitivity (b_t)**
1 – 6	1	1
7 – 12	1	2
13 – 18	2	1
19 – 24	2	2

Input parameter values:

Table 3. Input parameter values

Length of Planning Horizon	T	24 periods
Number of Products	J	4 Products
Maximum potential output for each time interval	K_1	500 units
Parameter of Curvature	K_2	100
Demand for each product at zero cost and zero lead time	M_j	1000 units
Fixed Lead time	L	1 period 2 periods 3 periods 4 periods 5 periods
Utilization Level	U	0.95 (high) 0.7 (low)
Initial work in process for CF & FLT Models (L=1)	W_0	400
Work in process period 23 for CF & FLT models	W_{23}	400
Work in process period 24 for CF & FLT Model	W_{24}	400
Initial work in process for CF & FLT Mode (L=2)	W_0	900
Work in process at ending of period 23 for clearing function and fixed lead time Models	W_{23}	900
Work in process period 24 for clearing function and fixed lead time Models	W_{24}	900

Initial work in process for clearing function and fixed lead time Mode (L=3)	W_0	1400
Work in process period 23 for clearing function and fixed lead time Models	W_{23}	1400
Work in process period 24 for clearing function and fixed lead time Models	W_{24}	1400
Initial work in process for clearing function and fixed lead time Models (L=4)	W_0	1900
Work in process period 23 for clearing function and fixed lead time Models	W_{23}	1900
Work in process 24 for CF & FLT Models	W_{24}	1900
Initial work in process for clearing function and fixed lead time Models (L=5)	W_0	2400
Work in process period 23 for clearing function and fixed lead time Models	W_{23}	2400
Work in process period 24 for clearing function and fixed lead time Models	W_{24}	2400
Unit material cost (per unit)	c_{jt}	1
Unit production cost (per unit)	ϕ_{jt}	1
Unit WIP holding cost (per unit per period)	ω_{jt}	1
Unit FGI holding cost (per unit per period)	h_{jt}	1
Reference price	p_0	1000
Reference lead time	L_0	2
Amount of Resources (e.g., machine time/processing time)	ξ_{jt}	Exponentially distributed with means 8, 12, 16, and 20

Input for the P_MCFS model (Lead time and according to WIP levels)

Table 4. Input for the P_MCFS model (Lead time and according to WIP Levels

Lead time L	WIP for t=0,23,24
2	$W0$=400,$W23$=400,$W24$=400
3	$W0$=900,$W23$=900,$W24$=900
4	$W0$=1400,$W23$=1400,$W24$=1400
5	$W0$=1900,$W23$=1900,$W24$=1900

Table 5. Unit cost for all products

Products	Unit Material Cost	Unit Production Cost	Unit WIP Holding Cost	Unit FGI Holding Cost
1	1/unit	1/unit	1/unit/period	1/unit/period
2	0.5/unit	1/unit	1/unit/period	1/unit/period
3	1/unit	1/unit	0.5/unit/period	1/unit/period
4	0.5/unit	1/unit	0.125/unit/period	0.25/unit/period

Assumptions:

1. WIP equals planned production for period 1 (P_MFLT).
2. The final work in progress in periods 23 and 24 matches the production objective from period 1.
3. At the end of a period, the WIP inventory is calculated by adding the releases from previous periods.
4. There are no remaining requests from past planning periods to address during this time.

When evaluating the clearing function graph depicted in Figure 1, the WIP and output are calculated in the same time units, and the proportional part of the function slope is 1 / L, where L is the average lead time. Furthermore, it is evident that a bigger lead time L results in a longer work-in-progress for a given amount of output. This research aims to introduce the relationship of load-dependent lead time into their study.Additionally, two distinct levels of utilization are employed, specifically a level of 70% and 95%, to represent low and high usage, respectively. A low responsiveness to demand is correlated with a high degree of utilization. It could be explained by the fact that since consumers are not prone to pricing and lead time changes set by a firm when they purchase a commodity, there is a lower risk that demand will decline due to price changes or lead times. Moreover, the highest potential demand would be reduced from a lower value if the demand sensitivity is set to a higher value, implying a lower price and lead time sensitivity. The subsequent demand will be higher and will lead to higher production plant efficiency expected.

Table 6. Demand sensitive for all products

	U=0.7 => α = 0.7		U=0.95 => α = 0.5	
$\frac{\alpha_p}{\alpha_l} = 1$	$\alpha_p = 0.35$	$\alpha_l = 0.35$	$\alpha_p = 0.25$	$\alpha_l = 0.25$
$\alpha_l = \alpha$	$\alpha_p = 0$	$\alpha_l = 0.7$	$\alpha_p = 0$	$\alpha_l = 0.5$
$\frac{\alpha_p}{\alpha_l} = 0.5$	$\alpha_p = 0.23$	$\alpha_l = 0.47$	$\alpha_p = 0.17$	$\alpha_l = 0.33$
$\alpha_p = \alpha$	$\alpha_p = 0.7$	$\alpha_l = 0$	$\alpha_p = 0.5$	$\alpha_l = 0$
$\frac{\alpha_p}{\alpha_l} = 1.5$	$\alpha_p = 0.42$	$\alpha_l = 0.28$	$\alpha_p = 0.3$	$\alpha_l = 0.2$

In this experiment, this research did not address the scenario in which consumers are solely responsive to lead time. It is assumed that consumers do not prioritize price in their decision-making process ($\alpha_p = 0$). While lead time is low, the results of the model lead to unbounded (to infinity). Also, for longer lead time (L=3,4,5), we are faced with an unfeasible model, which may mean that consumers are not able to wait too long.

4.3.2. Demand Sensitivity and Aggregate Planning

Aggregate production planning is the term for the simultaneous determination of a company's production, inventory and employment levels over a finite time horizon [19]. The goal is to minimize the total relevant costs while meeting time-varying demand under the assumption of fixed sales and production capacity. From the table above, depending on the demand sensitivity, different utilization levels are obtained. When the sensitivity of the demand is lower (α=0.5), the customer is less affected by changes in the price or lead time. Therefore, more sales will be generated, and thus, a higher utilization level is needed. The higher utilization level was set at 95%. A higher sensitivity of the customers (α=0.7) towards changes will result in a lower utilization level (U=0.7).

4.3.3. Price, Demand, and Profit in P_MCF Model with P_MCFF and P_MCFS Model over 24 Periods for Multiple Products

In order to compare the P_MCF with P_MCFF and P_MCFS models, all model parameters must be estimated, and the models must be run to generate price products, demand, and profit. Then, we evaluate the performance of the plans, which take into account the effect of load-dependent lead times. To effectively implement this planning strategy, it is imperative to address the fundamental equations governing production planning. This necessitates measuring profit under various sensitivity and utilization rates to evaluate income and other relevant output factors.

To facilitate comparison with two existing models, the input parameters have been meticulously adjusted. Where to illustrate the low utilization level (U=0.7) demand sensitivity = 0.7 with 4 products can be seen in Figures 3 and 4.

The situation when the consumer is not sensitive to the product's lead time sets specific costs for each type. For a high utilization, this price is significantly greater and can be clarified by the reduced responsiveness to demand correlated with this degree of utilization. The price and lead times set for people are less affected. The P_MCF models set the maximum price while the consumer is primarily involved in the product, but the formula measures the lowest demand. As can be seen in Figures 3 and 4, in the first six periods, the price has increased with an amount more than 50 compared to the following periods.

In this period, the buyers pay attention to the price but are still more affected by the lead time. While the utilization level is set at 70%, this means that due to lower revenue produced, the organizations will use less capacity. Where illustrate the high utilization level (U=0.95) and demand sensitivity = 0.95 with 4 products can be seen in Figures 5 and 6.

If consumers find lead time to be more relevant than price, firms may demand a higher price for this product because they are able to pay more for a shorter lead period. A high utilization (95%) suggests a typically indifferent market, which in such situations describes a higher price. As can be seen from the figure, in the first six periods, there are higher prices which means demand will be lower as well.

Another reason is that high utilization led to greater exposure to the market; changes in pricing and lead time had little impact on consumers, contributing to increased prices than when there is a low utilization. Where to illustrate the profit and optimal lead time with low and high utilization with 4 products can be seen in figure 7.

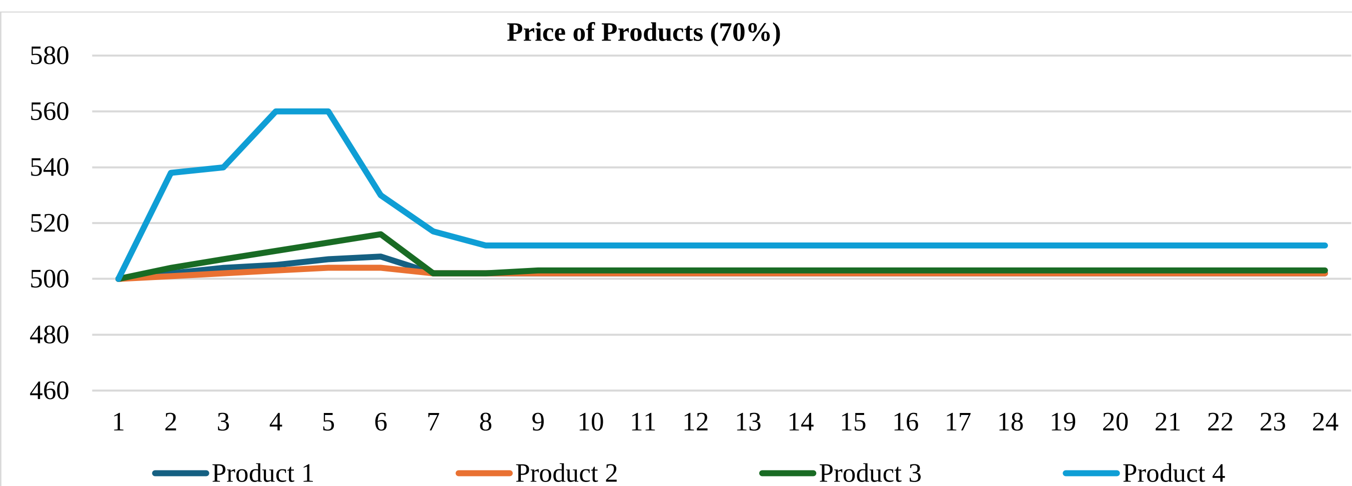

Fig. 3 Price of products with different demand sensitivities U=0,7 and L=1

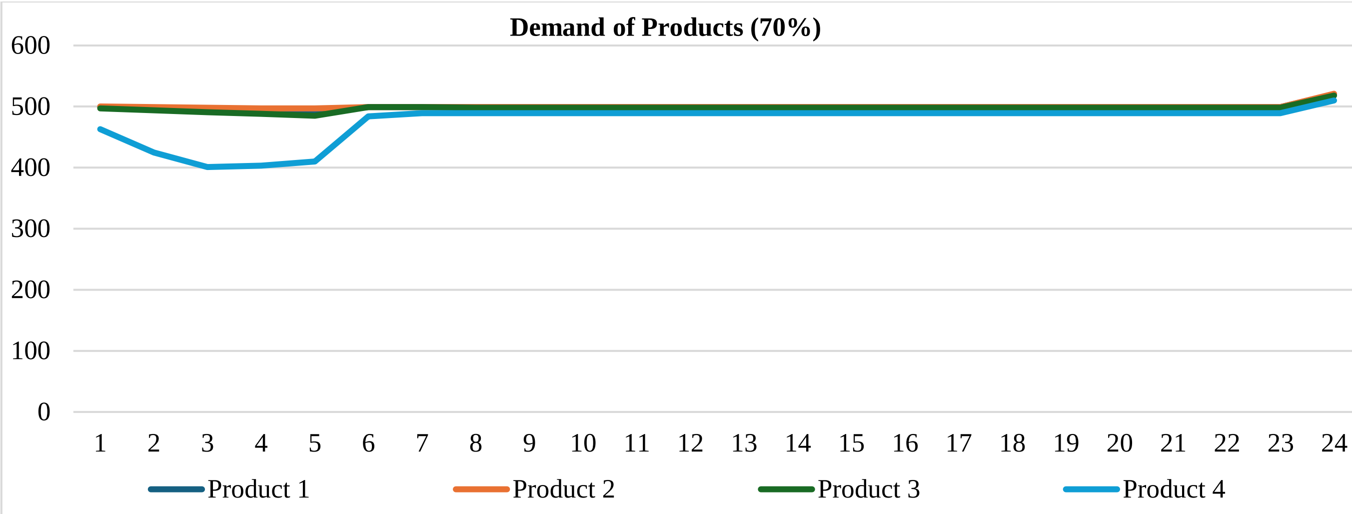

Fig. 4 Demand of products with different demand sensitivities U=0,7 and L=1

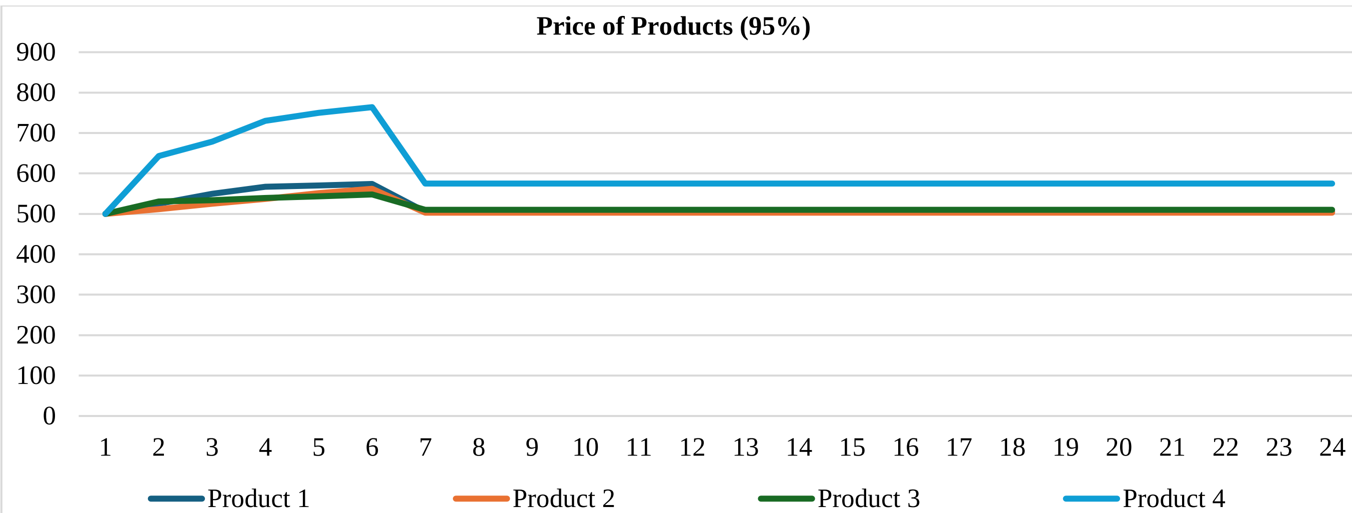

Fig. 5 Price of products with different demand sensitivities U=0,95 and L=1

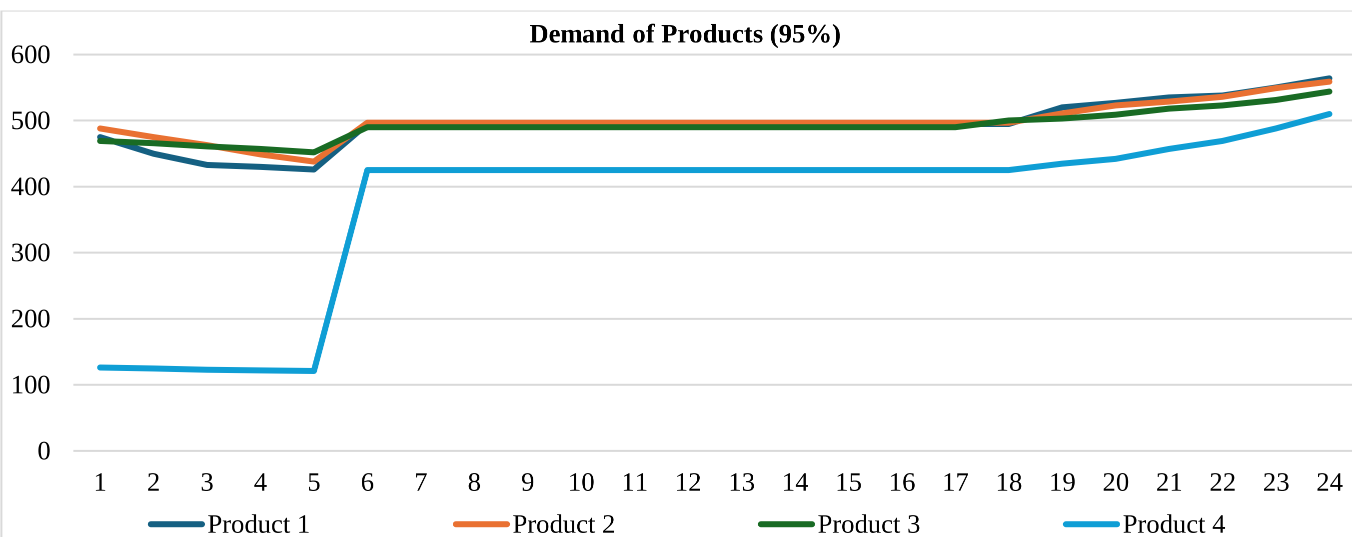

Fig. 6 Demand of products with different demand sensitivities U=0,7 and L=1

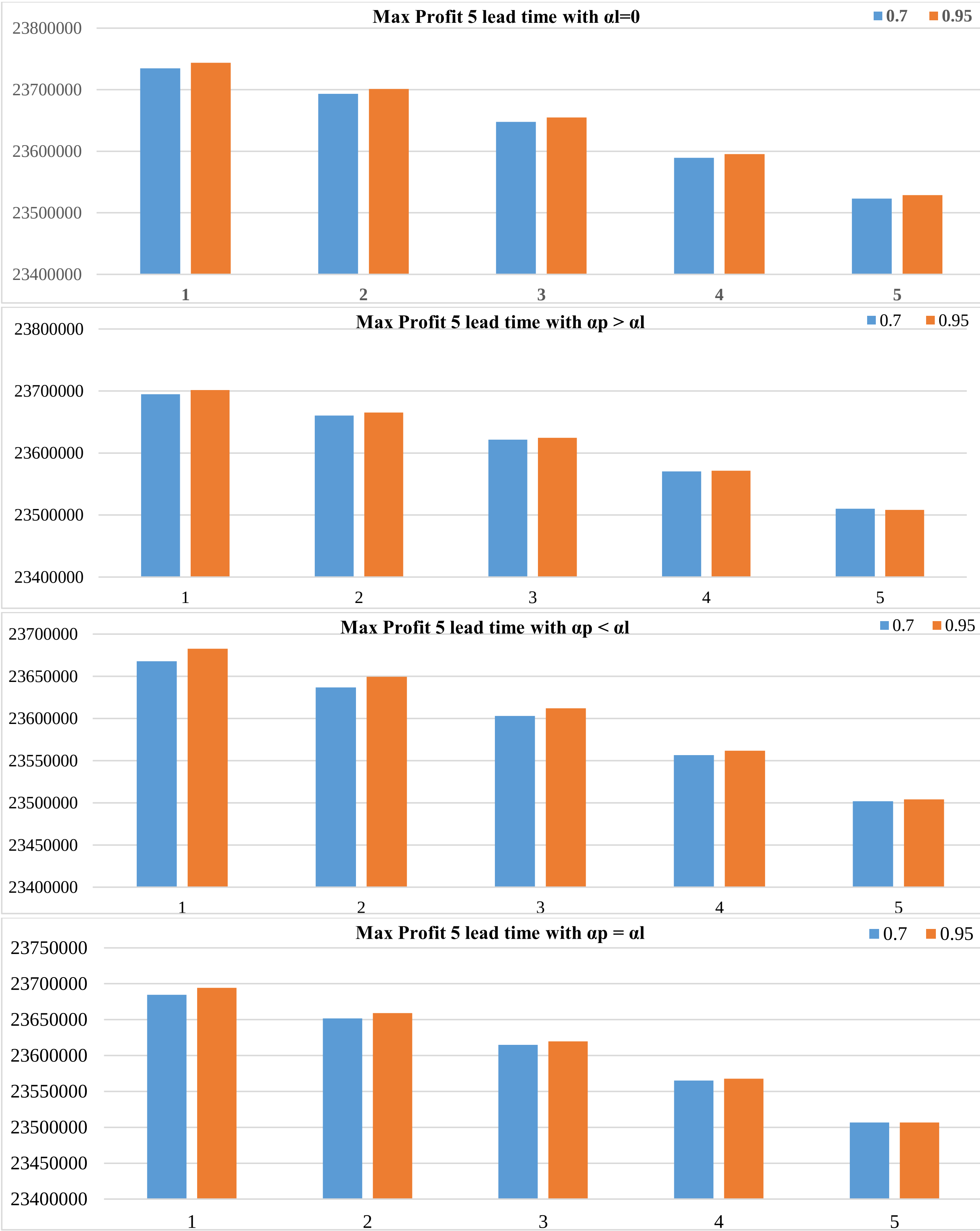

Fig. 7 Maximum Profit for different sensitivities and the two utilization levels

As mentioned before, the profit is a similar explanation in the price and demand because consumers become more responsive to price owing to the same prices measured for demand and price for the two utilizations. Due to the greater utilization of units the firms produce over the 24 periods, the income is usually higher during a high utilization scenario than under a low utilization point.

As can be seen in Figure 7, the lowest lead time (L=1) has a higher profit rather than the higher lead time (L=5). Regardless of the profits being decreased or the cheaper pricing that has to be demanded to draw consumers who simply pay attention to the price of products and search for alternatives because they find a commodity too costly, the income declines.

4.3.4. Price Sensitive Demand (High and Low Utilization)

Within this chapter, three models were executed with the feedback provided in Section 4.3.1. The implications of the more stringent constraints employed in the two models contributed by the authors, as well as their susceptibility to variations in demand, are evident in the provided graph and will be fully elaborated upon. Such a model was introduced with one and two of lead time. The authors sought to enhance the clarity of the summary by adopting this approach. They determine that lead time effectively conveys the repercussions for the section addressing price-sensitive demand.

The PCF model with Flexible production or, namely, P_MCFF, allows for output to come out before X_{jt} when the material for that order was released in R_{jt-L}. Moreover, it is more flexible with smoothing due to the fact that the outputs do not have to be of the same amount. Next, beginning with the possibility where demand is just price-sensitive for low utilization. Since integrating the P_MCF model into P_MCFF and P_MCFS models, the formulas become unfeasible. The two versions, due to the rising demand, are unable to cope with this low valuation.

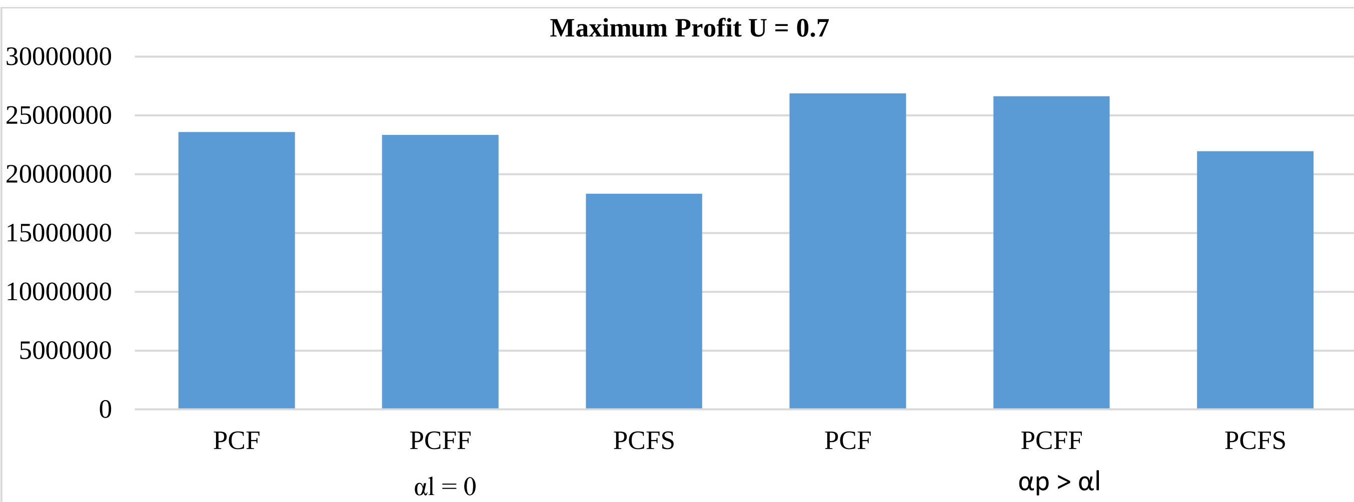

Fig. 8 Maximum profit of P_MCF, P_MCFF, and P_MCFS in price sensitive demand (U=0.7)

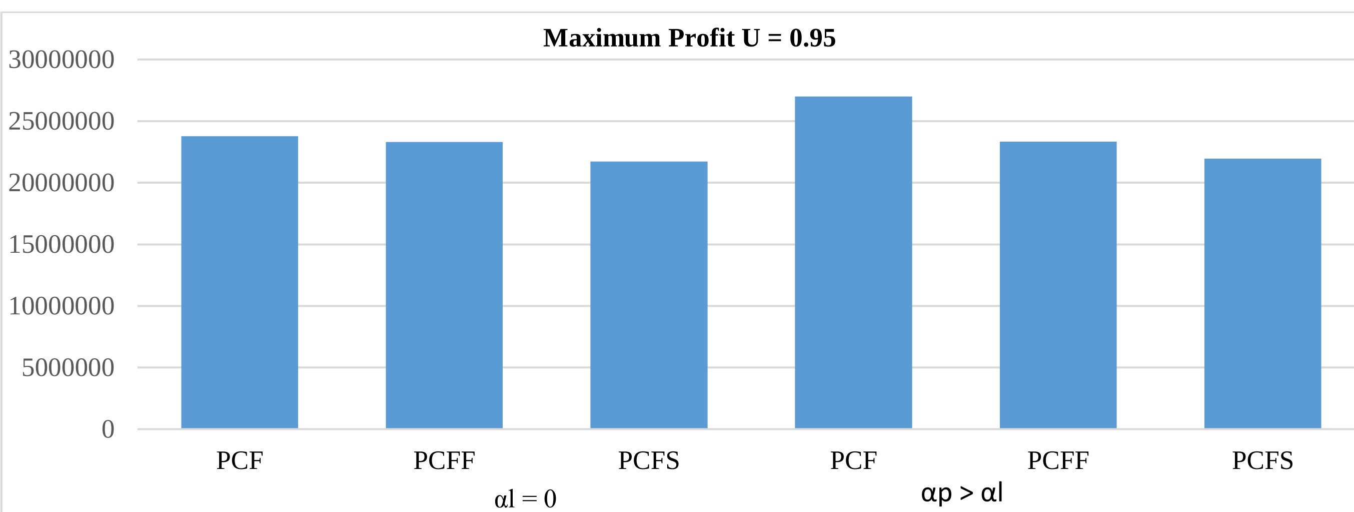

Fig. 9 Maximum profit of P_MCF, P_MCFF, and P_MCFS CF in price sensitive demand (U=0.95)

If the lead time in flexible production (P_MCFF) is set to two periods, it may set the orders. Since consumers are only demand reactive, a company may only use this attribute to lure investors, and they adjust the demand at a lower value. This can be shown in the result of the profit of P_MCFF is less than P_CF with a difference of around 2000. Despite initial intentions to adjust the lead time to two, it was deemed necessary to extend it to three for the P_MCFS project. This adjustment was prompted by the increased complexity of the project's circumstances. However, it should be noted that extending the lead time beyond two units has historically proven to be impractical. Secondly, the assessment considered demand and lead time-dependent firms, which typically exhibit higher price sensitivity for lower utilization.

This can be seen in the figure above; the benefit from the flexible output and P_MCF in the multi-product framework is greater than before, which implies the better costs that the customers might be asking for. This is seen that P_MCF and P_MCFF have higher benefits than P_MCFS, that is because it was not practical for the P_MCFS to measure a profit over a one-period lead time. Consumers pay attention to the lead time, and directly affects the gain in this case.

Thirdly, as can be shown in Figures 8 and 9 above, the profit between P_MCF and flexible production is about the same, around 23,500,000, with a gap of around 2000. The gap between P_MCF and P_MCFS is therefore greater, it is around 20,000,000. It is noteworthy that the lead time for P_MCFF is set at two periods, while that for P_MCFS is fixed at three periods. This configuration ensures the feasibility of the P_MCFF model. Once again, that may be explained by the customers being simply market sensitive, which causes the demand to be cheaper than the reference level and the output and WIP to increase to a rather high point. The analysis revealed a strong relationship between product sales and price for the right-hand side of the equations. The lead time was determined to have a lesser impact. Extending the lead time for product P_MCFS to three periods resulted in a significant profit reduction of 50,000,000 compared to product P_MCF. This observation highlights the customer's sensitivity to lead time. Extended lead times or consumer willingness to delay purchases can adversely affect product demand and subsequent revenue generation.

4.3.5. Price-Sensitive Demand (High and Low Utilization)

Numerical research was conducted on three different models under both price- and lead time-sensitive demand scenarios. The research compared lead times of L = 1 and L = 2 and considered both low and high utilization levels (70% and 95%, respectively). This analysis aimed to determine the performance of each model under varying lead time constraints and demand profiles. As stated earlier, due to the high WIP rates experienced, the P_MCFS model is infeasible for L=1. For this purpose, the P_CF and P_MCFF model relation correlates to the P_MCFS model's contrast between L=2 and L=3.

Figure 10 reflects the scenario of the utilization of 70%, and lower figures depict the utilization of 95%. Figure 11 figures depict the condition where customers find lead time more relevant than price while the right side depicts the scenario where consumers are similarly sensitive to price and lead time. It can be seen in Figures 10 and 11 that the profit is better with a shorter lead time in each case because, in a certain way, the consumer always worries about the lead time in each case. Profit is better if the lead time is deemed more relevant than the price because firms are permitted to pay a higher price per unit while offering a shorter lead time in exchange. The requirement cannot be met with a lead time of one period in this situation, suggesting uncertainty and the inflexibility of the process compared to the P_MCFF models. The lead time for the P_MCFS was established at three units, resulting in a significant reduction in the projected profit margin. The cumulative gaps in demand and supply amounted to approximately 10,000,000.

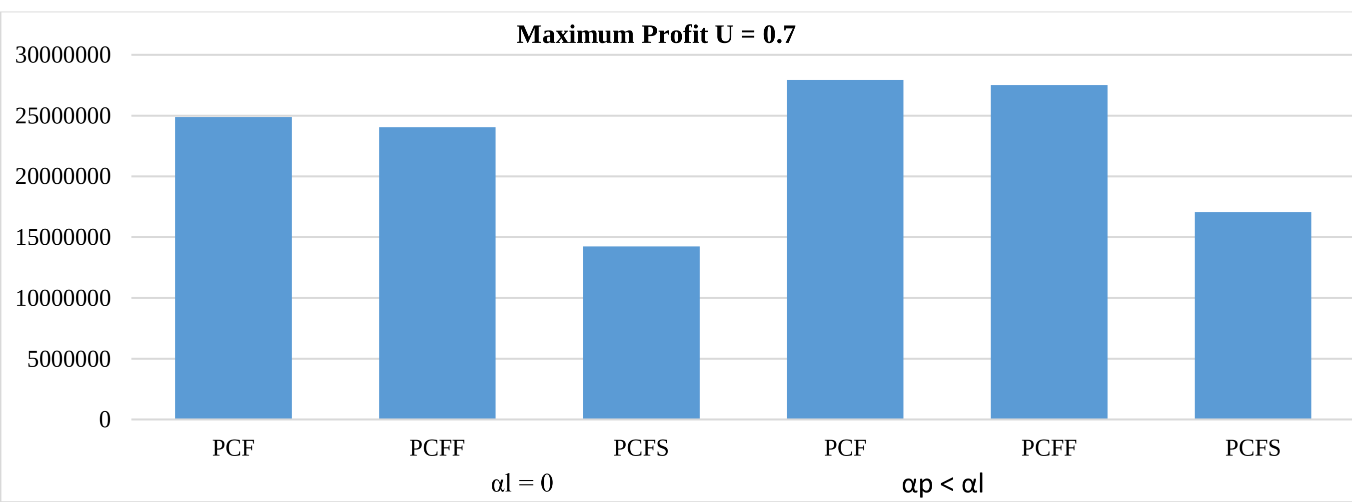

Fig. 10 Maximum profit of P_MCF, P_MCFF, and P_MCFS in lead time sensitive demand (U=0.7)

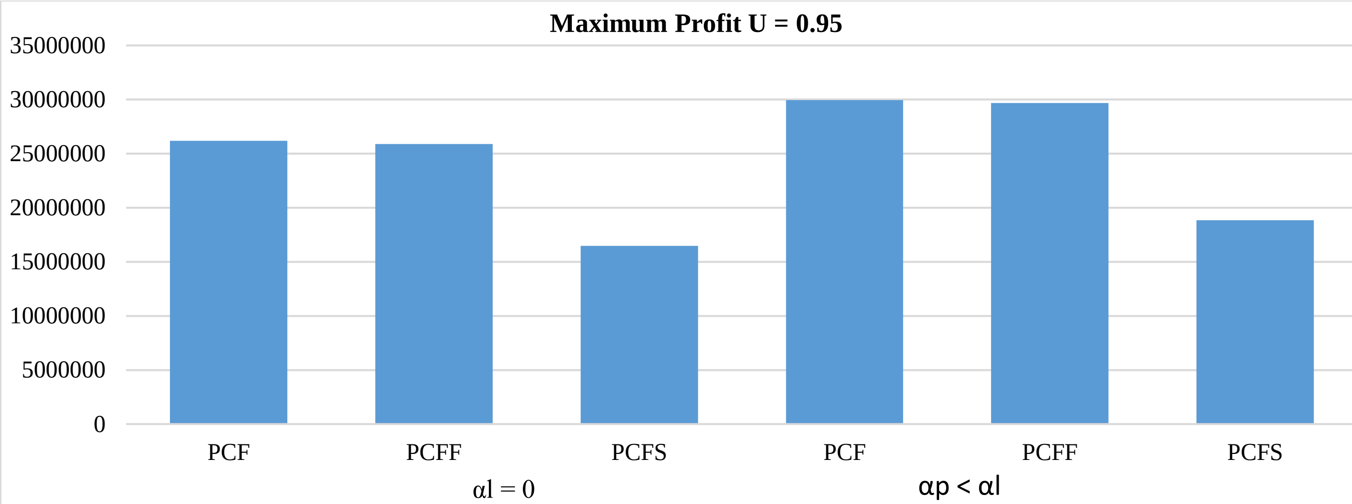

Fig. 11 Maximum profit of P_MCF, P_MCFF, and P_MCFS in lead time sensitive demand (U=0.95)

5. Conclusion

This developed an integrated model for price and lead time-sensitive demand over time for a manufacturing organisation experiencing resource congestion by utilizing the clearing function concept from the multi-item production planning literature. The analytical results demonstrate how crucial it is to thoroughly consider how pricing decisions affect lead times because of the interaction of these two demand function components. The P_MCFS is less robust than the P_MCFF model as it means smooth output and only makes the same quantity of development units in a period. In the development models, the updated demand feature was implemented with the intention of representing the different sensitivities that consumers have towards price, lead time, or both. When evaluating the adjusted production models, numerical experiments have shown that it is essential for companies to consider congestion when planning production. It is evident upon reflection that the price determined by the CF model considers the costs incurred due to inflation, such as work-in-progress. The contribution to this research subject was to devise two new models that not only provide the clearing function but also enable scalable output across many periods and levels output.

It has specifically seen the impact of these two latest formulas on the factors of output and the sales and expenses that come with them. A second contribution was to take into consideration the market lead time and price response. The study conducted by this research shows the importance of identifying the consumers within a market group and understanding their preferences, whether it be price or lead time. The research not only examined the effects of consumers who are solely focused on price or lead time but also those who fall in between, such as individuals who are slightly more price-sensitive or demand-responsive or those who do not have a strong preference for either factor. By making pricing and purchasing choices based on consumer needs, businesses will automate their development methods and thereby increase income.

For future research, another logical extension is to incorporate these models into a multi-stage stochastic programming system where, over time, simulations will assume multiple demand sensitivities for specific goods. Due to the significant growth of the scenario tree, this model poses a variety of difficulties but can still be realistic for composite models of the kind suggested in this paper.

References

[1] Mohammad Amin Yazdani, Amirhosssein Khezri, and Lyes Benyoucef, “A Linear Multi-Objective Optimization Model for Process and Production Planning Generation in a Sustainable Reconfigurable Environment,” *IFAC-PapersOnLine*, vol. 54, no. 1, pp. 689-695, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[2] Hubert Missbauer, “Order Release Planning with Clearing Functions: A Queueing-Theoretical Analysis of the Clearing Function Concept,” *International Journal of Production Economics*, vol. 131, no. 1, pp. 399-406, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[3] Sébastien Beraudy, Nabil Absi, and Stéphane Dauzère-Pérès, “Timed Route Approaches for Large Multi-Product Multi-Step Capacitated Production Planning Problems,” *European Journal of Operational Research*, vol. 300, no. 2, pp. 602-614, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] Martin Benfer, Niklas Steinkühler, and Gisela Lanza, “Dual-Perspective Capacity Planning in Interconnected Multi-Product Production Networks Using Stochastic Optimisation,” *CIRP Annals*, pp. 1-4, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Horizon Basis et al., “Multi-Product Multi-Stage Production Planning with Lead Time on a Rolling,” *IFAC-PapersOnLine*, vol. 48, no. 8, pp. 1162-1167, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[6] Rayan Saleem M. Omar, Uday Venkatadri, and Claver Diallo, "Estimating the Clearing Function for a Multi-Product Production Network Based on Mean-Value Analysis," *IFAC-PapersOnLine*, vol. 49, no. 12, pp. 1755-1760, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[7] Hamed Jalali et al., "Quality and Pricing Decisions in Production/Inventory Systems," *European Journal of Operational Research*, vol. 272, no. 1, pp. 195-206, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[8] Abhijit Upasani, and Reha Uzsoy, *Integrated Production Planning and Pricing Decisions in Congestion-Prone Capacitated Production Systems*, Essays in Production, Project Planning and Scheduling, vol. 200, pp. 29-68, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[9] J. Asmundsson, R.L. Rardin, and R. Uzsoy, "Tractable Nonlinear Production Planning Models for Semiconductor Wafer Fabrication Facilities," *IEEE Transactions on Semiconductor Manufacturing*, vol. 19, no. 1, pp. 95-111, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[10] J.B. Munyaka, and V.S.S. Yadavalli, "Inventory Management Concepts and Implementations: A Systematic Review," *South African Journal of Industrial Engineering*, vol. 33, no. 2, pp. 15-36, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Ehsan Ardjmand et al., "A Robust Optimisation Model for Production Planning and Pricing under Demand Uncertainty," *International Journal of Production Research*, vol. 54, no. 13, pp. 3885-3905, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[12] Simon Li, Bahareh Eshragh, and Akposeiyifa Joseph Ebufegha, "Simulation-Based Study of the Resilience of Flexible Manufacturing Layouts Subject to Uncertain Demands of Product Variants," *Sustainability*, vol. 15, no. 20, pp. 1-20, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Rameshwar Dubey et al., "Dynamic Digital Capabilities and Supply Chain Resilience: The Role of Government Effectiveness," *International Journal of Production Economics*, vol. 258, pp. 1-16, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] Umar Muhammad Modibbo et al., "An Integrated Multi-Objective Multi-Product Inventory Managed Production Planning Problem Under Uncertain Environment," *Annals of Operations Research*, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[15] Anh Chi Phan et al., "Effect of Total Quality Management Practices and JIT Production Practices on Flexibility Performance : Empirical Evidence from International Manufacturing Plants," *Sustainability*, vol. 11, no. 11, pp. 1-21, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[16] Maja Trstenjak et al., "Integrated Multilevel Production Planning Solution According to Industry 5.0 Principles," *Applied Sciences*, vol. 14, no. 1, pp. 1-24, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] Ammar Salah, Dilber Çağlar, and Khaled Zoubi, "The Impact of Production and Operations Management Practices in Improving Organizational Performance: The Mediating Role of Supply Chain Integration," *Sustainability*, vol. 15, no. 20, pp. 1-18, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Sonu Kumar Das, and Thyagaraj S. Kuthambalayan, "Matching Supply and Demand with Lead-Time Dependent Price and with Safety Stocks in a Make-to-Order Production System," *Systems*, vol. 10, no. 6, pp. 1-19, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[19] Ali Cheraghalikhani, Farid Khoshalhan, and Hadi Mokhtari, "Aggregate Production Planning: A Literature Review and Future Research Directions," *International Journal of Industrial Engineering Computations*, vol. 10, no. 2, pp. 309-330, 2019. [CrossRef] [Google Scholar] [Publisher Link]