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SIMULATION-BASED HYBRID CONTROL RESEARCH ON WIP IN A MULTI-TIGHTLY-COUPLED-CELLS PRODUCTION SYSTEM

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ABSTRACT

This paper studies Work-In-Process (WIP) inventory problems in a multi-tightly-coupled-cells production system. Through an analysis of an AS-IS simulation model, ineffective control of tightly coupled cells cause serious system bottlenecks, higher WIP inventory levels and longer cycle times. Aiming to resolve these problems, a hybrid control method and a corresponding centralized hybrid controller are developed. This optimized method is used to monitor the changes in WIP and improve WIP control by integrating the Pull and Push modes. In a TO-BE simulation model, the centralized hybrid controller is embedded to execute this optimized control idea. The model is explored with a control objective to maintain the WIP inventory and cycle times at low levels by dynamically regulating the processing rate of distributed workstations. The simulation results demonstrate that this optimized method avoids system instability and eliminates bottlenecks. By comparison, the proposed approach significantly improves the system's performance, rapid response and robustness.

1 INTRODUCTION

In a tightly coupled cell, the part-arrival process is restricted by the limited space for part buffering between sequential workstations. The pre-workstation is easily blocked until this limited buffer space becomes available (Kelton et al. 2003). For the modern manufacturing industry, many enterprises that are qualified as having high automation levels and are equipped with robot agent sets have applied this advanced production mode with multiple tightly coupled cells. This mode can accurately operate parts, use SMED (Single Minute Exchange of Die) technology to improve flexibility and reduce manufacturing costs (Monden 2011). These improvements satisfy the diverse demands of consumers and rapid responses to market needs. However, ineffective control of multiple tightly coupled cells easily lead to high WIP levels and "block"/"starvation" frequency, which is caused by many random events (Tao et al. 2008). Moreover, unreasonable WIP management extends production cycle times, decreases market responsiveness and causes system instability (Tsourveloudis et al. 2000). Therefore, a reasonable WIP control method in a multi-tightly-coupled-cells production system, which is associated with a lower WIP inventory level and better production performance, is an important and urgent issue in modern production research.

Many studies have recently investigated WIP control policy problems. Optimization methods for WIP control are focused on by improving production scheduling or adjusting the production capacity. Yang et al. (2007) presented a simulation optimization approach to resolve a constant WIP strategy problem. Bai and Gershwin (1994) introduced a WIP control algorithm to schedule multiple part-type production lines. Tamani et al. presented artificial intelligence-based methods for WIP control of realistic continuous manufacturing systems (Tamani et al. 2009; Tsourveloudis et al. 2010). Additionally, internal WIP control for

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a CONWIP production system received a great deal of attention. Cao and Chen (2005) developed a non-linear mixed integer programming model for a CONWIP-based production system to obtain an optimal production plan. Jose et al. (2006) proposed a new method for optimizing the card number of a CONWIP system to control the WIP level by comparing it with the Kanban system. These studies resulted many successful applications and provided beneficial suggestions for WIP control. However, few studies have focused on developing simulation models to analyze WIP level changes and identifying system bottlenecks caused by unreasonable control of multiple tightly coupled cells to design a WIP control method.

This study expands on a previous study (Zhao and Takakuwa 2012) on WIP control for a discrete production system with one tightly coupled cell. Although the production system still applies the heuristic control policy, its characteristics are changed, and the corresponding optimized method is improved. The control objective involves keeping the WIP inventory at low levels for the entire system while eliminating bottlenecks caused by ineffective control of tightly coupled cells by dynamically the regulating processing rate of distributed workstations. The next section describes the improved method for WIP control, which is a hybrid mode and has a rapid response for system stability. The third section presents a case study about a real production system, and a corresponding original simulation model is constructed to analyze current production problems. In the fourth section, a simulation model applying the optimized control method is developed to improve the entire system performance. Finally, simulation results are presented along with comparisons and remarks to validate the effectiveness of the proposed approach.

2 APPROACH

2.1 Approach Review

The case study in the present work is considered to be a surplus-based system, and a control policy is made based on whether the real-time WIP level is higher or lower than a hedging point (safety stock). Additionally, the entire production system is divided into multistage production cells for control. The system's merits are to monitor the change in WIP level for the entire system and to master dynamic parts processing in a cell. This system is viewed as a network of cells, workstations and buffers that is restricted by various random factors. Accurately controlling these factors to achieve predetermined objectives is complicated, and NP-hard problems are frequently encountered. A heuristic control policy has been considered gradually to achieve a satisfactory strategy (Gershwin 2000). Consequently, this study develops a heuristic hybrid control method. Applying this approach can avoid disturbances from bottlenecks caused by ineffective control while achieving lower WIP levels and better production performance.

The heuristic fuzzy method for controlling WIP was used in production systems by Tamani et al. (Tamani et al. 2009; Tamani et al. 2011). Their research achievements and applications provide useful suggestions. To allow an easier analysis, their study cases are simulated by viewing the production system as a continuous system while only considering two random factors: machine failure/repair probability and demand change. However, most real production systems are classic discrete systems in which various stochastic factors cause WIP random changes and lower system performance. Bottlenecks in a system with a high "block"/"starvation" frequency can also disturb system stability. Additionally, the fuzzy method that they applied is not qualified as a rapid response ability to obtain a satisfactory WIP control policy. Based on the studies of Tamani et al., this case study is considered to be a discrete system with more uncertain factors. The present study also improves the fuzzy control method that was used in a previous study (Zhao and Takakuwa 2012), which can more effectively enhance a system's performance in a hybrid mode.

2.2 Hybrid Control Method

The present study improves the fuzzy control method that was used in a previous study (Zhao and Takakuwa 2012). The controller used in this method is a hybrid controller (dual-mode) that integrates a switching control mode and a fuzzy control mode with a self-correction factor. The advantages of this controller are that it satisfies multiple conflicting criteria and has a better convergence to obtain a reasonable level of control that rapidly maintains the system stability. The inputs for this hybrid controller are the relative and absolute error values in the WIP levels for each distributed workstation. According to a surplus-based system, the relative error value is the difference between the actual WIP value and the safety stock. The absolute error value refers to the difference between successive WIP values. These two inputs are seriously affected by dynamic and stochastic factors, which can cause discrete WIP level and system performance changes. Figure 1 shows the logic structure of this hybrid controller. The functions and rules bases are as follows:

(1) Switching control mode: When the relative or absolute error values are higher than a certain threshold value, the switching control mode is triggered to take an urgent control policy to rapidly reduce the WIP inventory to a relatively low level.

(2) Fuzzy control mode: When both error values are lower than the threshold value, the fuzzy control mode is triggered. If the errors are relatively higher, the mode will quickly respond to eliminate the errors; if the errors are moderate, then the mode will avoid over-control and maintain system stability; if the errors are relatively lower, then the mode will eliminate errors, avoid over-control and maintain a steady state. These policies are taken based on fuzzy rules by applying a corresponding self-correction factor.

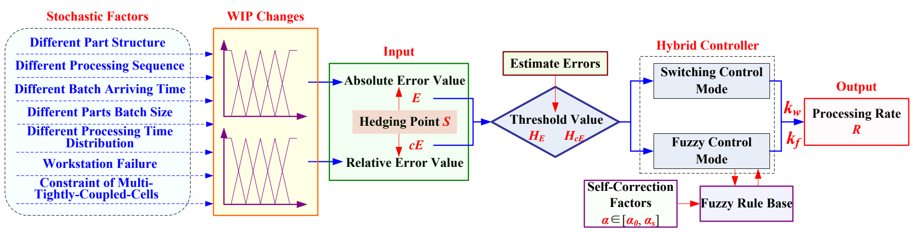


Figure 1: The logic structure of a hybrid controller.

For this hybrid controller, a control policy is described using linguistic IF-THEN rules. Unlike the general fuzzy controller, it is a dual IF-THEN rule for dual-mode with the following form:

Rule 1 *IF* [Switching Control Mode]

$\boldsymbol{E} \geq \boldsymbol{H_E}$ *OR* $\boldsymbol{cE} \geq \boldsymbol{H_{cE}}$, *THEN* $\boldsymbol{R}$ *is* $\boldsymbol{Z_W}$

ELSEIF [Fuzzy Control Mode]

IF $\boldsymbol{E}$ *is* $\boldsymbol{X}$ *AND* $\boldsymbol{cE}$ *is* $\boldsymbol{Y}$, *THEN* $\boldsymbol{R}$ *is* $\boldsymbol{Z_F}$

Here, $\boldsymbol{E}$ and $\boldsymbol{cE}$ are the inputs' relative and absolute WIP error values, respectively. $\boldsymbol{H_E}$ and $\boldsymbol{H_{cE}}$ are the threshold values for two errors. $\boldsymbol{R}$ is the output or processing rate. For the switching control mode, the output policy is determined as $\boldsymbol{Z_W}$ = (Over Large). For the fuzzy control mode, the inputs and output are divided into five corresponding linguistic variations sets: $\boldsymbol{X}=\boldsymbol{Y}=\boldsymbol{Z_F}$={***PL*** (Positive Large), ***PS*** (Positive Small), ***O*** (Zero), ***NL*** (Negative Large), ***NS*** (Negative Small)}.

In the fuzzy control mode, the self-correction factor, $\boldsymbol{\alpha} \in [\boldsymbol{\alpha_0}, \boldsymbol{\alpha_s}]$, is a real number between 0 and 1, with $\boldsymbol{\alpha_0} < \boldsymbol{\alpha_s}$. The analytical expression for the fuzzy controller is corrected as follows:

Rule 2

$$\boldsymbol{R} = -\left[\, \boldsymbol{\alpha} \times \boldsymbol{E} + (1-\boldsymbol{\alpha}) \times \boldsymbol{EC} \,\right]$$

$$\boldsymbol{\alpha} = \frac{1}{\mathrm{N}} \times (\boldsymbol{\alpha_s} - \boldsymbol{\alpha_0}) \times |\, \boldsymbol{E} \,| + \boldsymbol{\alpha_0}$$

Here, $\boldsymbol{\alpha}$ is self-corrected by changing the absolute value of $\boldsymbol{E}$. It presents that the control policy has different requirements for $\boldsymbol{\alpha}$ in different states. The outputs of the activated rules are aggregated to form the value of the overall control output with $\boldsymbol{\alpha}$, which are then defuzzified into a crisp number, $\boldsymbol{Z_F}$.

The processing time for each distributed workstation $\boldsymbol{i}$ is regulated by $(1\text{-}\boldsymbol{r_i} \times \boldsymbol{k})$ of the original processing time, which is the hybrid controller output and can be calculated by a VBA module in the simulation model, as illustrated in Section 4, where, $\boldsymbol{k}=\{\boldsymbol{k_f}, \boldsymbol{k_w}\}$ is a quantizer, and $(\boldsymbol{r_i} \times \boldsymbol{k})$ denotes the regulation value for the processing time.

3 CASE STUDY

3.1 Case Description

The present study considers a case of a multi-variety and small-batch discrete production system with multiple tightly coupled cells. This system is located in a variator component manufacturing workshop of a Japanese company. It applies robot agent sets in a tightly coupled cell, and has a high level of automation. Figure 2 shows a simplified structure for this system. It mainly comprises 6 tightly coupled cells and 3 main production lines sharing some same machines or production cells. Each part order that enters the system includes three types in random proportions. In each tightly coupled cell, two robot agents are used to accurately operate parts between two fine workstations, and the buffer space is limited to 12. For other uncoupled cells, the WIP buffers with unlimited space are used to balance workstation capabilities, improve system stability, and meet the processing demands for diversified part types. Additionally, there are two loosely coupled cells with machines that act like conveyors and can perform continuous processing.

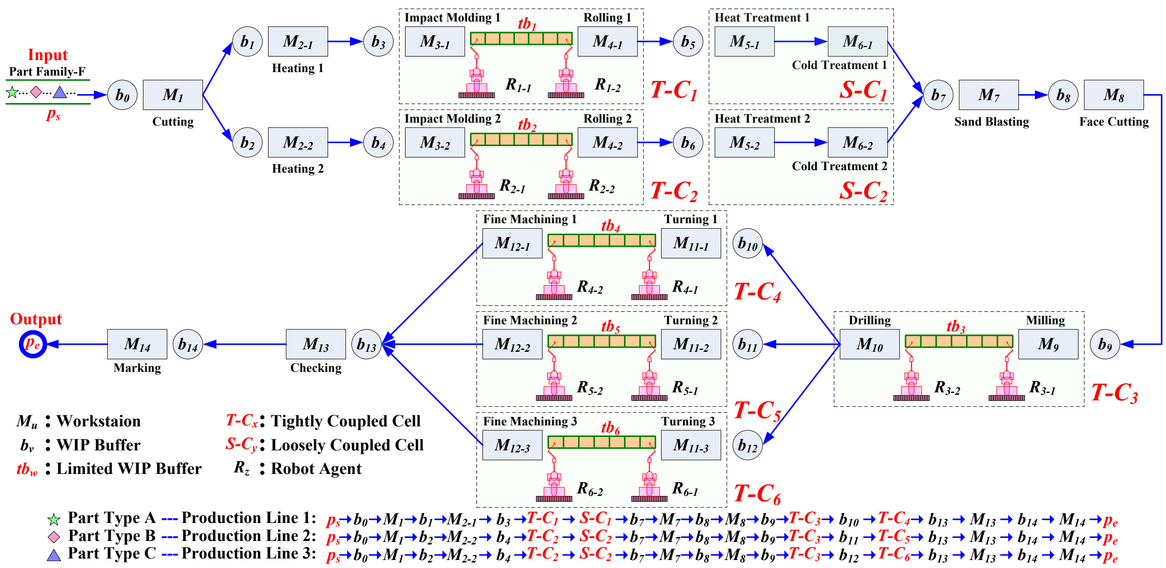


Figure 2: A simplified structure model for a multi-tightly-coupled-cells production system.

3.2 Original Simulation Model (AS-IS Model)

3.2.1 Simulation Model Construction

This study mainly analyzes changes in the WIP level to obtain an optimized control policy for reducing the WIP inventory level of the entire system. Based on the characteristics and structure of the real system, an original simulation model is constructed, called AS-IS model. By running the simulation, the capacity of the limited buffer in tightly coupled cells can be easily adjusted, and the bottlenecks can be identified clearly. Furthermore, the production performance of the entire system can be monitored. The AS-IS model can be used to analyze current problems for this production system. The present study uses the Arena simulation platform to build this AS-IS model comprising four sub-models, shown in Figure 3. The Order Arriving sub-model is designed to simulate part order arriving. The Orders Operation sub-model is used to randomly create part quantities in an order, and determine the production line. The Parts Processing sub-model is constructed to process parts on the corresponding production line. The Data Statistics sub-model creates WIP level change statistics and other performance statistics. The Parts Completion sub-model is designed to ensure that all parts in an order are completed.

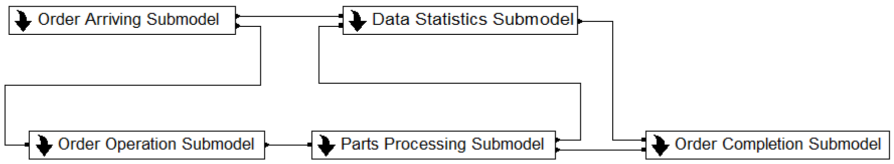


Figure 3: Original simulation model (AS-IS model).

Statistical analysis data from the latest two months of real production are used as input parameters. To run the simulation, a steady-state simulation is appropriate. The warm-up period is selected as 5000 minutes, 20 replications are performed, and a common random number method is applied. To ensure simulation randomness similar to the real system with the stochastic factors described in Figure 1, the random distribution data and main parameters are set in the AS-IS model, shown in Table 1.

Table 1: Main simulation data and parameters.

Tightly Coupled Cell		Parts Processing Time *Unit/min* Production Line 1	Production Line 2	Production Line 3	Workstaion Failure Up Time	Down Time
$T\text{-}C_1$	Impact Molding 1 ($M_{3\text{-}1}$)	TRIA(9.1,11.7,15.1)			EXPO(1000)	EXPO(30)
	Rolling 1 ($M_{4\text{-}1}$)	TRIA(9.7,12.5,15.9)			EXPO(1200)	EXPO(25)
$T\text{-}C_2$	Impact Molding 2 ($M_{3\text{-}2}$)		TRIA(3.0,4.2,5.4)	TRIA(3.2,4.3,5.2)	EXPO(1000)	EXPO(30)
	Rolling 2 ($M_{4\text{-}2}$)		TRIA(3.2,4.5,5.7)	TRIA(3.1,4.4,5.8)	EXPO(1200)	EXPO(25)
$T\text{-}C_3$	Milling (M_9)	TRIA(2.7,3.2,4.1)	TRIA(2.8,3.1,4.2)	TRIA(2.6,3.0,4.3)	EXPO(1000)	EXPO(30)
	Drilling (M_{10})	TRIA(2.9,3.4,4.2)	TRIA(3.0,3.4,4.1)	TRIA(3.1,3.2,4.5)	EXPO(1200)	EXPO(25)
$T\text{-}C_4$	Turning 1 ($M_{11\text{-}1}$)	TRIA(14.3,14.7,15.2)			EXPO(1000)	EXPO(30)
	Fine Machining 1 ($M_{12\text{-}1}$)	TRIA(14.6,15.1,15.5)			EXPO(1200)	EXPO(25)
$T\text{-}C_5$	Turning 2 ($M_{11\text{-}2}$)		TRIA(9.9,10.5,11.2)		EXPO(1000)	EXPO(30)
	Fine Machining 2 ($M_{12\text{-}2}$)		TRIA(10.1,10.7,11.3)		EXPO(1200)	EXPO(25)
$T\text{-}C_6$	Turning 2 ($M_{11\text{-}2}$)			TRIA(9.3,10.0,10.7)	EXPO(1000)	EXPO(30)
	Fine Machining 3 ($M_{12\text{-}3}$)			TRIA(9.5,10.3,10.8)	EXPO(1200)	EXPO(25)

Loosely Coupled Cell		Run Speed *Unit m/min*	Unit Size *Unit m*	Length *Unit m*
$S\text{-}C_1$	Heat Treatment 1 ($M_{5\text{-}1}$)	0.72	0.9	7.2
	Cold Treatment 1 ($M_{6\text{-}1}$)	0.64	0.9	5.4
$S\text{-}C_2$	Heat Treatment 2 ($M_{5\text{-}2}$)	0.96	0.9	7.2
	Cold Treatment 2 ($M_{6\text{-}2}$)	0.72	0.9	5.4

Other Uncoupled Workstaion Failure		*Unit/min* Up Time	Down Time
Cutting	(M_1)	EXPO(2000)	EXPO(10)
Others	($M_{2\text{-}1}$,$M_{2\text{-}2}$) (M_7,M_8) (M_{13},M_{14})	EXPO(750)	EXPO(20)

Parts Order Data	
Parts Type Proportion	DISC(0.28,1,0.63,2,1,3)
Parts Order Arriving Time *Unit/min*	TRIA(320,450,480)
Each Order Parts Quantity *Unit/Quantiy*	AINT(TRIA(126,142,160))

3.2.2 Simulation Validation

After the simulation model has been generated, validation of the model is necessary. The correlative validation data were compared to the existing data statistics from the real system, shown in Table 2. As shown in Table 2, each data point from the AS-IS model is close to that of the real system. All of the difference ratios are below 10%. Moreover, in the AS-IS model, when the part quantity of each order is respectively increased, the "block" frequency of the tightly coupled cells is also increased and the "starvation" frequency is decreased. These results are consistent with those of the real system. Additionally, when extreme cases are tested by setting the same constant processing time for any parts on a workstation and eliminating machine failure, the average WIP level for a workstation processing only one type part was close to 1. Consequently, all of these tests are validated, confirming that the AS-IS simulation model behaves in the same manner as the real system.

Table 2: Validation data comparing the AS-IS model with the real system.

	(*Unit/Quantity*)	AS-IS Model (Simulation System)		Existing Data Statistics (Real System)		Difference Ratio %	
		Avg	*SD*	*Avg*	*SD*	*Avg*	*SD*
WIP	Production Line 1	733	401	785	434	6.62 %	7.60 %
	Production Line 2	659	344	710	372	7.18 %	7.53 %
	Production Line 3	804	409	876	446	8.22 %	8.30 %
	(*Unit/%*)	*BF*	*SF*	*BF*	*SF*	*BF*	*SF*
Tightly Coupled Cells	$T\text{-}C_1$	5.41 %	1.78 %	5.67 %	1.91 %	4.59 %	6.81 %
	$T\text{-}C_2$	5.93 %	2.54 %	6.11 %	2.72 %	2.95 %	6.62 %
	$T\text{-}C_3$	5.05 %	3.30 %	5.36 %	3.59 %	5.78 %	8.08 %
	$T\text{-}C_4$	4.47 %	2.98 %	4.81 %	3.22 %	7.07 %	7.45 %
	$T\text{-}C_5$	5.02 %	2.62 %	5.35 %	2.79 %	6.17 %	6.09 %
	$T\text{-}C_6$	4.34 %	2.27 %	4.70 %	2.43 %	7.66 %	6.58 %

Notes * *Avg*: Average Value *SD*: Standard Deviations *BF*: "Block" Frequency *SF* : "Starvation" Frequency

3.2.3 Simulation Results from the AS-IS Model

After the simulation, the results of the AS-IS model are shown in Table 3. The average WIP level for each workstation is over 100, and the standard deviation is large. The values of the tightly coupled cells are almost as large as those of uncoupled cells. Additionally, the probability distribution of WIP in Cutting, which is the first workstation in the system, shows that most orders can completely enter production before the next order arrives. However, only 20.57% of orders presented from the normal distribution of cycle time are completed within the delivery time of 3 days.

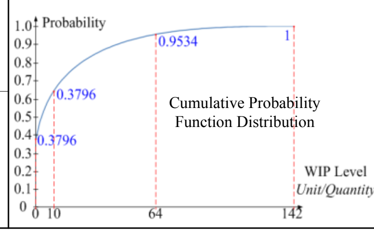
Table 3: Simulation results of the AS-IS model.

WIP Level (*Unit/Quantity*)			*Avg* (Average Value)	*SD* (Standard Deviations)
Tightly Coupled Cells	*T-C₁*	b_3	225	143
	$T\text{-}C_2$	b_4	317	179
	$T\text{-}C_3$	b_9	243	152
	$T\text{-}C_4$	b_{10}	198	131
	$T\text{-}C_5$	b_{11}	177	124
	$T\text{-}C_6$	b_{12}	272	156
Uncoupled Cells	Heating 1	b_1	154	71.5
	Heating 2	b_2	153	78.9
	Sand Blasting	b_7	142	70.5
	Face Cutting	b_8	100	46.6
	Checking	b_{13}	121	84.4
	Marking	b_{14}	19.7	13.1

Cutting b_0 WIP Level

Probability Density Distribution Function：

Beta Distribution: -0.001 + 144 * BETA(0.315, 2.71)

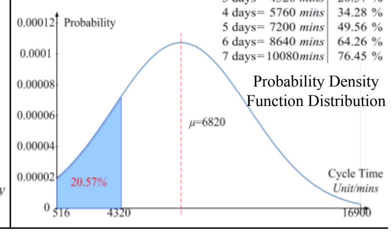


Cycle Time

Normal Distribution：

$X\sim N(\mu = 6820, \sigma^2 = 2720)$

Cycle Time	Probability
1 day = 1440 *mins*	2.90 %
2 days= 2880 *mins*	9.97 %
3 days= 4320 *mins*	20.57 %
4 days= 5760 *mins*	34.28 %
5 days= 7200 *mins*	49.56 %
6 days= 8640 *mins*	64.26 %
7 days=10080*mins*	76.45 %



Additionally, the sensitivity analysis results, obtained by adjusting the limited buffer spaces of tightly coupled cells, shown in Figure 4. Increasing the limited spaces of the WIP buffer improves the production ability of tightly coupled cells. The WIP levels of b_7 and b_{13}, located downstream of tightly coupled cells, are increased gradually. However, the WIP levels of b_3, b_4 and b_9, located upstream of tightly coupled cells, are decreased. Moreover, the inventory level changes of b_{10}, b_{11} or b_{12}, located between two sequential tightly coupled cells, are almost smooth because the improved productivity of these two cells is offset.

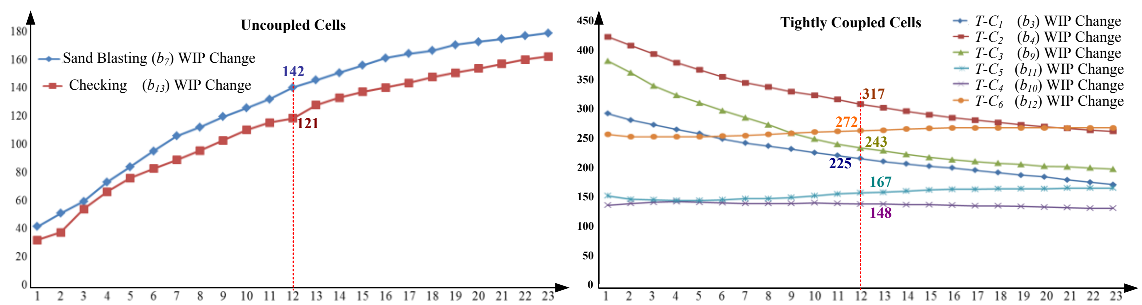


Figure 4: WIP level changes by adjusting the limited buffer spaces of tightly coupled cells.

Consequently, the simulation results analysis suggests that ineffective control of tightly coupled cells cause higher WIP levels and longer cycle times. Thus, tightly coupled cells are system bottlenecks and seriously restrict production capacity.

4 OPTIMIZED CONTROL

4.1 Description of the Optimized Control Method

In this study, to resolve the problems caused by unreasonable control of tightly coupled cells, a hybrid control method integrating the Pull and Push mode is applied. First, the entire system is divided into multistage production cells. Each tightly coupled cell is a CONWIP control cell in which the Push mode is used to drive the parts process. In this cell, various operations and "block"/"starvation" situations can be monitored easily. Second, for the entire system, among multistage CONWIP cells, the Pull mode is used because of the merits of applying the JIT idea. By constantly checking the upstream buffers of production cells, the changes in WIP level are mastered, and bottlenecks are identified. Following system global regulation, a corresponding reasonable control policy is taken. The logic for this optimized control method is shown in Figure 5.

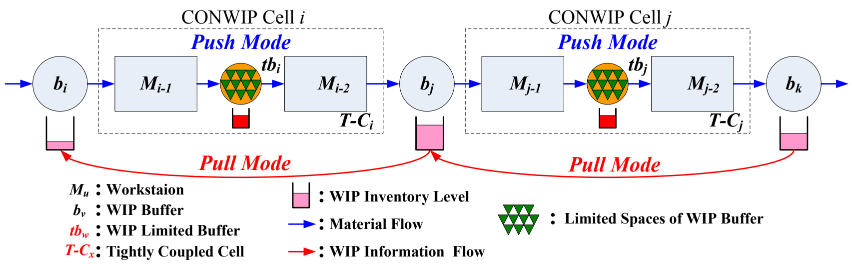


Figure 5: A hybrid control method for the multi-tightly-coupled-cells production system.

4.2 The Centralized Hybrid Controller

To execute the optimized control idea, a corresponding controller is developed that integrates a switching control mode and a fuzzy control mode with a self-correction factor. This controller is used to monitor the WIP level and make a reasonable control policy to reduce the WIP level and eliminate system bottlenecks. In this study, the hybrid controller is designed to be centralized, as shown in Figure 6. It has the advantage that WIP changes in distributed cells are monitored, so a global optimized policy can be made easily. For distributed workstations, the relative and absolute WIP error values ($\boldsymbol{e}$ and $\boldsymbol{ce}$) are inputs into the centralized hybrid controller. After checking based on the threshold value ($\boldsymbol{H_{ce}}$ and $\boldsymbol{H_e}$), the corresponding control mode is selected. For the Fuzzy control mode, based on **Rules 1 and 2,** fuzzy calculation steps are processed in the same manner as in a previous study (Zhao and Takakuwa 2012). Regardless of the control mode selected, the global performance of the system is considered and the output $\boldsymbol{r}$ is adjusted. Then, an optimized control policy is used to regulate the processing time for each distributed workstation.

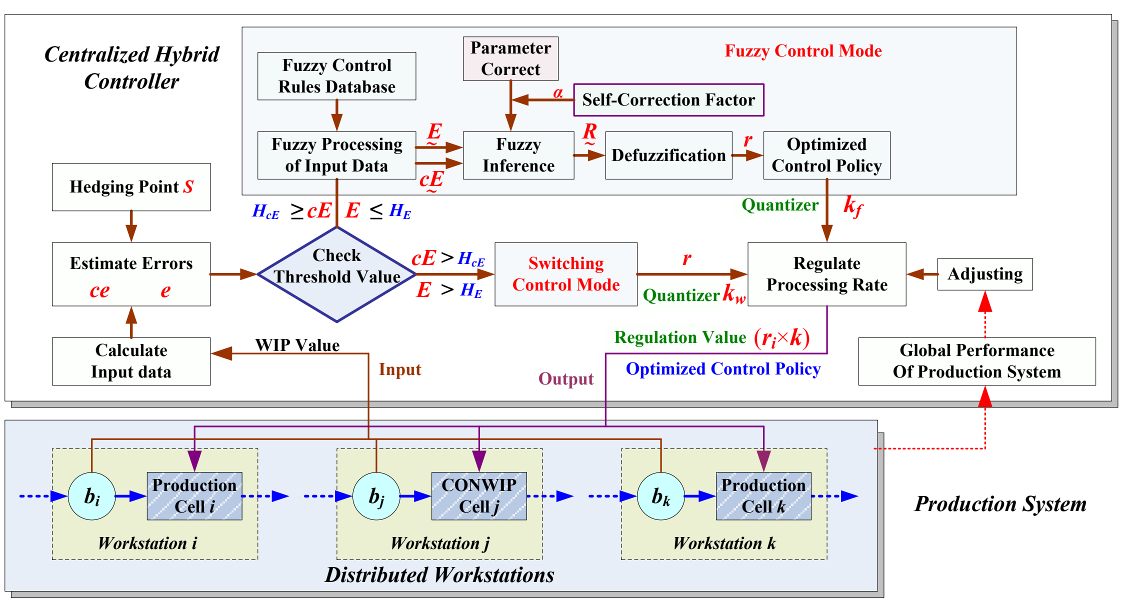


Figure 6: The centralized hybrid controller for distributed workstations.

4.3 Simulation for Optimized Control Method

4.3.1 Constructing the TO-BE Model

A centralized control sub-model, executing the optimized control method and hybrid controller, is added into the AS-IS model, which is now called the TO-BE model. In this sub-model, a VBA module operates all calculation and control steps at each checking time interval. As analyzed, because of ineffective control, tightly coupled cells are considered as system bottlenecks. Controlling the WIP level of these cells is the primary objective for optimization. After the VBA module calculation, the hybrid controller makes an optimized control policy to regulate the processing time for each distributed workstation. The corresponding control instruction needs to be adjusted by considering the global performance of the production system and then sent to the Parts Processing sub-model for execution. Figure 7 shows the main control parameters and corresponding simulation logic for the centralized control sub-model.

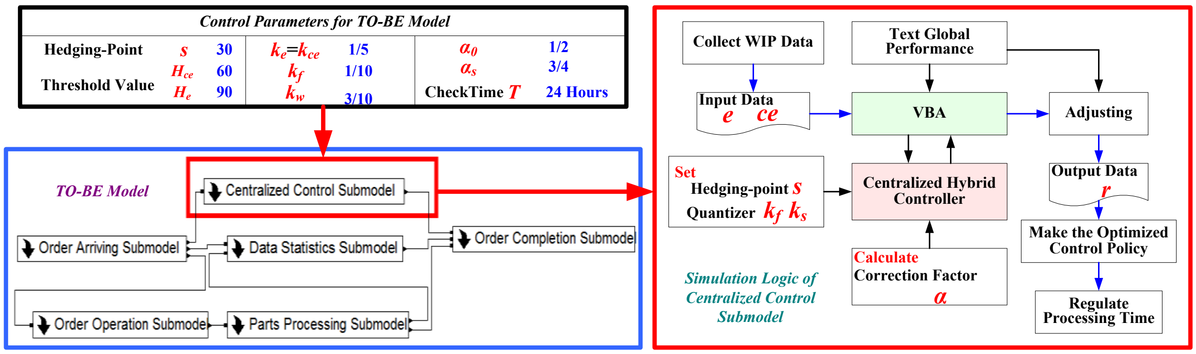


Figure 7: Simulation for optimized control method (TO-BE model).

4.3.2 Simulation Results from the TO-BE Model

In the TO-BE model, the average WIP level of the production system is dynamically monitored and calculated. As shown in Table 4, the average WIP level of each production line and each production cell are dramatically reduced. The standard deviations are also decreased, which means that the system stability is effectively enhanced. Furthermore, by a paired-t comparison of the means difference between the AS-IS model and the TO-BE model, there is a statistically significant difference for most of data points except for the Marking station. The average difference and confidence interval are both negative. These results demonstrate that the optimized control approach used in the TO-BE model shows better performance.

Table 4: Simulation results of the WIP inventory level from the TO-BE model.

WIP Level (*Unit/Quantity*)			*Avg* (Average Value)	*SD* (Standard Deviations)	Paired-t Comparison of Means Difference between the AS-IS model and the TO-BE model (95% CL low / Diff / high; Test Value 0)
	Production Line 1		252	36	-572 / -559 / -545
	Production Line 2		211	30	-511 / -501 / -491
	Production Line 3		233	34	-637 / -626 / -614
Tightly Coupled Cells	*T-C*$_1$	b_3	29.8	9.04	-216 / -213 / -210
	T-C$_2$	b_4	30.5	11.3	-296 / -294 / -291
	T-C$_3$	b_9	52.3	19	-202 / -200 / -198
	T-C$_4$	b_{10}	59.1	14.9	-111 / -108 / -106
	T-C$_5$	b_{11}	38.6	15.4	-145 / -143 / -141
	T-C$_6$	b_{12}	42.9	14.9	-245 / -242 / -239
Uncoupled Cells	Heating 1	b_1	30.7	9	-140 / -138 / -137
	Heating 2	b_2	28	10.2	-132 / -131 / -130
	Sand Blasting	b_7	47.5	18.6	-105 / -104 / -103
	Face Cutting	b_8	52.3	19.9	-58.7 / -58.1 / -57.5
	Checking	b_{13}	71	24.8	-70.2 / -69.2 / -68.1
	Marking	b_{14}	24.1	8.6	-1.3 / 2.7 / 4.1

Figure 8 provides the "block" and "starvation" times comparison between the AS-IS model and the TO-BE model. In the TO-BE model, the "block" time of each tightly coupled cell is reduced to less than 1000 minutes, and the "starvation" time is reduced to less than 500 minutes. Compared to the AS-IS model, the ranges of decreased values are both over 65%. These results mean that system bottlenecks are essentially eliminated.

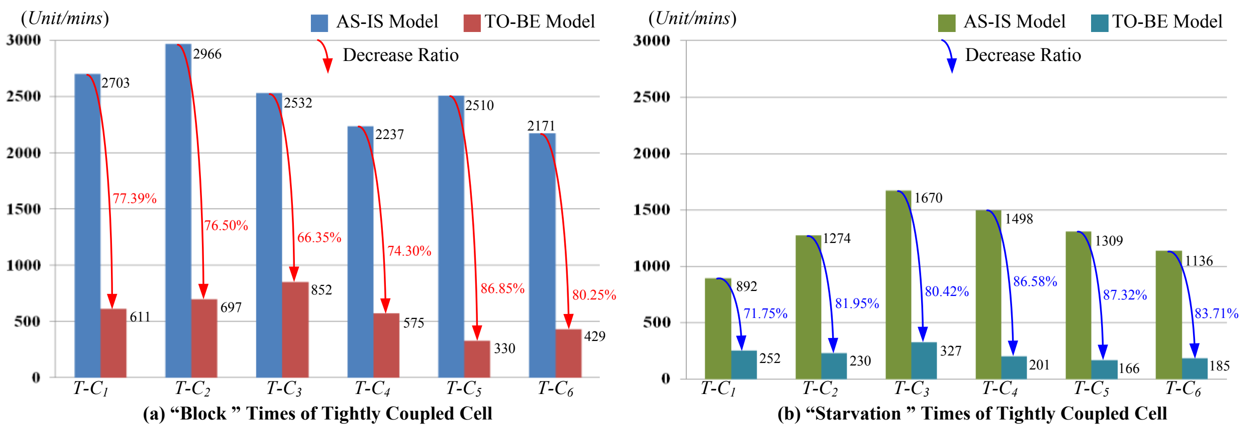


Figure 8: "Block" and "Starvation" times comparison between the AS-IS model and the TO-BE model.

Figure 9 shows the cycle time for the TO-BE model, which obeys a normal distribution (***X~N*** (***μ***=2350, ***σ***^{2}=516)). Approximately 84.73% of the part orders can be completed in less than 2 days, and 100% of the orders are completed in less than 3 days. The delivery date is thus reduced and met.

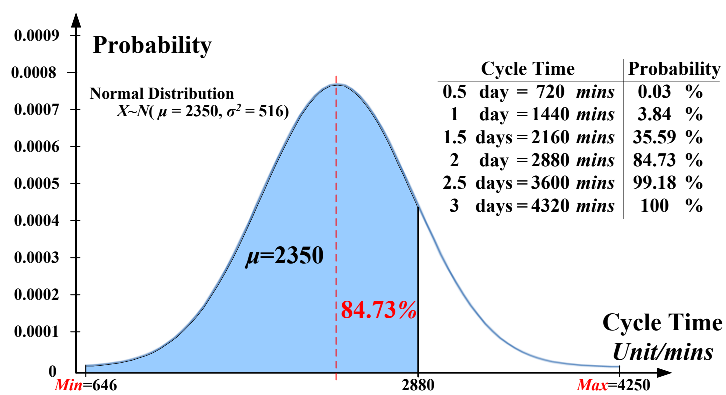


Figure 9: Probability distribution of cycle time for the TO-BE model.

These results show that the TO-BE model has a higher stability, stronger capacity for resisting disturbance, and greater flexibility than the AS-IS model. The optimized control method is also demonstrated to have greater effectiveness in eliminating bottlenecks and improving the production capacity.

4.3.3 Remarks

In a previous study (Zhao and Takakuwa 2012), a fuzzy control method was used and demonstrated to have good performance. However, under the same case and production data as in the present study, the simulation model using the fuzzy method as applied in the previous study (OM model) presented a worse performance than the simulation model using the improved optimized control method applied in the present study (NM model). As shown in Figure 10, the average value and SD of the WIP level in the OM model are both larger than those of the NM model. Moreover, the system response time of the OM model to make a control policy is longer than that of the NM model. Therefore, the optimized control method improved in the present study has an improved efficiency in reducing the WIP level and maintaining the system stability rapidly.

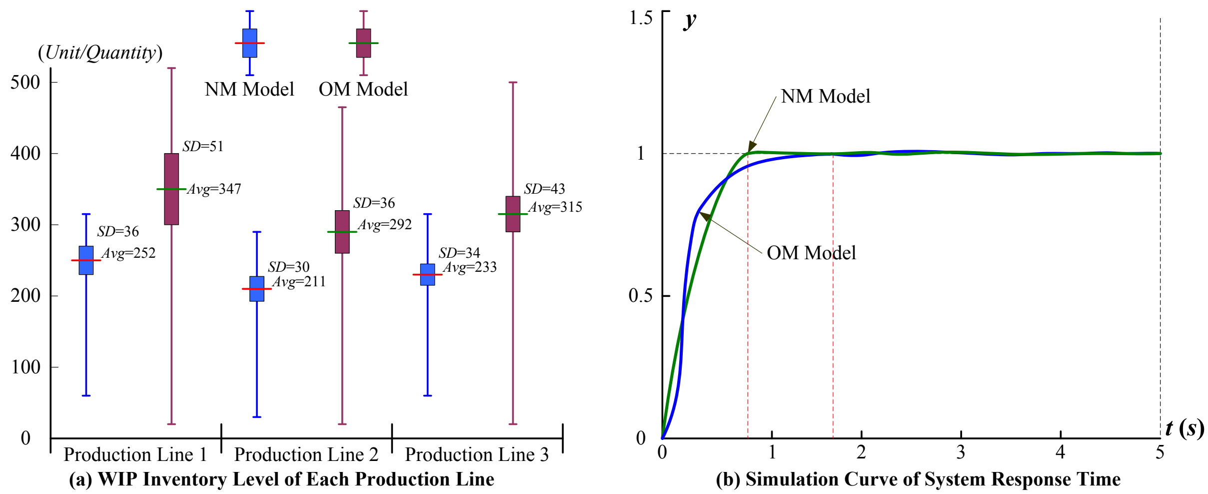


Figure 10: Comparison between the OM model and the NM model.

By running several different simulation scenarios, Figure 11 shows the completion probability of part orders in 1, 2 and 3 days with variations in the Hedging Point ***s*** (safety stock). By increasing ***s*** gradually, the completion probability decreases in different curves. This decreasing trend obeys Little's Law. However, regardless of the change in ***s***, over 95% of part orders meet the delivery time of 3 days. This result indicates that the optimized method (TO-BE model) has greater robustness and stability with an increased randomicity tolerance capability for stochastic factors. The results thus mean that the optimized method used in the present study is strong and performs better than the previous method.

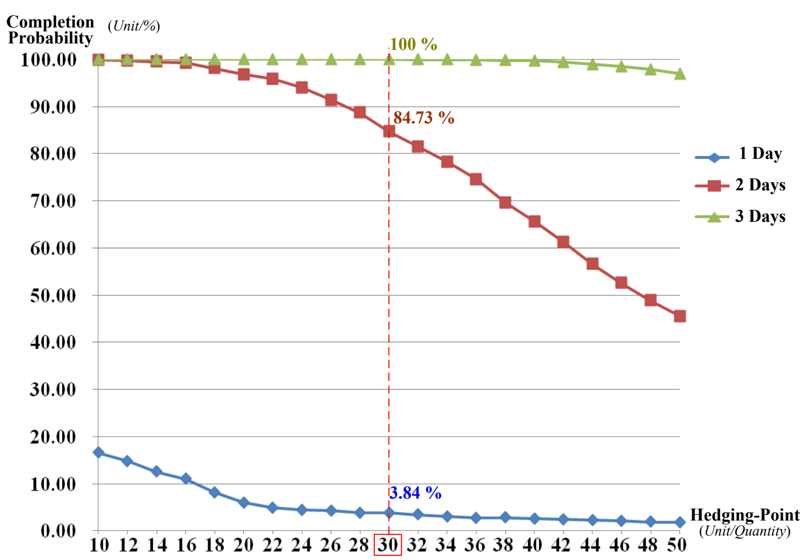


Figure 11: Completion probability of part order with changing Hedging Point s.

5 CONCLUSIONS

The present study, aiming to resolve production problems in a multi-tightly-coupled-cells production system, has developed a hybrid control method and a corresponding centralized hybrid controller. These tools are used to eliminate system bottlenecks and maintain the WIP level and cycle times at low levels by checking the inventory levels of WIP buffers and dynamically adjusting the processing rate of distributed workstations. To effectively resolve current problems caused by unreasonable control of tightly coupled cells in this case, by analyzing the system characteristics, the proposed optimized approach is designed as a hybrid control method with a mixed Pull and Push mode, which divides the system into multistage CONWIP cells and other production cells. It applies the JIT operation ideology and easily monitors the dynamic parts process in a production cell. To execute this optimized control idea, the corresponding centralized hybrid controller is developed, which consists of two parts: a switching control mode and a fuzzy control mode with a self-correction factor. According to the surplus-based system, this hybrid controller makes the dynamic real-time WIP level changes close to the hedging point and maintains the system stability. The merit is that this system utilizes the superiority of fuzzy control, satisfies multiple conflicting criteria, and has a rapid response ability to obtain a reasonable control policy. In the TO-BE simulation model, a VBA module operates all calculation processes for the optimized method. Compared with the AS-IS model, the simulation results presents that the TO-BE model provides a remarkable control ability to reduce WIP and cycle times. As illustrated in the previous sections, the present study improved the method used in a previous study (Zhao and Takakuwa 2012). By comparing the NM and OM models, noticeable performance improvements, rapid response and robustness are achieved with the optimized control method proposed in the present study. This approach thus more successfully improves production capacity, reduces WIP inventory and shortens cycle times for a modern production system.

Future studies will consider a corresponding relationship between the WIP inventory level and delivery date in a multi-tightly-coupled-cells production system. More stochastic factors will be adjusted and system flexibility with satisfying multiple-part-types will also be studied.

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