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THROUGHPUT IMPROVEMENT STRATEGY FOR NONLINEAR CHARACTERISTICS IN THE PRODUCTION PROCESSES

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Abstract. *Synchronization between production processes is essential for improving the throughput in these processes. This study examines the improvements in throughput by improving the synchronization between production processes. In our strategy, we improved throughput by dividing a process into preprocess and postprocess segments, and tested our strategy on both open and cyclic production flow processes. For a cyclic production flow process, the rate of return and net sales relationships exhibited nonlinear characteristics when they were defined by the Van der Pol differential equation. For an open production flow process, we represented the process cycle time and the number of ongoing processes by analyzing the actual data. For both the types of production flow processes, we observed that nonlinearities in production were related to the deviations in process worker throughput. Using queuing theory, we calculated the utilization of process cycle time and the average number of commencement processes in open production flow processes. We presented actual data from examples in which we tested our strategy; the data showed that we were able to improve throughput in both open and cyclic production flow processes.*
Keywords: Nonlinear characteristics, Synchronous process, Throughput, Lead time, Deviation of the working time

1. **Introduction.** Several studies have addressed the problem of productivity improvement in industrial production processes [1, 2]. Moreover, various theories have been applied to improve and reform production processes and increase productivity. In [3], an analysis that uses the queuing model and applies a log-normal distribution to model a system in the steel industry is described.

Several studies have reported approaches to shorten lead times [4, 5]. From the time of product ordering, the lead time is dependent on the work required to prepare the system for production.

We have reported that an analysis of the rate-of-return deviation for a certain equipment manufacturer over the past ten years displays "power-law distribution characteristics". Because the power-law distribution reveals the existence of a phase transition phenomenon, we expect that the rate-of-return deviation and the production system are correlated in a manner that is mediated by the power-law distribution [6]. By performing a data analysis, the relation between the rate-of-return deviation and production throughput has been clarified to some extent. The "fluctuation model of rate-of-return deviation" is self-similar and shows a fractal nature [7, 18]. Also, this power-law distribution characteristic has a "fluctuating" nature during phase transition. For example, occurrence of fluctuation is found at where the phase transition occurs at the point. Then, we have reported on the self-similarity of these fluctuations and noted the f^{-1} and f^{-2} fluctuations [8]. We have also verified self-similarity in the system through experiments on the supply chain system, and have used the supply chain system to produce control equipment. In total, nine workers were involved, and the production process was composed of six stages. To compare the forms of production, we roughly conducted four patterns of asynchronous and synchronous methods. In this report, we propose that it is possible to increase manufacturing profits by adopting a management strategy that purposefully leads to a state of excessive production or excessive order entries. This management strategy is ideal on the basis of analysis of the cost rate of the production process.

Although the traditional approach to avoid bottlenecks in production processes is to use the theory of constraints [9], we have reported that the synchronization method is superior for shortening throughput in production processes. This method requires synchronization between processes [10].

In our previous study [11], we constructed a state in which the production density of each process corresponded to the physical propagation of heat [18]. Using this approach, we showed that a diffusion equation dominates the production process. In other words, when minimizing the potential of the production field (stochastic field), the equation, which is defined by the production density function $S_i(x, t)$ and boundary conditions, is described by the use of diffusion equation with advection to move in transportation speed ρ. The boundary conditions describe a closed system in the production field. The adiabatic state in thermodynamics represents the same state [11].

With respect to the production flow system, generally, low volumes of a wide variety of products are produced through several stages in the production process. This method is good for producing specific control equipment such as semiconductor manufacturing equipment in our experience. We have reported many research findings in this area. The production flow process has nonlinear characteristics [12]. Moreover, we have made it clear that the manufacture of products proceeds in multiple stages from the beginning of production. Such volatility is encountered in every stage of manufacturing, and delays in the production line propagating this volatility to the successive steps. A delay in the production process is equivalent to a "fluctuation" in physical phenomena [13].

To achieve the production system goals, we propose the use of a mathematical model that focuses on the selection process and adaptation mechanism of the production lead time [14]. We model the throughput time of the production demand/production system in the production stage by using a stochastic differential equation of the log-normal type, which is derived from its dynamic behavior. Using this model and risk-neutral integral, we define and compute the evaluation equation for the compatibility condition of the production lead time. Furthermore, we apply the synchronization process and show that the throughput of the production process is reduced [14, 15].

In accordance with this result, we show that Kalman filter theory, conventionally used in state estimation problems in control theory, can be applied under an incomplete information state. In addition, by applying a theory of ongoing assessment in real option, the conditions that determine throughput rate are clarified and confirmed by numerical value calculations [15].

In this study, we report a strategy for improving throughput in both open and cyclic production processes. The open production flow process involves the production of different control equipment, whereas the cyclic production flow process involves the production of similar control equipment. The factors that lead to nonlinear characteristics in the underlying production process are because of the deviations in worker throughput.

In a previous study, we found that the rate of return and net sales relationships exhibited nonlinear characteristics when they were defined by the Van der Pol differential equation. Furthermore, nonlinear production characteristics, such as process cycle time and the number of processes in progress, could be attributed to the deviations in the throughput of in-process workers [12].

We used queuing theory to calculate the utilization of process cycle time and the average number of commencement processes. On the basis of actual data from a high-mix, low-volume production process, we verified that cycle time, number of commencement processes, utilization rate, and worker deviations contributed to the nonlinear characteristics of a production process. Finally, we present actual data from examples in which we tested our strategy, which improved the throughput of both production flow processes. To the best of our knowledge, a throughput improvement strategy has not been previously applied to nonlinear production process characteristics.

2. **Rate of Return and Nonlinear Characteristic of Net Sales.** Figures 1-3 display graphs in which no significant difference is apparent between cumulative revenues related to production costs and revenues related to production throughput [12].

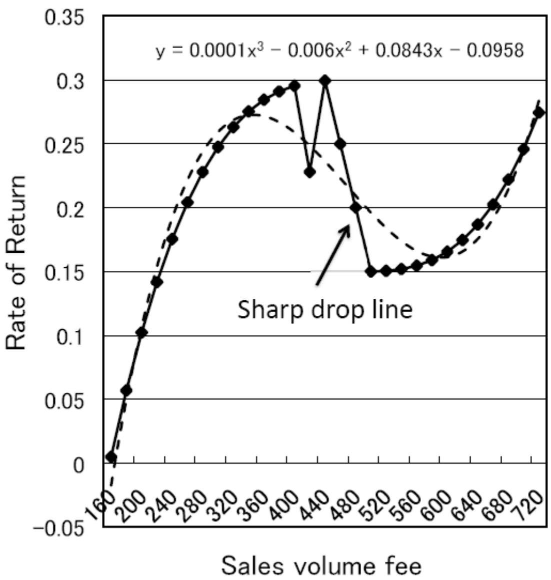

FIGURE 1. Rate of return on sales volume 1

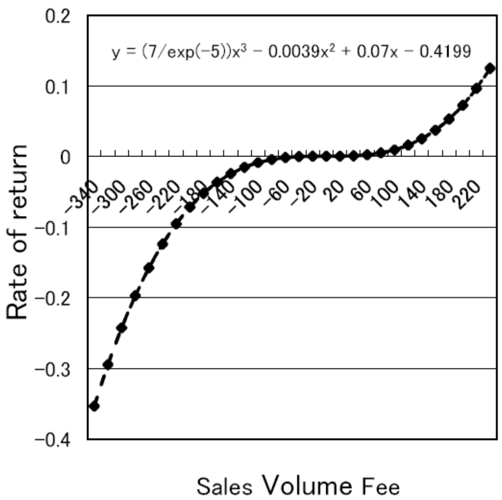

FIGURE 2. Rate of return on sales volume 2

Figures 1-3 plot the rate of return on net sales of specific control equipment produced by some domestic enterprises from 1996 to 1998. The rate of return on sales gives rise to the nonlinear characteristics [12].

The dashed line in the figures is the fitted curve representing the relationship between the rate of return on sales and sales volume fee. In the data, the return rate plummeted from 0.3 at a sales fee of 480 to 0.15 at a sales fee of 440 (see Figure 1). This sharp drop represents the relationship in Equation (7).

The resulting straight line appears in the vicinity of the phase transition and is equivalent to the oscillation point of the reference line in elements displaying nonlinear characteristics (such as the Esaki diode) [17].

$$h_s(S) = F(S) + \xi(h_{s_0}) \tag{1}$$

where $F(S)$ represents the basic characteristics of the return rate, and $\xi(h_{s_0})$ is a neighborhood of local nonlinearity around h_{s_0}. The following mathematical model is derived from the data plotted in Figures 1-3 [17].

$$a\frac{dh_s}{dt} + bh_s + S = S_E \tag{2}$$

$$h_s = h_{s_1} + h_{s_2} \tag{3}$$

$$h_{s_2} = \tilde{F}(S') \tag{4}$$

$$S' = c\int h_{s_1} dt \tag{5}$$

$$\tilde{F}(S') = F(S) + \xi(h_{S_0}) \tag{6}$$

$$S_E - bh_{s_0} = S' \tag{7}$$

where a, b, and c are cost coefficients, h_s is the rate of return and h_{s_1} is the rate of return contributing to the sales volume. h_{s_2} is a nonlinear characteristic of the rate of return (introduced by costs that cannot contribute directly to sales and that lead to production delays), and (h_{s_0}, S_0) is the median of the nonlinear characteristic.

Physically, Equation (2) represents the temporal deviation of the rate of return h_s; that is, the relationship between the deviation of the rate of return and the sales or rate of return. Although sales are essentially proportional to production costs, not all of the production cost can be invested in sales.

Equation (3) is the sum of the rate of return and the nonlinear element. In other words, it embodies the cost of production and no production costs that make no contribution to sales.

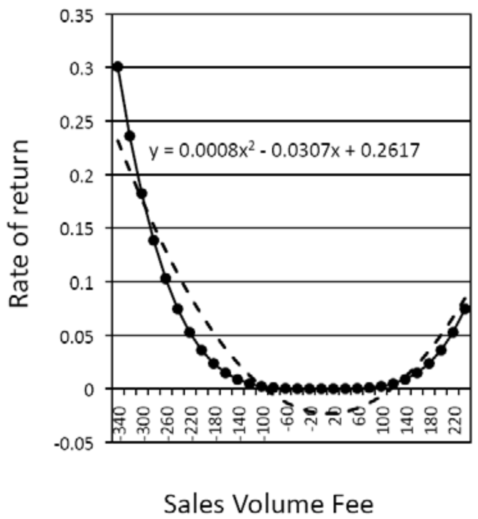

FIGURE 3. Rate of return on sales volume 3

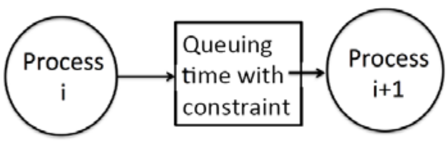

FIGURE 4. Queuing time with constraint

3. **Analysis of Cycle Time and Utilization in the Open Production Flow Process.** The relationship between worker and lead time exhibits nonlinear characteristics, as is shown in Figure 11, which is obtained from actual data. Therefore, we analyze the relationship between utilization and cycle time using queuing theory. The relationship between utilization and cycle time is as follows.

$$CT = \frac{1}{1-u} t_e \quad ({}^{\forall} t_e \equiv constant) \tag{8}$$

The maximum throughput is $TH_{\max} = 1/t_e$, and when the utilization is u, the throughput TH is obtained as follows.

$$TH = u \times TH_{\max} = \frac{u}{t_e} \tag{9}$$

Therefore, the average working time in process WIP is as follows.

$$WIP = CT \times TH = \frac{1}{1-u} t_e \times \frac{u}{t_e} = \frac{u}{1-u} \tag{10}$$

Nonlinear characteristics can be observed in the work time for utilization u in any case.

$$u = \frac{T_R}{T_R + T_a}, \quad 0 \leq u \leq 1 \tag{11}$$

where T_R is the actual lead time, and T_a is the inter-process idle time.

u decreases as idle time increases. The utilization rate represents the percentage rate for each process when processing is occupied. For example, when the proportion of actual processing time in the process is 60% and the percentage of idle time is 40%, u is calculated as follows.

$$u = \frac{60}{60+40} = 0.6$$

On the assumption that u is derived in the production flow system as follows.

$$u \equiv 1 - \frac{\text{Setting lead time}}{\text{Actual lead time}} \tag{12}$$

Moreover, from Figure 6, queuing time decreases with decreasing u, and the process is estimated as an idling situation; i.e., there is no job in the process and the acceptance of a job is possible because of the lack of latency constraints.

4. **Analysis of Queuing Time and the Probability Distribution in Open Flow Production Process.** Here, we analyze the open system model (no cyclic production) shown in Figure 9. When a new job arrives in the process for the number of k processes, we obtain the following equation as the existing probability of the number of k jobs from queuing theory [19].

$$P(k) = u^k(1-u) \tag{13}$$

The queuing time for an arriving job is the sum of the stochastic variable and the exponential distribution of the average time t_e of each k. This is represented by Erlang distribution and is also represented by the sum of the exponential distribution of average $1/\lambda$ of each k.

$$\frac{\lambda^k t^{k-1}}{(k-1)!} \exp(-\lambda t) \tag{14}$$

When $\lambda = 1/t_e$, we obtain it as follows.

$$\frac{\left(\frac{1}{t_e}\right)^k t^{k-1}}{(k-1)!}\exp\left(-\frac{t}{t_e}\right) = \frac{t^{k-1}}{t_e^k (k-1)!}\exp\left(-\frac{t}{t_e}\right) \tag{15}$$

Here, we set $f(k;t)$ to Equation (15), and $f(k;t)$ represents the queuing distribution of an arriving job. Therefore, the queuing distribution of an arriving job is derived by the following queuing theory equation [19].

$$\begin{aligned} f_q(t) &= \sum_{k=1}^{\infty} f(k;t)P(k) \\ &= \frac{(1-u)u}{t_e}\exp\left\{-\frac{(1-u)t}{t_e}\right\} \end{aligned} \tag{16}$$

Next, we calculate the cumulative probability distribution. For $t = 0$, we obtain the following.

$$F_q(0) = 1 - u \tag{17}$$

$F_q(t)$ is derived as follows.

$$F_q(t) = F_q(0) + \int_0^t f_q(s)ds \tag{18}$$

Then the second term on the right-hand side in Equation (18) is as follows.

$$\int_0^t f_q(s)ds = u\left[1 - \exp\left\{-\frac{(1-u)t}{t_e}\right\}\right] \tag{19}$$

We obtain as follows by substituting Equations (17) and (18) to Equation (19)

$$F_q(t) = 1 - u\exp\left\{-\frac{(1-u)t}{t_e}\right\} \tag{20}$$

Figure 5 shows the calculation results of Equation (20). According to the definition of Equation (12), when $u \to 0$, the working throughput approaches synchronization because

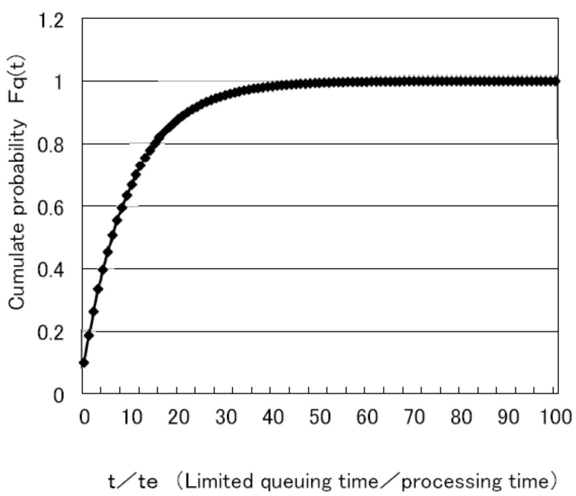

FIGURE 5. Cumulative probability of limited queuing time (M/M/1)

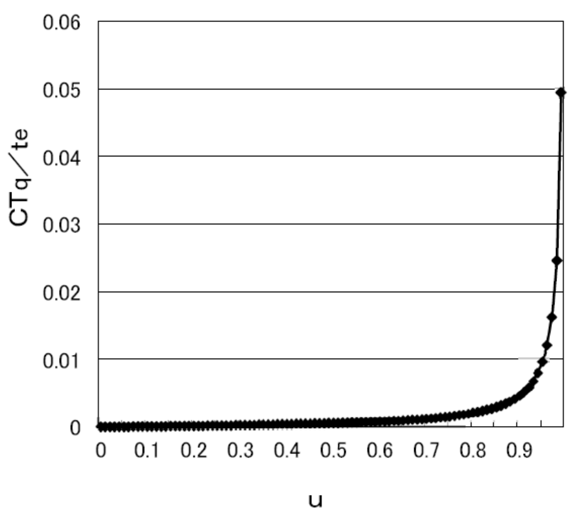

FIGURE 6. Queuing time (GI/G/1)

the actual lead time → the target working time. Therefore, when $u \to 0$, the cumulative queuing time distribution becomes a sharp curve.

When the average processing time of a device increases, the queuing time constraint also increases, as is shown in Figure 6. We can obtain an approximate equation from Kingman's equation.

$$CT_q = \left(\frac{C_a^2 + C_e^2}{2}\right) \cdot \frac{u}{1-u} t_e$$
$$\frac{CT_q}{t_e} = \left(\frac{C_a^2 + C_e^2}{2}\right) \cdot \frac{u}{1-u} \tag{21}$$

where $C_a \leq 1$ and $C_e \leq 1$. Additionally, t_e represents the average processing time for a device, and for throughput $TH = 1/t_e$, $CT_q = (u/(1-u)) \cdot t_e$.

5. Actual Data Examples of the Production Process Having a Nonlinearity.

We present the actual data examples both the open and the cyclic production flow process having a nonlinearity.

5.1. Example of the open production flow process.

After we observed the nonlinear characteristics in the production process, we focused on an attempt to improve throughput [14]. At present, we have maintained a synchronized process. Using asynchronous logistics phenomenon and supply chain delays, we present a throughput improvement example, in which a production flow process is used for throughput improvement.

Here we investigate improved and standard process flows using a control device as an example. As a result, we found that according throughput improvement post-process priority is appropriate. Using a buffer of the previous process to overcome bottlenecks in the post process, the previous process can synchronize the post process, leading to significantly improved lead time.

Figure 9 illustrates the concept of process synchronization. Here X_{PR} represents the previous process, X_P represents the pre-work start date of the post process, and X_M represents the start date of the post process.

If we set the required production number $S(X_M)$ (i.e., required production number in a post process) to a synchronization point in time X_M, there is at least the following relationship between production numbers $S_P(X_{MP})$ among $[T_{MP}]$ and production numbers

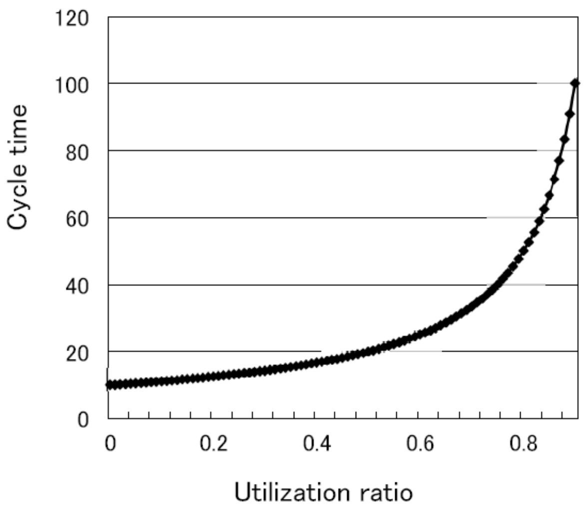

FIGURE 7. Cycle time for constant average processing time

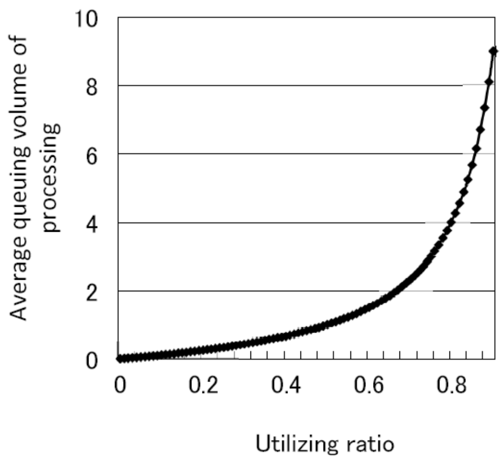

FIGURE 8. Average queuing volume of processing

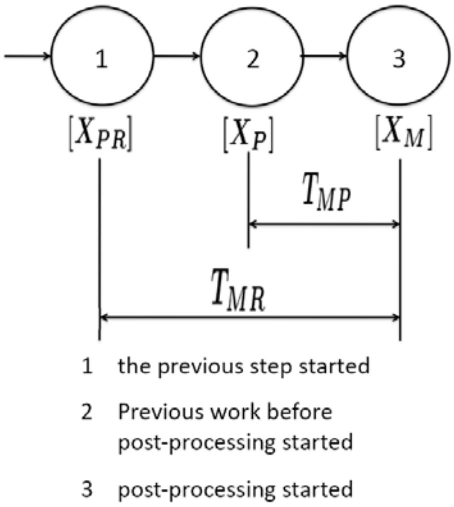

FIGURE 9. Conceptual diagram of the production process synchronization

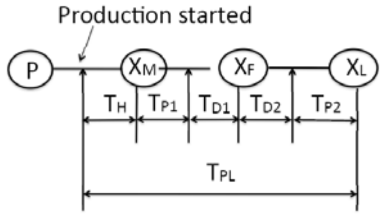

FIGURE 10. Production lead time in entire process

$S_R(X_{PR})$ among $[T_{MR}]$:

$$S_M(X_M) \leq S_P(X_{MP}) + S_R(X_{PR}) \tag{22}$$

where each symbol is as follows.

$$S_P(X_M) \equiv k_P \cdot [T_{MP}] \cdot n_P \tag{23}$$

$$S_R(X_{PR}) \equiv k_R \cdot [T_{MR}] \cdot n_R \tag{24}$$

Here n_P, n_R are the number of working people, k_P, k_R represent the process throughput variable (i.e., number of productions/all working people), and $[T_{MP}]$ and $[T_{MR}]$ represent the lead times of each period.

$$[T_{MP}] \equiv P_P[X_{MP}] > \bar{X}_P \cdot |X_M - X_P| \tag{25}$$

$$[T_{MR}] \equiv P_R[X_{PR}] > \bar{X}_R \cdot |X_M - X_{PR}| \tag{26}$$

where when $\bar{X}_P > 0$, $\bar{X}_P$ is integer and when $\bar{X}_R > 0$, $\bar{X}_R$ is integer.
$P_P[X_{MP} > \bar{X}_P]$ and $P_R[X_{PR} > \bar{X}_R]$ are as follows:

$$P_P[X_{MP} > \bar{X}_P] = \Phi_P[\bar{X}_P/\sigma_{MP}] \tag{27}$$

$$P_R[X_{PR} > \bar{X}_R] = \Phi_R[\bar{X}_R/\sigma_{PR}] \tag{28}$$

where $\Phi_P[\bullet]$ and $\Phi_R[\bullet]$ represent standard normal distribution function respectively.

Thus, the following can be established.

$$S_M \leq S_R + S_P, \quad {}^{\forall}S_R > S_P \tag{29}$$

Equation (36) provides the relationship model of lead time and actual production manpower (input personnel). The lead time model is constructed from the model shown in Figure 10. We obtain several concepts from this model, i.e., the relationship between lead time and start date, the relationship between lead time and production manpower, and the lead time reduction equation. The model enables the consideration of the production flow.

Ideally, the relationship between production lead times and production start date in real companies is defined quantitatively. In particular, we select typical production equipment with different specifications for production and measure the final inspection time from start time to production completion. For any unforeseen situation, using statistical data, we can determine specific numerical targets.

We focus on the lead times of off-premise and on-premise production. In Figure 10, T_{PL} represents the production lead time, T_{P1} represents the production lead time for off-premise production (stochastic variable including deviation), T_{P2} represents the production lead time for on-premise production (stochastic variable including deviation), T_{D1} represents the residence time (idle time) of on-premise production, and T_H represents a previous process (harness processing). Thus, the production lead time can be obtained as follows.

$$T_{PL} = (T_{P1} + T_{P2}) + (T_{D1} + T_{D2}) + T_H \tag{30}$$

Here the production lead time is obtained from X_P (starting date) until X_E (production completion date) and is described as follows.

$$T_{PL} = |X_L - X_P| \tag{31}$$

If $P[T_{LM} > T_{PL}]$ provides a deviation of $|X_L - X_M|$, the evaluation of T_{DP}, which provides the production lead time of an actual process, is described as follows.

$$T_{DP} \leq T_{LM} - (T_{D1} + T_{D2}), \quad {}^{\forall}T_{LM} = |X_L - X_M| \tag{32}$$

$$= P[T_{LM} > T_{PL}] \cdot |X_L - X_M| - (T_{D1} + T_{D2}) \tag{33}$$

Here we refer to $P[T_M > T_{PL}]$ as an incompatibility factor versus $|X_L - X_M|$, where M is any positive integer.

Example 5.1. *If the risk rate is 5%,* $|X_L - X_M| = 18$ *(date) and* $(T_{D1} + T_{D2}) = 5$ *(days); thereafter,* T_{DP} *can be obtained as follows.*

$$T_{DP} \leq 0.95 \times 18 - 5 = 12 \tag{34}$$

From Equation (34), a post process must be completed within 12 days.

From the above description, we can evaluate the standard lead time in a post process in advance. Therefore, if the standard lead time is measured as $[T_{LM}]_{nom.}(h)$, the production lead time is as follows.

$$[T_{PL}]_{nom.} \geq \frac{[T_{LM}]_{nom.}(h) + T_H(h)}{8n(people)} \tag{35}$$

Thus, we can conduct a production process within the standard process time. We rewrite Equation (35) for $n(people)$. Then, we can obtain the production lead time as follows.

$$n \geq \frac{[T_{LM}]_{nom.}(h) + T_H(h)}{8 \cdot [T_{PL}]_{nom.}} \tag{36}$$

Figure 11 can be obtained from Equation (35). Figure 12 illustrates the standard production flow for equipment and represents a real production flow diagram rather than the lead time concept shown in Figure 10. Figure 14 illustrates the measurement lead time for a real production number. From the above description, if n_P and n_R are fixed, we have no choice but to alter the production rate to satisfy the synchronization condition. Considering risk in lead times, it is best to employ process flattening and process coupling.

To control the production capacity variable, we must deploy fair and flexible manpower planning and measure the lead time of production equipment. Figure 12 shows a standard production flow, and Figure 13 illustrates an improved flow obtained by flattening a cable production process. By incorporating a cable production process as a pre-process, we were able to obtain an improved process. Figure 14 shows the measurement results of production lead time from data obtained for a produced device. Here after receiving an

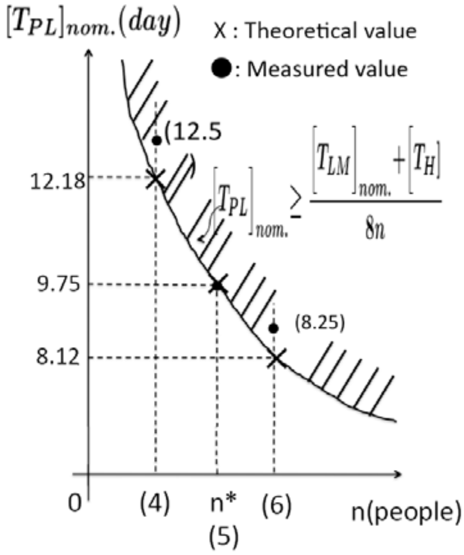

FIGURE 11. Relationship between lead time and work people

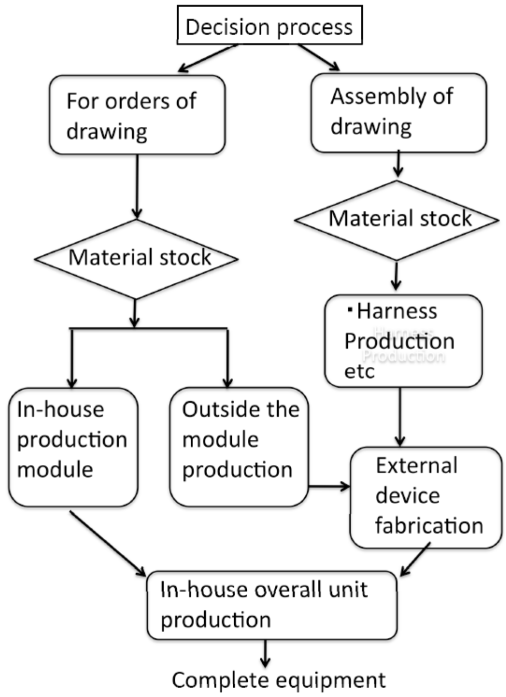

FIGURE 12. Standard equipment fabrication flow 1

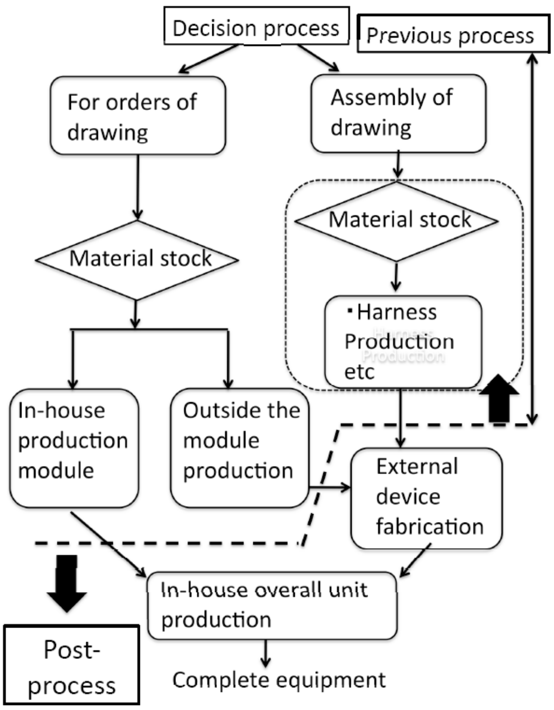

FIGURE 13. Improved equipment fabrication flow 2

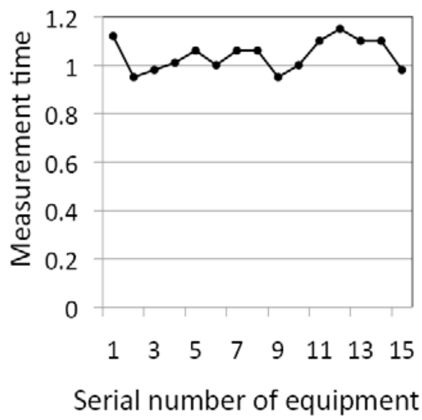

FIGURE 14. Production lead time variability

order to manufacture equipment and confirm parts distribution, we can determine the start date by considering the delivery date, as is shown in Figure 14.

Then, Figure 14 provides the actual measurement data, which is the lead time of each process and time until final inspection is completed from the start date of production.

The production lead times are obtained by (measurement lead time)/(standard lead time).

Here the average production lead time is 1.0275 and the standard deviation is 0.051. From these results, the production lead times are relatively stable; however, a minor difference occurs in production lead times due to production equipment specifications.

Thus, we calculate the reduction rate of lead time to obtain (improved production flow)/(standard production flow) = 0.826 in the improved production flow 1, and (improved production flow)/(standard production flow) = 0.7239 in the improved production flow 2.

Therefore, the reduction rate of lead time is improved by approximately 13% in the improved production flow 1 and is improved by approximately 20% in the improved production flow 2. Here we define a throughput coefficient based on a standard production flow as follows.

Definition 5.1. *Throughput coefficient based on a standard production flow*

$$\eta \equiv \frac{[\textit{Number of production man-power}] \times [\textit{Number of real working time}]}{[\textit{Production risk rate}] \times [\textit{Reduction rate of lead time}]} \times \frac{1}{[\textit{Real working time of lead time}]} \tag{37}$$

If the numerator is constant, i.e., [production risk rate] = 1 and [real lead time] = constant, $\eta \cong 1.21$ (21% increase) in the improved production flow 1 and $\eta \cong 1.35$ (35% increase) in the improved production flow 2.

From the above description, by using a previous process as a buffer in a post process, we can realize synchronization between a previous process and post process. In other words, we have realized a post process with priority higher than the previous process.

5.2. **Example of the cyclic production flow process.** Figure 15 depicts a production process that is termed as a production flow process. This production process is employed in the production of control equipment. In this example, the production flow process consists of six stages. In each step S1−S6 of the production process, materials are being produced.

The direction of the arrows represents the direction of the production flow. In this process, production materials are supplied through the inlet and the end-product is shipped from the outlet. For this flow production system, we make the following two assumptions.

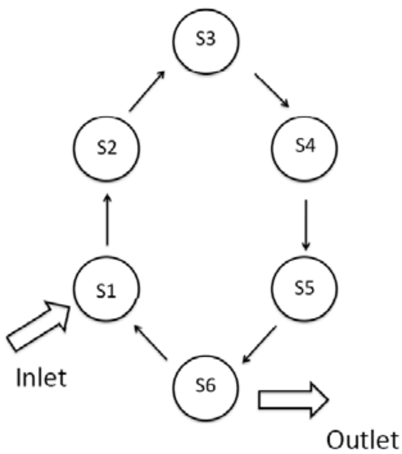

FIGURE 15. Cyclic production flow process

6. Analysis of the Test−run Results.

- (Test−run1): Because the throughput of each process (S1−S6) is asynchronous, the overall process throughput is asynchronous. In Table 2, we list the manufacturing time (min) of each process. In Table 3, we list the volatility in each process performed by the workers. Finally, Table 2 lists the target times. The theoretical throughput is obtained as $3 \times 199 + 2 \times 15 = 627$ (min). In addition, the total working time in stage S3 is 199 (min), which causes a bottleneck. In Figure 16, we plot the measurement data listed in Table 2, which represents the total working time of each worker (K1−K9). In Figure 17, we plot the data contained in Table 2, which represents the volatility of the working times.
- (Test−run2): Set to synchronously process the throughput. The target time listed in Table 4 is 500 (min), and the theoretical throughput (not including the synchronization idle time) is 400 (min). Table 5 presents the volatility of each working process (S1−S6) for each worker (K1−K9).
- (Test−run3): Introducing a preprocess stage. The process throughput is performed synchronously with the reclassification of the process. As shown in Table 6, the theoretical throughput (not including the synchronization idle time) is 400 (min). Table 7 presents the volatility of each working process (S1−S6) for each worker (K1−K9). On the basis of these results, the idle time must be set to 100 (min). Moreover, the theoretical target throughput ($T_s^{'}$) can be obtained using the "Synchronization with preprocess" method. This goal is as follows:

$$\begin{aligned} T_s &\sim 20 \times 6 \text{ (First cycle)} + 17 \times 6 \text{ (Second cycle)} \\ &\quad + 20 \times 6 \text{ (Third cycle)} + 20 \text{ (Previous process)} + 8 \text{ (Idol-time)} \\ &\sim 370 \text{ (min)} \end{aligned} \tag{38}$$

The full synchronous throughput in one stage (20 min) is

$$T_s^{'} = 3 \times 120 + 40 = 400 \text{ (min)} \tag{39}$$

Using the "Synchronization with preprocess" method, the throughput is reduced by approximately 10%. Therefore, we showed that our proposed "Synchronization with preprocess" method is realistic and can be applied in flow production systems. Below, we represent for a description of the "Synchronization with preprocess".

In Table 6, the working times of the workers K4, K7 show being shorter than others. However, the working time shows being around target time. Next, we manufactured one piece of equipment in three cycles. To maintain a throughput of six units/day, the production throughput must be as follows:

$$\frac{(60 \times 8 - 28)}{3} \times \frac{1}{6} \simeq 25 \text{ (min)} \tag{40}$$

where the throughput of the preprocess is set to 20 (min). In Equation (40), the value 28 represents the throughput of the preprocess plus the idle time for synchronization. Similarly, the number of processes is 8 and the total number of processes is 9 (8 plus the preprocess). The value of 60 is obtained as 20 (min) $\times$ 3 (cycles).

TABLE 1. Correspondence between the table labels and the Test−run number

	Table Number	Production process	Working time	Volatility
Test−run1	Table 2	Asynchronous process	627 (min)	0.29
Test−run2	Table 4	Synchronous process	500 (min)	0.06
Test−run3	Table 6	"Synchronization with preprocess" method	470 (min)	0.03

TABLE 2. Total manufacturing time at each stage for each worker

	WS	S1	S2	S3	S4	S5	S6
K1	15	20	20	25	20	20	20
K2	20	22	21	22	21	19	20
K3	10	20	26	25	22	22	26
K4	20	17	15	19	18	16	18
K5	15	15	20	18	16	15	15
K6	15	15	15	15	15	15	15
K7	15	20	20	30	20	21	20
K8	20	29	33	30	29	32	33
K9	15	14	14	15	14	14	14
Total	145	172	184	199	175	174	181

TABLE 3. Volatility of Table 2

K1	1.67	1.67	3.33	1.67	1.67	1.67
K2	2.33	2	2.33	2	1.33	1.67
K3	1.67	3.67	3.33	2.33	2.33	3.67
K4	0.67	0	1.33	1	0.33	1
K5	0	1.67	1	0.33	0	0
K6	0	0	0	0	0	0
K7	1.67	1.67	5	1.67	2	1.67
K8	4.67	6	5	4.67	5.67	6
K9	0.33	0.33	0	0.33	0.33	0.33

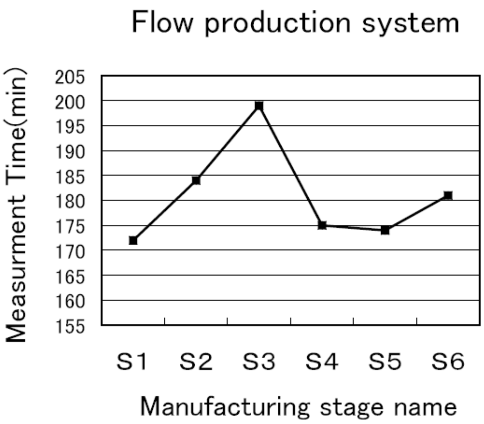

FIGURE 16. Total work time for each stage (S1−S6) in Table 2

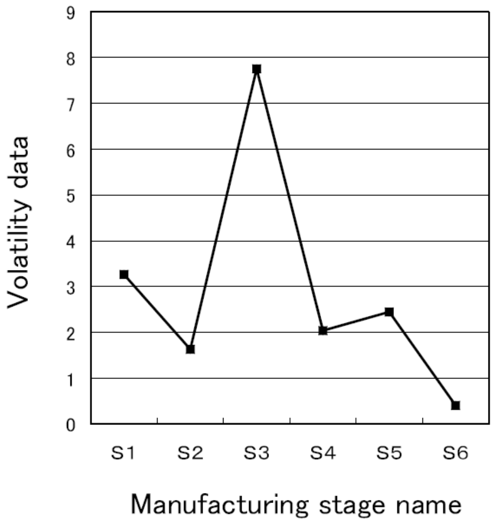

FIGURE 17. Volatility data for each stage (S1−S6) in Table 2

In Table 1, Test−run3 indicates a best value for the throughput in the three types of theoretical working time. Test−run2 is ideal production method. However, because it is difficult for talented worker, Test−run3 is a realistic method.

The results are as follows. Here, the trend coefficient, which is the actual number of pieces of equipment/the target number of equipment, represents a factor that indicates the degree of the number of pieces of manufacturing equipment.
Test−run1: 4.4 (pieces of equipment)/6 (pieces of equipment) = 0.73,
Test−run2: 5.5 (pieces of equipment)/6 (pieces of equipment) = 0.92,
Test−run3: 5.7 (pieces of equipment)/6 (pieces of equipment) = 0.95.
Volatility data represent the average value of each Test−run.

7. **Conclusion.** We developed a strategy for improving throughput in both open and cyclic production flow processes that exhibit nonlinear characteristics. We obtained 21%-35% improvement in an open production flow process, and 10% improvement of production equipment in a cyclic production flow process. We were able to identify a nonlinear factor caused by deviations in worker performance at different stages of a process. We

Table 4. Total manufacturing time at each stage for each worker

	WS	S1	S2	S3	S4	S5	S6
K1	20	20	24	20	20	20	20
K2	20	20	20	20	20	22	20
K3	20	20	20	20	20	20	20
K4	20	25	25	20	20	20	20
K5	20	20	20	20	20	20	20
K6	20	20	20	20	20	20	20
K7	20	20	20	20	20	20	20
K8	20	27	27	22	23	20	20
K9	20	20	20	20	20	20	20
Total	180	192	196	182	183	182	180

Table 5. Volatility of Table 4

K1	0	1.33	0	0	0	0
K2	0	0	0	0	0.67	0
K3	0	0	0	0	0	0
K4	1.67	1.67	0	0	0	0
K5	0	0	0	0	0	0
K6	0	0	0	0	0	0
K7	0	0	0	0	0	0
K8	2.33	2.33	0.67	1	0	0
K9	0	0	0	0	0	0

Table 6. Total manufacturing time at each stage for each worker, K5 (*): Preprocess

	WS	S1	S2	S3	S4	S5	S6
K1	20	18	19	18	18	18	18
K2	20	18	18	18	18	18	18
K3	20	21	21	21	21	21	21
K4	16	13	11	11	13	13	13
K5	16	*	*	*	*	*	*
K6	16	18	18	18	18	18	18
K7	16	14	14	13	14	14	13
K8	20	22	22	22	22	22	22
K9	20	20	20	20	20	20	20
Total	148	144	143	141	144	144	143

Table 7. Volatility of Table 6 K5(*): Preprocess

K1	0.67	0.33	0.67	0.67	0.67	0.67
K2	0.67	0.67	0.67	0.67	0.67	0.67
K3	0.33	0.33	0.33	0.33	0.33	0.33
K4	1	1.67	1.67	1	1	1
K5	*	*	*	*	*	*
K6	0.67	0.67	0.67	0.67	0.67	0.67
K7	0.67	0.67	1	0.67	0.67	1
K8	0.67	0.67	0.67	0.67	0.67	0.67
K9	0	0	0	0	0	0

observed that productivity could be improved by dividing a process into preprocess and postprocess segments; this division allows us to improve the synchronous state from the asynchronous state, resulting from deviations in worker performance.

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