

LEAD-TIME, INVENTORY, AND SAFETY STOCK CALCULATION IN JOB-SHOP MANUFACTURING

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ABSTRACT. The purpose of this article is to present a method for calculating the lead-time, the inventory, and the safety stock or buffer in job shop manufacturing, which are essentially stochastic variables. The research method is quantitative modelling. The theoretical foundation of the method relies on the techniques belonging to the WLC (workload control) body of knowledge on the manufacturing management. The study includes an application of the method in a manufacturing plant of the furniture industry, whose operation strategy requires high dependability. The company operates in a supply chain and must have high reliability in deliveries. Adequate safety stocks, lead times, and inventory levels provide the protection against the lack of reliability in the deliveries. The inventory should remain within a certain range, being as small as possible to maintain low lead times, but not too small that it could provoke a starvation, configuring an optimization problem. The study offers guidelines for a complete application in industries. Further research shall include the influence of the variability of the lot size in the stochastic variables.

KEYWORDS: lead-time; inventory; safety stock; dependability; workload control; queuing theory.

1. INTRODUCTION

Workload Control (WLC) is a production planning and control technique suitable for high-variety job shop manufacturing [1] and focused mainly on Make-to-Order (MTO) production [2]. The WLC integrates two control mechanisms, the input and the output control. The input control regulates the income of workload into the manufacturing system by priority rules. The output control regulates the outcome of the orders by adjustments in the production capacity. The extant literature considers the load-based order release as the main input control technique and adding or removing equipment and workforce as the main output control technique [1]. The dependent variable is the lead-time, the time between the arrival and the completion of an order, controlled by the work-in-process inventory, the orders waiting for service. Small inventories decrease the time an order waits for service, decreasing the lead-time.

This study focuses on the Southern Brazilian furniture industry. The main strategic objective of the industry is a high dependability, which includes high speed (short due dates), high reliability (accuracy in quantity and quality), and on-time deliveries (no tardiness). In the furniture industry, the manufacturing operates mostly in job shop plants based on the MTO production. The industry produces furniture items and mattresses and covers activities that range from the extraction and reception of raw materials from suppliers to the delivery, installation, and technical assistance of goods. A typical manufacturing company designs and produces a high variety of items with wood, steel, plastic, and specific materials. The industry must comply with various and rigorous technical specifications, whose application may require, at the same time, the use of advanced technologies and artisanal skills. The innovation depends mainly

on the development of new materials and new design techniques, in a close cooperation with suppliers [3]. The main elements of a furniture design are plates, fasteners, paints and resins, upholstery, and packaging. Some products, like rectilinear items, support a high automation level, while others, like solid wood items, require artisan skills [4].

Although the WLC originally focused on highly balanced production lines, further results indicate that the WLC could also be effective in unbalanced situations, like those found in the furniture industry. Not only bottlenecks but also non-bottlenecks work centres receive close attention [2]. Otherwise, the WLC performance might strongly deteriorate if the protective capacity of critical resources is not sufficiently high [5]. Despite most reported implementations are in large manufacturing plants, the WLC is particularly suitable for Small and Medium-sized Enterprises [6], such as those found in the furniture industry. In the furniture industry, a large part of the production comes from small and medium size plants, organized in the job-shop MTO production, which makes the WLC a useful tool in the manufacturing control function [7].

The purpose of this article is to present a method for calculating the lead-time, the inventory, and the safety stock in a job shop MTO manufacturing. The research method is quantitative modelling. The theoretical foundation of the method relies on proper contributions and on some issues extracted from the WLC body of knowledge. The research object is a manufacturing plant of the furniture industry of Southern Brazil. The company aims at a high dependability and must rely on adjusted levels of safety stocks, lead-times, and inventory levels to ensure on-time deliveries. The decision on inventory levels in the manufacturing stems from risk hedge policies due to unreliable suppliers, seasonal

production, short-term deliveries, or low-consumption items. The calculation of the inventory level creates an optimization problem. If a given level of inventories ensures a satisfaction of some specific customers, it also entails financial costs to maintain the cash flow [16–18]. The remainder of the article contains the review, methodology, results, discussion, and conclusions.

2. THEORETICAL BACKGROUND

The WLC or Load-Oriented Control aims at controlling the manufacturing workload controlling the inventory level [8]. Over time, the WLC balances the workload releases to and from the manufacturing system. As inventory does not grow above a given level, the lead-time remains low. As the inventory does not fall below a given level, efficiency remains high [9]. As the MTO manufacturing works with low quantity and high variety production, the control requires stochastic approaches [10].

The model employs five stochastic variables: lead-time (LT), work-in-process (WIP), arrival rate (RI), throughput (P), and safety stock (SS). The LT (measured in days or hours) varies according to the time waiting for service and the processing time. Order LT considers only the time to completion. Part LT considers also the size of the orders. WIP (measured in parts, tons, or other units) is the queue in the manufacturing system and represents the instantaneous quantity of materials waiting for service in the shop-floor. RI is the rate of arrival of orders, measured in pieces or tons per day or per hour. P is the rate of orders or parts delivery, measured by the same unit as RI . Imbalances between RI and P modify the queue length and, consequently, the WIP . Finally, SS is the minimum level of WIP that, under a given confidence level, prevents the starvation produced by instantaneous differences between RI and P [8, 12, 13]. The calculation model is valid for an isolated work centre as well as for a complete production line [8], and it looks as follows:

$$LT_i = TPEU_i - TPE_i, \tag{1}$$

$$LT_m = \sum_{i=1}^n \frac{LT_i}{n}, \tag{2}$$

$$LT_{\sigma m} = \sqrt{\frac{\sum_{i=1}^n (LT_m - LT_i)^2}{n - 1}}, \tag{3}$$

$$LT_{mw} = \frac{\sum_{i=1}^n LT_i Q_i}{\sum_{i=1}^n Q_i}, \tag{4}$$

$$LT_{\sigma w} = \sqrt{\frac{\sum_{i=1}^n (LT_m - LT_i)^2 Q_i}{\sum_{i=1}^n Q_i}}, \tag{5}$$

$$RI_m = \frac{\sum_{i=1}^n Q_i}{\max TPI_i - \min TPI_i}, \tag{6}$$

$$WIP_m = RI_m LT_{mw}, \tag{7}$$

$$P_m = \frac{\sum_{i=1}^n Q_i}{\max TPEU_i - \min TPEU_i}, \tag{8}$$

$$SS_m = P_m \Delta T_{\max}, \tag{9}$$

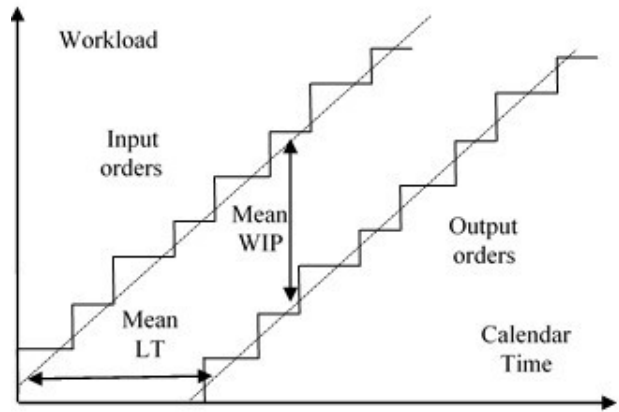


FIGURE 1. The Throughput Diagram.

in which: LT_i – lead-time (LT) of order i in the current work centre; TPE_i – completion time of order i in the previous work centre (time of liberation); $TPEU_i$ – completion time of order i in the current work centre. n – number of orders. LT_i – lead-time of order i ; LT_m – mean order LT ; $LT_{\sigma m}$ – standard deviation of the order LT ; LT_{mw} – mean part LT ; Q_i – amount of value added by order i ; $\sum_{i=1}^n Q_i$ – total amount dispatched by all orders; $LT_{\sigma w}$ – standard deviation of the part LT ; RI_m – mean arrival rate of orders or parts; WIP_m – mean WIP ; P_m – mean throughput; ΔT_{\max} – maximum time elapsed between the arrival of two successive orders.

The Throughput Diagram (TD) derives from the queue theory and represents the materials’ flow through the manufacturing system. The TD is a graphical method to verify the analytical calculation of the LT and WIP [7, 8]. In the shop-floor, the TD also helps with the control of the queue, keeping LT short and stable over time [2, 12]. Figure 1 illustrates the TD.

3. METHODOLOGY AND RESULTS

The research procedures are:

- (1.) data collection in a company of the furniture industry that manufactures desk-chair sets for offices (one set contains one or two chairs and one desk);
- (2.) application of the calculation model;
- (3.) analysis of the results regarding strategic priorities.

The company operates an MTO job shop manufacturing that processes orders with a size of multiples of ten. Eventual surplus routs to distribution centres for fast delivery. The company’s manufacturing information system provided the data from the first hundred orders served in 2018. The company uses a Manufacturing Execution System (MES) to control the orders. The information retrieved from the MES are the size of the order, the release date, and the completion date. Tables 1 and 2 show the raw data and the results of the application respectively.

Order #	Q_i (sets)	TPE_i	$TPEU_i$	LT_i	$Q_i LT_i$	$(LT_{mw} - LT_i)^2$	$(LT_{mw} - LT_i)^2 Q_i$
1	20	02/01	04/01	2	40	88.6	1772.6
2	40	02/01	17/01	15	600	12.9	514.3
3	50	02/01	03/01	1	50	108.5	5423.0
4	30	02/01	15/01	13	390	2.5	75.4
5	70	03/01	21/01	18	1260	43.4	3035.9
6	30	03/01	22/01	19	570	57.5	1726.2
7	30	04/01	24/01	20	600	73.7	2211.4
8	40	04/01	14/01	10	400	2.0	80.0
9	30	07/01	08/01	1	30	108.5	3253.8
10	80	07/01	18/01	11	880	0.2	13.7
11	30	08/01	17/01	9	270	5.8	174.9
12	30	09/01	15/01	6	180	29.3	879.5
13	30	10/01	17/01	7	210	19.5	584.6
14	60	10/01	17/01	7	420	19.5	1169.2
15	40	11/01	21/01	10	400	2.0	80.0
16	30	11/01	30/01	19	570	57.5	1726.2
17	60	14/01	02/02	19	1140	57.5	3452.4
18	40	15/01	01/02	17	680	31.2	1247.9
19	90	16/01	27/01	11	990	0.2	15.5
20	30	16/01	06/02	21	630	91.9	2756.5
21	80	21/01	04/02	14	1120	6.7	534.8
22	20	22/01	27/01	5	100	41.1	822.9
23	20	24/01	28/01	4	80	55.0	1099.5
24	20	25/01	28/01	3	60	70.8	1416.1
25	20	25/01	22/02	28	560	275.1	5501.6
26	50	28/01	13/02	16	800	21.0	1051.4
27	20	30/01	31/01	1	20	108.5	2169.2
28	90	01/02	08/02	7	630	19.5	1753.9
29	40	04/02	14/02	10	400	2.0	80.0
30	30	04/02	06/02	2	60	88.6	2658.9
31	20	04/02	07/02	3	60	70.8	1416.1
32	30	04/02	20/02	16	480	21.0	630.8
33	20	04/02	22/02	18	360	43.4	867.4
34	40	05/02	13/02	8	320	11.7	466.3
35	40	05/02	14/02	9	360	5.8	233.2
36	40	05/02	16/02	11	440	0.2	6.9
37	30	05/02	06/02	1	30	108.5	3253.8
38	50	05/02	19/02	14	700	6.7	334.3
39	20	05/02	22/02	17	340	31.2	624.0
40	70	05/02	25/02	20	1400	73.7	5159.8
41	30	06/02	18/02	12	360	0.3	10.3
42	50	06/02	20/02	14	700	6.7	334.3
43	30	06/02	22/02	16	480	21.0	630.8
44	20	07/02	14/02	7	140	19.5	389.7
45	20	07/02	14/02	7	140	19.5	389.7
46	60	07/02	19/02	12	720	0.3	20.6
47	20	07/02	19/02	12	240	0.3	6.9
48	50	07/02	25/02	18	900	43.4	2168.5
49	60	07/02	25/02	18	1080	43.4	2602.2
50	80	07/02	21/02	14	1120	6.7	534.8

(continued on the next page)

TABLE 1. Raw data and the model application. Part 1/2.

(continued)

Order #	Q_i (sets)	TPE_i	$TPEU_i$	LT_i	$Q_i LT_i$	$(LT_{mw} - LT_i)^2$	$(LT_{mw} - LT_i)^2 Q_i$
51	20	08/02	25/02	17	340	31.2	624.0
52	20	08/02	26/02	18	360	43.4	867.4
53	20	13/02	15/02	2	40	88.6	1772.6
54	40	13/02	26/02	13	520	2.5	100.6
55	30	13/02	27/02	14	420	6.7	200.6
56	40	13/02	25/02	12	480	0.3	13.7
57	40	13/02	21/02	8	320	11.7	466.3
58	60	18/02	26/02	8	480	11.7	699.5
59	40	18/02	26/02	8	320	11.7	466.3
60	20	18/02	25/02	7	140	19.5	389.7
61	40	18/02	26/02	8	320	11.7	466.3
62	20	18/02	26/02	8	160	11.7	233.2
63	30	19/02	26/02	7	210	19.5	584.6
64	20	20/02	05/03	13	260	2.5	50.3
65	20	21/02	27/02	6	120	29.3	586.3
66	20	21/02	11/03	18	360	43.4	867.4
67	50	21/02	11/03	18	900	43.4	2168.5
68	90	21/02	12/03	19	1710	57.5	5178.7
69	50	22/02	04/03	10	500	2.0	100.0
70	40	22/02	05/03	11	440	0.2	6.9
71	50	25/02	28/02	3	150	70.8	3540.1
72	20	27/02	12/03	13	260	2.5	50.3
73	20	28/02	06/03	6	120	29.3	586.3
74	20	28/02	06/03	6	120	29.3	586.3
75	80	01/03	19/03	18	1440	43.4	3469.6
76	20	01/03	07/03	6	120	29.3	586.3
77	30	04/03	06/03	2	60	88.6	2658.9
78	20	04/03	22/03	18	360	43.4	867.4
79	60	05/03	22/03	17	1020	31.2	1871.9
80	20	06/03	12/03	6	120	29.3	586.3
81	50	06/03	11/03	5	250	41.1	2057.3
82	50	06/03	20/03	14	700	6.7	334.3
83	30	07/03	13/03	6	180	29.3	879.5
84	40	07/03	14/03	7	280	19.5	779.5
85	20	07/03	11/03	4	80	55.0	1099.5
86	40	11/03	13/03	2	80	88.6	3545.3
87	50	11/03	13/03	2	100	88.6	4431.6
88	20	11/03	21/03	10	200	2.0	40.0
89	20	11/03	22/03	11	220	0.2	3.4
90	30	12/03	26/03	14	420	6.7	200.6
91	30	12/03	27/03	15	450	12.9	385.7
92	20	12/03	27/03	15	300	12.9	257.1
93	30	13/03	28/03	15	450	12.9	385.7
94	30	13/03	27/03	14	420	6.7	200.6
95	50	15/03	19/03	4	200	55.0	2748.7
96	20	15/03	27/03	12	240	0.3	6.9
97	30	18/03	26/03	8	240	11.7	349.8
98	30	18/03	01/04	14	420	6.7	200.6
99	40	18/03	27/03	9	360	5.8	233.2
100	30	20/03	03/04	14	420	6.7	200.6

TABLE 1. Raw data and the model application. Part 2/2.

Time interval	Proportion (p_n)	Accumulated
0	58 %	58 %
1	25 %	83 %
2	6 %	89 %
3	7 %	96 %
4	1 %	97 %
5	3 %	100 %

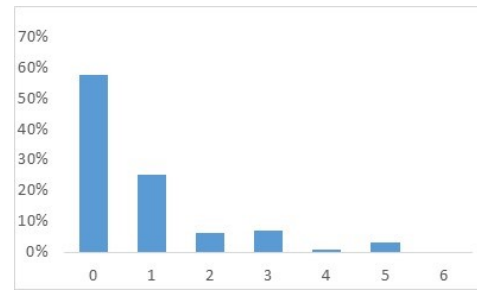


FIGURE 2. Distribution of the time intervals between arrivals of orders.

Variable	Result	Unit	Equation
LT_m	= 10.9	days	(2)
$LT_{\sigma m}$	= 5.8	days	(3)
LT_{mw}	= 11.4	days	(4)
$LT_{\sigma w}$	= 5.6	days	(5)
RI_m	= 48.6	sets/day	(6)
WIP_m	= 554.4	sets	(7)
P_m	= 41.6	sets/day	(8)
SS_m	= 207.8	sets	(9)

TABLE 2. Results of the application.

4. DISCUSSION

The mean order LT and mean part LT are close (10.9 and 11.4 days respectively), but not equal due to the variability in the order size ($\mu = 37.4, \sigma = 18.4$ sets). To cope with this uncertainty, the model creates the bivariate stochastic variable LT_iQ_i , without a direct physical meaning that represents the use of the manufacturing system by an order. The rationale that explains LT_iQ_i is: *the smaller the time to completion or the order size, the smaller the use of the system; the larger the time to completion or the order size, the larger the use of the system*. The sum $\sum_{i=1}^n LT_iQ_i$ is a proxy variable representing the total use of the system in the period. The division of $\sum_{i=1}^n LT_iQ_i$ by the total number of parts produces a proxy variable that represents the expected time to completion of a single part.

The mean arrival rate RI_m is 48.6 sets per day. The mean throughput P_m is 41.6 sets per day. Since P_m is lower than RI_m , the manufacturing system accumulated an inventory in the period. The mean inventory WIP_m is 554.4 sets of parts, which is more than two times the required buffer number of sets ($SS_m = 207.3$) and ensures an excessive protection against a starvation. A reduction on the buffer would result in a much lower inventory cost, as it is usually required by manufacturing strategies. In the period, the maximum interval between two arrivals is five days, in three out of the 100 orders. Assuming a normal distribution for the inventory, a WIP_m of 207.3 sets provides a 50 % protection for the three orders with inter-arrival times of five days. For a full protection for the orders with inter-arrival times lower than five days, the upper limit for the safety level SL , the probability that the manufacturing system will

not be stopped by starvation, is $SL = 1 - 0.5 \cdot 3/100 = 98.5\%$, which is too high for the manufacturing purposes. The SL is expected to decrease when taking into account the inventory uncertainty.

Figure 2 shows the data and the distribution of the inter-arrival times. The data follow a negative exponential distribution.

Another usual requirement of a manufacturing strategy is the full attendance of the orders due dates, which requires managing the lead-time. The maximum order lead-time is 28 days. Therefore, promised dates of 28 or more days ensure a full compliance with due dates. On the one hand, a promised date of 28 days satisfactorily protects the majority of orders; on the other hand, it could jeopardize a fast-delivery sales policy. A compromise solution, a trade-off between the protection and speed is needed. Considering $LT_m = 10.9$ and $LT_{\sigma m} = 5.8$ days, the upper limit of a 95 % confidence interval for the order lead-time is $LT_{UL} = 10.9 + 1.96 \cdot 5.8 = 22.3$ days. A promised date of 23 days would protect 95 % of the sales. If the sales policy requires deadlines of no more than 20 days, the safety level would be $SL = 1 - N(20, 10.9, 5.8) = 94.2\%$, which usually suffices for a competitive manufacturing strategy.

The next stage is the use the TD to graphically verify the analytic calculation of LT_m and I_m . Figure 3 shows the inflow and outflow TD and regression models.

The figure shows the accumulation of arrivals and completion of orders in the period, the regression models and the respective R^2 . The figure shows two models for the outflow, one with the intercept that maximizes the fitting, the other with the intercept equal to zero. The reason is that the negative intercept that maximizes R^2 has no physical meaning and harms the analysis, distorting the angular coefficient. The first regression model serves to verify the calculation of LT_m and WIP_m . The second serves to verify P_m . As both R^2 are close to 1, the models can satisfactorily replace the raw data.

Regarding RI and P , the slopes are close to the analytical outcomes ($RI_m = 48.8$ and 48.6 ; $P_m = 41.6$ and 41.04), which reinforces the validity of the model. In the long term, the manufacturing control releases on average 48.8 parts per day to the production line that dispatches on average 41.6 parts per day, producing an increasing instantaneous WIP and a WIP_m larger than the minimum needed to avoid a starvation, the SS_m .

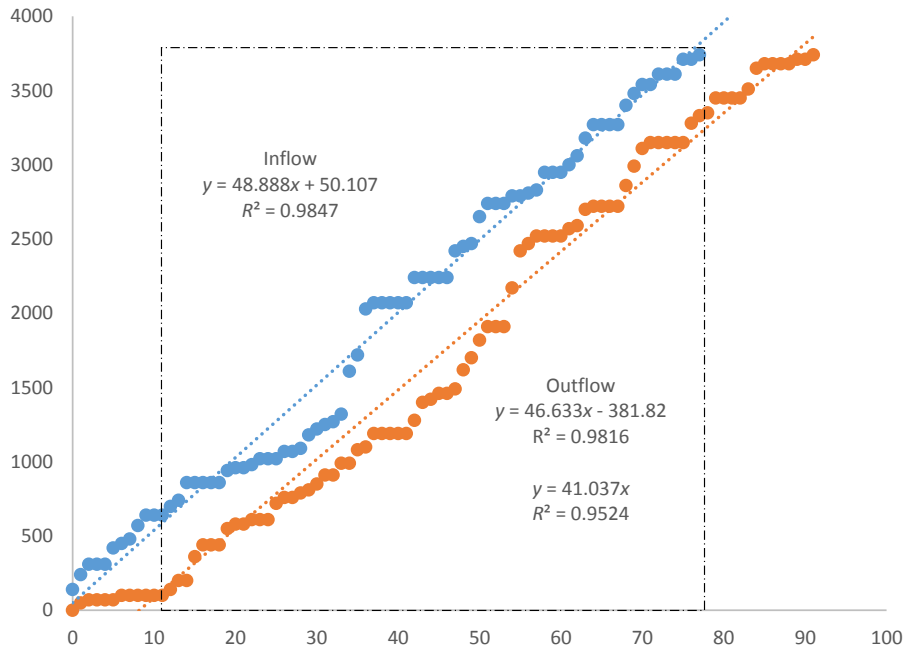


FIGURE 3. The TD and the regression models.

To reduce the excess, the manufacturing control should slow the order release, increase the processing capacity, or both, until WIP_m meets SS_m .

Regarding LT and WIP , the central points of the regression models are $(x, y) = (41.5, 1870)$, corresponding respectively to the centre of time and inventory ranges. The horizontal distance between the inflow and outflow model at $y = 1870$ and the vertical distance at $x = 45.5$ represent LT_m and WIP_m respectively. After some algebraic manipulation with the equations of the two regression models, it is possible to calculate the horizontal and the vertical distance between the central points of the lines. $LT_m = \frac{1870+381.8}{46.6} - \frac{1870-50.1}{48.8} = 11.02$ days corresponds to the horizontal distance. $WIP_m = (48.8 \cdot 45.5 + 50.1) - (46.6 \cdot 45.5 - 381.8) = 532$ sets corresponds to the vertical distance between the central points of the lines. Again, the graphical values are close (11.4 and 11.02; 554.4 and 532) to the analytical outcomes of the model. As the variables are stochastic, the approximations suffice for the analysis.

Finally, the TD also allows considering the inventory uncertainty. The orders arrived in 77 days, but only those inside the dashed area in Figure 3 are useful. The analysis discards the initial orders, as they require negative outflow accumulation to calculate the instantaneous inventory, which has no physical meaning. The mean and the standard deviation of the 67 valid instantaneous inventory values are 548.4 and 202.1 sets respectively. Assuming a fixed value $P_m = 41.04$, $WIP_m = 548.4$ and $WIP_\sigma = 202.1$, and using p_n , the proportion of orders whose inter-arrival time is $n = 1, \dots, 5$, $SL = 1 - \sum_{n=1}^5 p_n N(41.04n, 548, 202) = 99.3\%$, which is very high and confirms the excess of the inventory. If the management reduces the WIP_m to 207 sets, the analytical SS_m , the new value for the standard de-

viation is $WIP_\sigma = 202.1\sqrt{207/542.8} = 124.15$ and $SL = 1 - \sum_{n=1}^5 p_n N(41.04n, 207, 124) = 93.2\%$, which is still acceptable in a competitive manufacturing strategy. As expected, the uncertainty reduced the SL , whose upper limit was previously estimated at 98.5%.

5. CONCLUSION

The purpose of this article was to present a method for calculating lead-time, inventory, and the safety stock in job shop MTO manufacturing. The article included an application of the model in a job shop MTO manufacturing of the furniture industry. Besides the calculation of the variables, the application demonstrated that, due to unbalanced flows of material (arrival and completion of orders), the manufacturing produced excessive WIP , which possibly impairs the delivery deadlines and increases the operational cost. As the manufacturing strategy requires reliability in deliveries, the management should focus on reducing WIP_m to ensure a dependability and support the competition in the industry.

The article presented the initial development of the study. Further research shall focus on the influence of the uncertainty of the order size and the inventory in the lead-time. The research method is the simulation, which is widely used in manufacture control studies [14]. Further research shall also include fuzzy sets theory to manage the intrinsic uncertainty in the inventory management. A systematic review identified major achievements in fuzzy inventory management [15]. Further research should also focus on other companies in the same industry and in other industries, such as the footwear and the electronics industries that also rely on MTO job shop manufacturing systems.

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