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A HYBRID SIMULATION APPROACH TO DYNAMIC MULTI-SKILLED WORKFORCE PLANNING OF PRODUCTION LINE

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ABSTRACT

Workers cross-trained with multiple tasks can improve the workforce flexibility for the plant to handle variations in workload. Therefore, it is necessary to study the dynamic multi-skilled workforce planning problem of production line with the application of cross-training method. The conclusion is helpful to economize the cost of human resources when workload is low and enhance the productivity in the opposite case. This paper studies the dynamic multi-skilled workforce planning problem by exploring the effect of worker pool size and cross-training level on the performance of production line through simulation. A hybrid simulation model is built as the platform to study this problem with Discrete-event Simulation (DES) method and Agent-based Simulation (ABS) method. Besides, the effect of worker learning and forgetting is inevitably considered accompanied with the introduction of cross-training method and its impact on production line will be illustrated.

1 INTRODUCTION

This paper studies the dynamic multi-skilled workforce planning problem of production line based on a car engine parts plant located in Beijing and attempts to provide an improvement plan to make the best use of its facilities and workers. Considering the costly expense of introducing new equipments, it is more practical and cost-efficient to explore new possibilities within the flexibility of workforce to promote productivity. Therefore, the concept of dynamic multi-skilled workforce planning is brought in to handle this problem. This concept contains two meanings: the dynamic worker pool size control and the dynamic scheduling of multi-skilled workers under a fixed worker pool size. The purpose of the first layer meaning is to deal with variations in order quantity and delivery cycle of the plant by matching the realistic situation with the minimum worker pool size to decrease the cost of human resources under the precondition of fulfilling the order on time. The objective of the second layer meaning is to increase robustness so as to maintain the continuous running of the production line when some workers are absent. It can also maximum the productivity under a fixed worker pool size.

In this paper, a hybrid simulation model with ABS and DES is built to study the dynamic multi-skilled workforce planning problem of production line. The two main structures in the overall production line system are physical infrastructure and worker pool. Each simulation method has its unique division of work in the hybrid model. Considering that production line is a typical discrete-event system, it is accurate to use DES to describe the physical infrastructure of production line. As for worker pool model, the application of cross-training method provides workers with higher level of flexibility and autonomy. Workers are free to select working places based on their own ideas and priorities within the alternatives cross-training method offers. Therefore, the ABS method matches the demand of describing such a group of cross-trained

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workers better compared with other simulation methods. In the hybrid simulation model, the two submodels separately built with DES and ABS are interactional and they cannot work alone. For instance, workers need information acquired from the DES model to update their learning progresses while the processing speed of each station in the DES model depends on the real-time workforce distribution within the ABS model.

1.1 Literature Review

The purpose of cross-training is to strengthen the exchange among workers by introducing new operation skills of their teammates (Marks et al. 2002) and to improve the coordination of team members (Volpe et al. 1996). However, the concept of cross-training feels like a top-level design and needs to be realized via some strategies and restraints. There is adequate research about cross-training strategies and their applications to manufacturing systems. Blickensderfer employed cross-training policy to a team so that the team members could predict the needs of every team member and coordinate their actions. Blickensderfer conducted two tests based on cross-training and discussed the experience acquired from those tests (Blickensderfer, Cannon-Bowers, and Salas 1998). Cannon-Bowers examined 40 three-person teams which were processing a simulated radar task. The results proved that positional rotation was a valid cross-training method for highly interdependent tasks and workers obtained high level inter-positional knowledge because of the introduction of cross-training (Cannon-Bowers et al. 1998).

Inman raised a cross-training strategy called chaining policy. The specific meaning of chaining policy was that workers were trained to perform a second task and the appointment of tasks was joint up in a complete chain. Inman also performed a probability analysis to prove that chaining would increase the robustness of production and it was especially helpful for absenteeism in the production line (Inman, Jordan, and Blumenfeld 2004). Jordan implemented cross-training method to an automotive assembly plant and drew the conclusion that the application of cross-training truly promoted the productivity by reducing the MTTR (Mean Time To Repair) (Jordan, Inman, and Blumenfeld 2004). Hopp raised a new cross-training policy called cherry picking strategy, which made workers learn the operation skill of the bottleneck station. Moreover, Hopp extended the chaining policy Inman proposed to a multi-skill chaining policy and a partial chaining policy, as presented in Figure 1. Hopp summarized several worker coordination policies (static, queue length based and workload based) and performed experiments under different cross-training policies and worker coordination policies (Hopp, Tekin, and Van Oyen 2004).

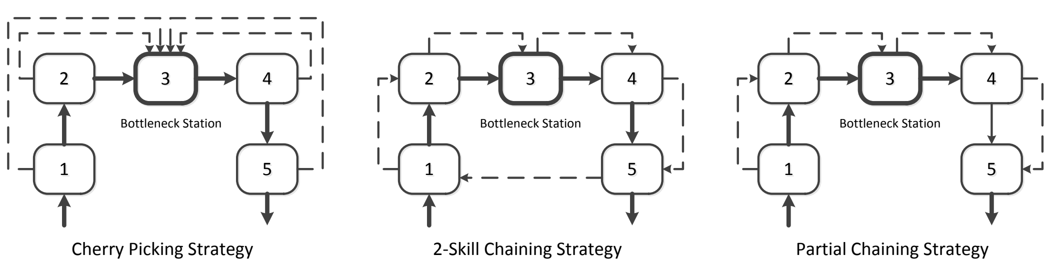

Figure 1: Three different cross-training policies.

The introduction of cross-training method extends the scope of stations where workers are able to work at and improves the productivity. However, it is also necessary and inevitable to pay attention to the side effect that the frequent switching between different stations might lead to insufficient training at some stations (Mccreery and Krajewski 1999). As the result of insufficient training, operations of workers at certain stations might not remain highly efficient. The research about learning effect and forgetting effect is abundant. Yelle performed a survey and review of the learning curve and illustrated the wide application of learning curve (Yelle 1979). Bailey performed a laboratory experiment to test how forgetting effect would be influenced by some selected variables. Bailey drew the conclusion that forgetting effect was not ignorable for repetitive tasks and forgetting was related to learning level rather than learning rate (Bailey 1989). Nembhard combined the learning effect and forgetting effect together and raised a learning and forgetting model based on the data collected by bar code readers and automated acquisition devices from the field study of an automotive electronics component plant (Nembhard and Uzumeri 2000). Shafer explored how the learning and forgetting effect and the heterogeneity of worker pool affected the productivity of production line (Shafer, Nembhard, and Uzumeri 2001).

As for the modeling and simulation of production line, DES is widely used in the manufacturing process design and operation. DES is quite beneficial for modeling a manufacturing system which needs to be qualified for throughput requirement. DES has been applied into the modeling and simulation of automotive manufacturing systems (Kendall, Mangin, and Ortiz 1998). Agent-based simulation is another powerful approach because it can realize important properties such as autonomy, responsiveness, redundancy, distributivity and openness (Monostori, Váncza, and Kumara 2006). Bussmann applied Agent-based Simulation method to a flexible production line. Elements including machines, conveyors, buffers, switches and work pieces were all built as agents (Bussmann and Schild 2001). In addition, System Dynamics is also used to describe the production line, it concentrates more on the dynamic character and influence of certain variables to the whole system (Feng and Fan 2014).

Rather than the normal assembly line balancing problem, this paper focuses on the research of simulation based workforce planning problem. DES is the most commonly used simulation method to study workforce planning problem (Jahangirian et al. 2010). Gert studied the personnel planning and reassigning problem to exploit the flexibility of human resources in manufacturing system through simulation (Zülch et al. 2004). Mjema did research about personnel capacity utilization in a maintenance department and tried to obtain the best utilization of personnel as well as the best throughput time of maintenance work orders (Mjema 2002).

1.2 Contributions

The work in this paper is original in the following ways. Firstly, a novel hybrid simulation model is built with DES and ABS to study the dynamic multi-skilled workforce planning problem of production line. Then, the learning and forgetting model is put forward to accommodate the cross-training environment. At last, several simulation experiments are conducted to study the influences of worker pool size, cross-training level and learning and forgetting level to the performance of production line.

2 SYSTEM MODEL

2.1 Production Line Model

The production line studied in this paper is made up of 21 stations and those 21 stations belong to 18 procedures. Stations within one procedure share the same operation skill and the operation skills of different procedures are not the same. For simplicity's sake, function $j = \delta(s)$ is proposed to present the relation between stations and their corresponding procedures. In function $j = \delta(s)$, j is the procedure corresponding to station s ($j \in \{1,2,\cdots,18\}$, $s \in \{1,2,\cdots,21\}$).

When the structure of production line has been built, the primary task is to acquire the real-time processing time of each station. The processing time of each station needs to be updated frequently because of the influences from learning and forgetting effect and cross-training method. Supposing that worker pool size is N, the machine processing time for station s is TM_s and the manual operation time for worker i in station s at time t is $W_{is}(t)$. The definition of function $\phi(x,y)$ is that $\phi(x,y) = 1$ when $x = y$ and $\phi(x,y) = 0$ when $x \neq y$. Besides, in function $k = \tau(i,t)$, k is the station that worker i is working in at time t. Therefore, the definition of processing time for station s at time t can be presented:

$$T_s(t) = \begin{cases} TM_s + \dfrac{1}{\sum_{i=1}^{N} \dfrac{\phi[\tau(i,t),s]}{W_{is}(t)}} & ,\sum_{i=1}^{N} \phi[\tau(i,t),s] > 0 \\ \infty & ,\sum_{i=1}^{N} \phi[\tau(i,t),s] = 0 \end{cases} \qquad i \in \{1,...,N\}, s \in \{1,2,...,21\} \tag{1}$$

In equation 1, 21 is the number of stations in production line. $\sum_{i=1}^{N} \phi[\tau(i,t),s] = 0$ indicates that the operation at station s is suspended because of no workforce available. On the contrary, $\sum_{i=1}^{N} \phi[\tau(i,t),s] > 0$ represents that there are at least one worker at station s. $T_s(t)$ is updated whenever some product comes into and out of station s. Station processing time stays constant while one product is under processing procedure in station s. Workers can alter their working places at the time epoches when a product accomplishes processing at its current station. Therefore, the workforce distribution before and after those time epoches might be different. In addition, when some worker is ready to join the operation area of certain station, the worker will undertake the next task rather than the current one.

2.2 Worker Model

Worker model contains four primary elements: worker attributes, worker states, cross-training model and learning and forgetting model. The basic framework of worker model is made up of worker attributes and worker states. The cross-training model and learning and forgetting model are the additional and multifunctional amendments to the basic framework. The detailed discussion and explanation of these elements will be carried out in the following text.

2.2.1 Worker Attributes and States

In the Agent-based worker model, the basic attributes include worker ID, worker's basic station (initially appointed before production), worker's current station and worker's reference manual processing time for each station. Besides, there are some additional attributes which are associated with cross-training model and learning and forgetting model. There is a state transition diagram in worker model to describe the states of workers and the detailed transition conditions.

2.2.2 Cross-training Model

The generalized concept of cross-training contains three sections: cross-training strategy, worker management policy and team structure. Within these three sections, team structure is more effective for labor-intensive industry, rather than the production line with automation in this paper. Thus only cross-training strategy and worker management policy need to be focused on. As for cross-training strategy, the most significant difference after the application of cross-training is that workers master additional operation skills of their teammates. Cross-training strategy provides a more complex mapping relationship between workers and stations than the traditional bijective relationship.

In the simulation model, the number of stations one worker is able to work at is measured with the concept of cross-training level. The cross-training level of n means that each worker can work in the stations belonging to n upstream procedures and n downstream procedures at most excluding the procedure of worker's basic station. Assuming the basic station of worker j is o_j, the available stations for worker j under cross-training level n will be $A_j = \{i| -n \leq \delta(i) - \delta(o_j) \leq n\}$.

After the integration of cross-training model, it is necessary to consider worker management policy, which dominates the rearrangement of workers during production process. Cross-training strategy only offers the confirmation whether one worker has the ability to work at some station, worker management policy will provide a priority list of stations limited within the scope where the worker is capable to handle. Worker management policy also determines which station worker is going to work at based on the priority list. When finishing the jobs at hand, workers will switch to the stations which rank first in their priority lists. In order to illustrate the priority list, the definition of *Load* is proposed to present the accumulated workload of each station. The *Load* value of station i is calculated as $Load_i(t) = B_i(t) \times T_i(t)$ ($B_i(t)$ is the number of products temporarily stored in the buffer area of station i at time t). Bigger $Load_i(t)$ value indicates station i ranks higher in the priority list. This is how workers adjust themselves to obtain the best performance of production line.

2.2.3 The Learning and Forgetting Effect Model

It is expressed above that the introduction of cross-training will bring about the phenomenon of insufficient learning to workers because of their frequent switching. Therefore, it is not accurate to ignore the effect of worker learning and forgetting. The learning and forgetting model Shafer et al. raised proved to be effective for production line with repetitive operations (Shafer, Nembhard, and Uzumeri 2001). However, their work doesn't take the situation that one worker masters more than one operation skills and can work in multiple stations into account. Therefore, the revised learning and forgetting model is presented in this paper. The processing time for worker i in station s at time t is presented as $W_{is}(t)$ and this expression is coordinated with equation 1. $W_{is}(t)$ is obtained as follows.

$$j = \delta(s),\ \ W_{is}(t) = \frac{\lambda_{ij}(t)[\xi_{ij}(t)]^{\alpha_i} + p_{ij} + r_{ij}}{\lambda_{ij}(t)[\xi_{ij}(t)]^{\alpha_i} + p_{ij}} \cdot TW_s \qquad i \in \{1,...,N\}, s \in \{1,2,...,21\} \tag{2}$$

In equation 2, $\lambda_{ij}(t)$ is the number of products worker i has processed on all stations belonging to procedure j at time t. The reason why the quantities of products processed on different stations of one procedure are amalgamated is that those products are processed with the exact same operation skill. So it makes no difference for worker to become more experienced when working at any station within procedure j. α_i is the learning and forgetting level of worker i and it is used to represent the degree of how easy worker i forgets the operation skill. Bigger α_i means worker i is easier to forget. The value of α_i should be fitted based on the data from the pre-testing of worker i. p_{ij} is the previous experience level of worker i for procedure j. p_{ij} can be both positive and negative. Positive value indicates that the previous training is helpful for the operation now, while the negative value means the previous skill is harmful to the current work. r_{ij} is the auxiliary variable for initializing $W_{is}(0)$ at the beginning of simulation.

TW_s is the reference manual processing time for one product in station s under the highest efficiency. $p_{ij} + r_{ij}/p_{ij}$ stands for the initial training level of worker i at all stations belonging to procedure j and it is adjustable depending on specific pre-training level. Since TW_s is a constant value and $\lambda_{ij}(0) = 0$, $W_{is}(0)$ is proportional to $p_{ij} + r_{ij}/p_{ij}$. Without loss of generality, $p_{ij} + r_{ij}/p_{ij}$ is set to 2 for all workers in the simulation experiments of section 4. $p_{ij} + r_{ij}/p_{ij} = 2$ means the manual processing time for each worker in station s at the beginning of production is twice as the reference manual processing time TW_s. The influence of previous experience ($p_{ij} + r_{ij}/p_{ij}$) will become more unconspicuous when simulation runs forward because that the accumulation of processed product for worker i increases the value of $\lambda_{ij}(t)[\xi_{ij}(t)]^{\alpha_i}$ and weakens the influence of previous experience. For example, when worker pool size is 21, cross-training level is 2, $p_{ij} = r_{ij} = 10$ ($p_{ij} + r_{ij}/p_{ij} = 2$), the outputs of production line between 0 to 10000 seconds, 10000 to 20000 seconds and 20000 to 30000 seconds are 96 pieces, 127 pieces and 129 pieces. If worker pool size and cross-training level remain unchanged, $p_{ij} = 10$, $r_{ij} = 20$ and $p_{ij} + r_{ij}/p_{ij}$ increases to 3, the outputs of production line between the same time periods are 68 pieces, 117 pieces and 125 pieces. It could be observed that the influence of previous experience is undermined over time. However, this influence might remain more durable when worker pool size is small and cross-training level is high.

$\xi_{ij}(t)$ is the discount factor to $\lambda_{ij}(t)$. $\xi_{ij}(t)$ represents the energy distribution ratio of worker i in procedure j. $\xi_{ij}(t)$ is obtained as below.

$$\xi_{ij}(t) = \frac{\lambda_{ij}(t)}{\sum_{j=1}^{18} \lambda_{ij}(t)} \qquad i \in \{1,...,N\} \tag{3}$$

In equation 3, 18 is the number of procedures in production line and $\sum_{j=1}^{18} \lambda_{ij}(t)$ is the quantity of products worker i has processed in all procedures (all stations) up to t.

3 SIMULATION MODEL

3.1 Model Structure

The production line model contains two main submodels: physical infrastructure submodel and worker pool submodel. These two submodels are independent and separately built with different simulation methods. Figures 2 presents the overall structure of production line. The diagram within the dotted line frame at the lower right part of Figures 2 is the structure of worker pool submodel based on ABS. The rest part is the structure of physical infrastructure submodel with DES.

As for physical infrastructure submodel, the left part is the physical structure of production line, which contains 18 procedures and 21 stations. Each station contains a operation area and a buffer zone. Operation area is equipped with workers and machines. The main function of buffer zone is to temporarily store the unfinished products which have just completed their processing by the previous stations.

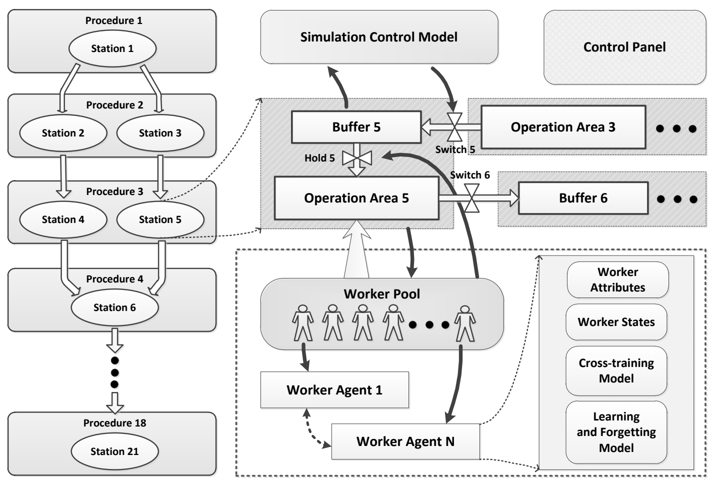

Figure 2: The structure of the overall production line.

3.2 User Interface

The modeling environment is AnyLogic Professional and the simulation model has an easy-to-use interface, as presented in Figure 3. The left image is the screenshot of Simulation Setup Panel and the right one is the screenshot of Simulation Monitoring Panel. Simulation Setup Panel provides an easier way to set parameters such as buffer size, cross-training level, worker pool size and learning and forgetting level by dragging the sliders or typing in the edit boxes. Moreover, a quicker approach to set various configuration scenarios for simulation experiments is also provided by clicking the corresponding radio button. The main functions of Simulation Monitoring Panel are monitoring the running status of the production line and saving relevant data to files for further study.

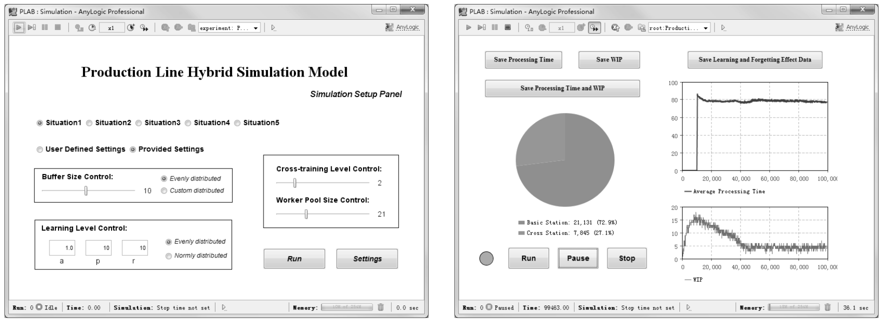

Figure 3: Screenshot of user interface.

4 SIMULATION EXPERIMENT

4.1 The Effect of Worker Learning and Forgetting

The effect of learning and forgetting during simulation will be presented in this section. Each worker has 18 independent learning and forgetting processes corresponding to 18 procedures at the same time. Worker's learning and forgetting degree is measured with Learning Progress. If station s belongs to procedure p ($p = \delta(s)$), the learning progress of worker i at procedure p is $U_{ip}(t) = W_{is}(t)/TW_s$ (referring to equation 2). If worker i is currently working at certain station of procedure p, worker i is under learning state at procedure p and forgetting state at other procedures. Therefore, $U_{ip}(t)$ increases and $U_{ip'}(t)$ ($p' \in \{1,2,\cdots,18\}$, $p' \neq p$) decreases. In the simulation experiments, the simulation model monitors the learning progresses of worker 15 at station 14 (procedure 12) and station 15 (procedure 13) under the condition of cross-training level 1 and pervious experience level 10.

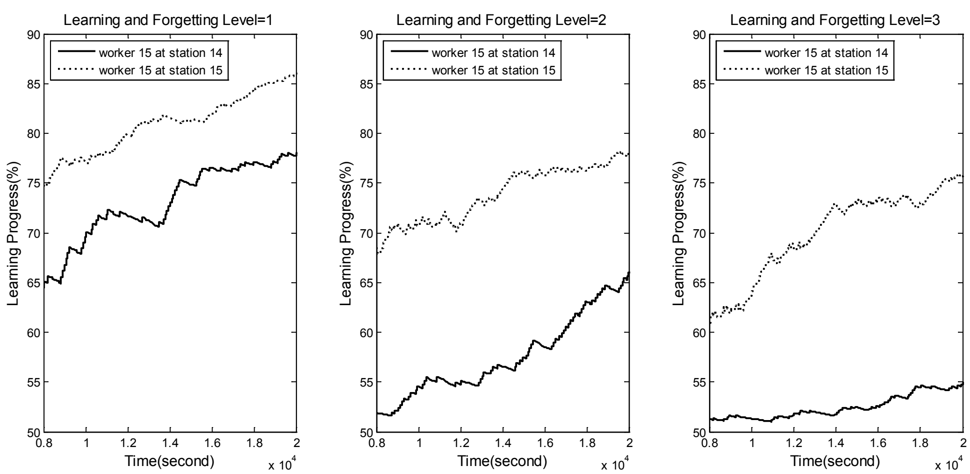

Figure 4: The effect of worker learning and forgetting with different learning and forgetting levels.

The curves in Figure 4 are all obtained within the initial learning period of worker 15 at station 14 and station 15. The only difference among those three diagrams is the value of learning and forgetting level. It is not hard to conclude that during the same period of time, bigger learning and forgetting level will result in a lower learning progress. In the left diagram, from $1.37 \times 10^4 second$ to $1.45 \times 10^4 second$, it is observable that worker 15 is under learning state at station 14 and is under forgetting state at station 15 at the same time. This phenomenon indicates during that time period, worker 15 spends most of time working at station 14 rather than station 15.

If ε_i $(i \geq 0)$ is used to record the moment when product i finishes the last procedure $(\varepsilon_0 = 0)$, the time interval between two neighboring finished products could be expressed as $\Delta\varepsilon_i = \varepsilon_i - \varepsilon_{i-1}$ $(i \geq 1)$. During production, $\Delta\varepsilon_i$ might vary greatly due to various workforce distribution caused by cross-training method. So only one interval alone doesn't precisely describe the actual processing speed of production line. Therefore, the time intervals of the latest 100 finished products (the current time is t and the latest finished product is j if $\varepsilon_j \leq t < \varepsilon_{j+1}$) are collected and the mean value of those time intervals ($\frac{1}{100}\sum_{i=j-100}^{j}\Delta\varepsilon_i$, $j > 100$) is regarded as the average processing time of one product. The unit of average processing time is seconds per piece.

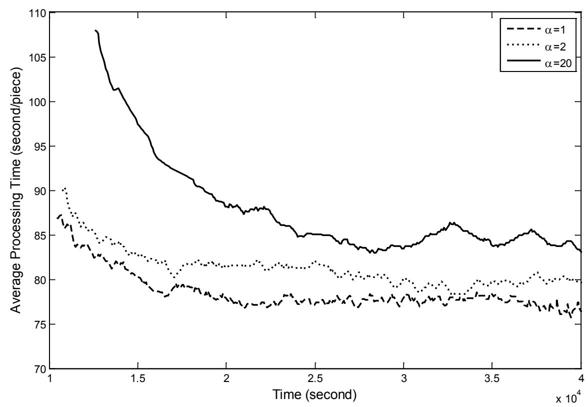

Figure 5: The effect of learning and forgetting level to the average processing speed.

Another experiment is performed to verify the influence of learning and forgetting level to the average processing time of production line. The average processing time is collected based on three different learning and forgetting levels: $\alpha = 1$, $\alpha = 2$ and $\alpha = 20$, as presented in Figure 5. The cross-training level is 1 and the pervious experience level is 10. Firstly, it is not difficult to find out there is a time range within which the average processing time declines (processing speed increases) at the beginning of simulation. This phenomenon demonstrates the learning periods of workers from the start. Then, it is discoverable that the rise of learning and forgetting level will increase the average processing time. A more detailed explanation of this phenomenon will be discussed in sections below. Moreover, it can found out that the starting point of the curve will be delayed by the increasing of learning and forgetting level, for that the slower worker operation time will postpone the production line to finish the first 100 products.

4.2 The Performance of Production Line under Different Worker Pool Sizes

The order quantity and delivery cycle of the car engine parts plant might not remain unchanged. Therefore, a solution to handle different situations needs to be provided. When workload is low, it will be a waste of workforce to maintain the same size of the worker pool as the situation when the plant has high workload. Besides, maintaining a large worker pool implies high payroll. So if the order quantity and delivery cycle are known, it is not hard to calculate the working plan for one day. Based on the results from simulation experiments, the plant manager should be able to find out the minimum worker pool size under the precondition of fulfilling the order on time. The basic workforce distribution plan is one worker per station, so the normal size of worker pool is 21. Considering the application of cross-training, when the training level is 1, the minimum worker pool size which can keep the uninterrupted and durative running of the production line is reduced to 6.

In this paper, simulation experiments are conducted with different worker pool sizes to demonstrate how worker pool size affects processing speed and WIP. The sizes of worker pool are between 6 and 21 (from the minimum size to the normal size), the cross-learning level is 1 and the pervious experience level is 10. Figure 6 presents the simulation results.

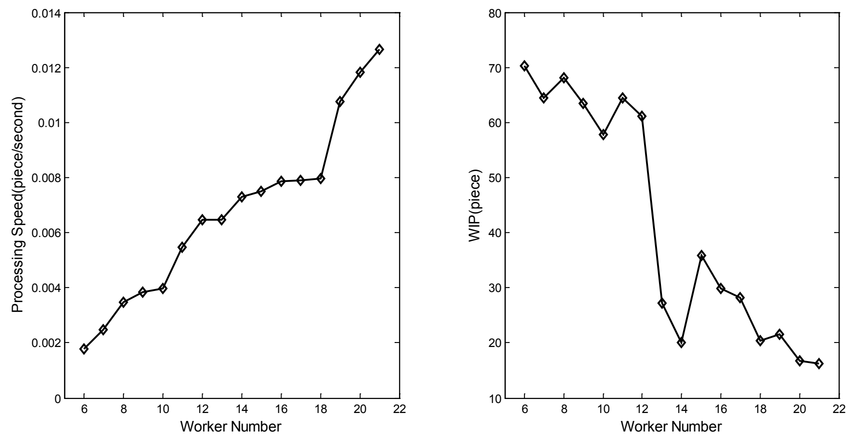

Figure 6: The effect of the worker pool size to processing speed and WIP.

Processing speed is the reciprocal of processing time. However, since $\Delta\varepsilon_i$ varies irregularly, it is not accurate to regard the reciprocal of average processing time as the processing speed of production line. The reason average processing time is used as the output characteristic of production line in the section above is that the experiment above focuses more on the dynamic character rather than the static character of production line. Bootstrap method is used to acquire more convincing confidence intervals of medians of processing speed and WIP. All confidence intervals are obtained at 95% confidence level.

If confidence interval could be expressed as $(\omega-\Delta\upsilon,\omega+\Delta\upsilon)$ and ζ is defined as $\frac{2\Delta\upsilon}{\omega}$, the maximum ζ is 0.511% for the median of processing speed and 0.158% for the median of WIP. Since the confidence intervals are relatively small, they make the results more comparable. The curves in Figure 6 are plotted based on the mean values of upper bounds $(\omega+\Delta\upsilon)$ and lower bounds $(\omega-\Delta\upsilon)$ of the median intervals of processing speed and WIP. The conclusion can be drew that the increase of worker pool size will promote the processing speed. Nevertheless, it is not obvious to find out the exact relation between worker pool size and WIP. It can only be observed that WIP declines as the worker pool size increases in rough. Since the value of WIP is small enough compared to the throughput of production line and it won't raise the cost of inventory too much, it is more advisable to concentrate more on the processing speed.

4.3 The Influence of Cross-training Level to the Performance of Production Line

In the sections above, all simulation experiments are conducted with cross-training level 1. In this section, research about how cross-training level affects the production line will be performed. Table 1 presents the result of simulation experiments. It is stated above that bootstrap method is used to obtain the confidence intervals of medians of processing speed and WIP. Since the confidence intervals are small enough, it is reasonable to treat the mean values of upper bounds and lower bounds of confidence intervals as the result to demonstrate the influence of cross-training level to the performance of production Line. It can be confirmed that all comparable confidence intervals (processing speed and WIP of different cross-training levels and different worker pool sizes) do not intersect each other. Therefore, the comparison is convincing.

From Table 1, it is observable that the increase of cross-training level indeed shifts the processing speed. Moreover, the increase of cross-training level will bring about more promotion to the processing speed when the size of worker pool is small in general. For example, when the worker pool size is 6, the processing speed of cross-training level 4 is 130.04% faster than the speed of cross-training level 1. However, when the worker pool size is 21, the processing speed of cross-training level 4 is only 7.00%

Table 1: Comparison of processing speed and WIP with different sizes of worker pool and cross-training levels

	$Throughput^{\star}$ (piece)				WIP (piece)			
Pool Size	CL^{*} 1	CL^{*} 2	CL^{*} 3	CL^{*} 4	CL^{*} 1	CL^{*} 2	CL^{*} 3	CL^{*} 4
6 workers	17.71	33.54	36.86	40.74	70.26	35.70	37.09	37.48
9 workers	38.58	52.91	58.32	60.42	63.40	4.28	6.83	10.51
12 workers	64.80	85.04	88.15	90.15	61.13	15.11	6.26	13.45
15 workers	75.15	102.59	110.91	113.01	35.80	22.53	17.21	11.02
18 workers	79.70	113.37	116.02	121.91	20.46	19.83	13.77	11.75
21 workers	126.58	133.55	134.61	135.43	16.19	5.80	6.11	6.14

$\star$ Number of Products Processed per 10000 Seconds. $*$ Cross-training Level.

faster than the speed of cross-training level 1. Therefore, the suggestion may be raised that if the car engine parts plant wants to enhance its productivity, increasing the cross-training level should be considered as well as enlarging the worker pool size. The advantage of cross-training is obvious, it can boom the throughput without increasing the cost of human resources. Nevertheless, a balance point needs to be found between the promotion that higher cross-training level brings about and the more evident side effect led up by learning and forgetting effect. As for WIP, it is discoverable that the WIP values of cross-training levels bigger than 1 are smaller than the values of cross-training level 1. Therefore, the pressure of inventory will be reduced as cross-training level rises.

4.4 The Influence of Learning and Forgetting Level to the Performance of Production Line

In this section, the influence of learning and forgetting level on the processing speed and WIP will be studied. The learning and forgetting levels are gained from a geometric progression from 2^{-1} to 2^{9}. The other configurations of production line remain constant. The size of worker pool is 21, the cross-training level is 2 and the pervious experience level is 10. Figure 7 presents the relation between learning and forgetting level and processing speed as well as WIP. Since the learning and forgetting levels are from a geometric progression, logarithmic coordinate is applied as the x axis coordinate. The value of the abscissa is the natural logarithm of learning and forgetting level.

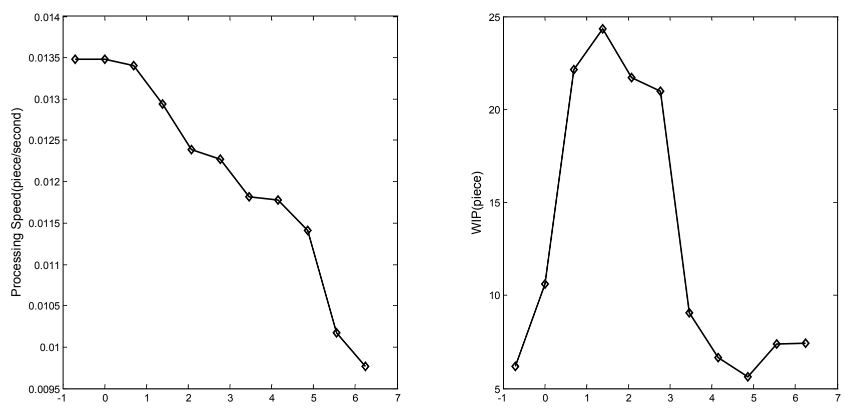

Figure 7: The effect of the learning and forgetting level to processing speed and WIP.

It is not hard to observe that processing speed will decrease as learning and forgetting level increases. Because when learning and forgetting level becomes higher, the insufficient training will extend workers' operation time. As a result, the processing speed will be affected negatively. In Figure 7, WIP is relatively small when learning and forgetting level is low enough and high enough. Considering that the maximum WIP of 25 is negligible to the total buffer volume, the influence of learning and forgetting level to the processing speed is more significant. Therefore, the speculation can be confirmed that the quality of workers is also needed to be taken into consideration as well as the quantity of workers and cross-training level. A high quality worker team will be helpful to promote the efficiency of production line.

5 CONCLUSION

In order to study the dynamic multi-skilled workforce planning problem of production line, a hybrid simulation model is built as the experimental platform with Discrete-event Simulation (DES) and Agent-based Simulation (ABS). The combination of two different simulation methods strengthens the authenticity, expandability and usability of the hybrid model by highlighting their own advantages in simulation.

The superiority of modeling queuing system offers DES method more accuracy and convenience in building a stable foundational structure of physical infrastructure for ABS model to achieve dynamic workforce planning. While ABS method is favored to model worker pool because of its advantage in describing worker's attributes, states and behaviors. Therefore, the main functions of the foundational structure are basic processing mechanism and the running control of all stations within the production line. The realizations of cross-training method, learning and forgetting effect are fulfilled in the ABS model.

Cross-training method is introduced to make the best use of available workforce to promote productivity. It can also maintain the uninterrupted running of production line under a relatively small worker pool. Nevertheless, the effect of worker learning and forgetting is inevitably taken into consideration because of the higher learning pressure cross-training method brings about. During simulation, the workers' learning progresses could be clearly observed. The simulation experiments also demonstrate the influence of learning and forgetting level to the learning progresses of workers and the processing speed of production line.

Considering that productivity and WIP are two vital factors influencing the performance of production line, the research is then conducted to study how production line is impacted by worker pool size, cross-training level and learning and forgetting level. It could be concluded from simulation that maintaining a constant worker pool size and increasing cross-training level at the same time is likely to be a more efficient way to raise productivity and reduce WIP without additional cost of human resources than simply enlarging worker pool size. However, it needs to be addressed that due to the learning and forgetting effect, the growth of productivity will slow down when cross-training level rises, and the promotion of productivity under certain worker pool size is bounded. Moreover, the learning and forgetting level should not be ignored because it also has a significate influence on the performance of production line.

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REFERENCES

Bailey, C. D. 1989. "Forgetting and the Learning Curve: A Laboratory Study". *Management Science* 35 (3): 340–352.

Blickensderfer, E., J. A. Cannon-Bowers, and E. Salas. 1998. "Cross-training and Team Performance". *In: A. Cannon-Bowers, E. Salas (Eds.), Making Decisions Under Stress: Implications for Individual and Team Training*:299–311.

Bussmann, S., and K. Schild. 2001. "An Agent-based Approach to the Control of Flexible Production Systems". In *Emerging Technologies and Factory Automation, 2001. Proceedings. 2001 8th IEEE International Conference on Emerging Technologies and Factory Automation*, Volume 2, 481–488. IEEE.

Cannon-Bowers, J. A., E. Salas, E. Blickensderfer, and C. A. Bowers. 1998. "The Impact of Cross-training and Workload on Team Functioning: A Replication and Extension of Initial Findings". *Human Factors: The Journal of the Human Factors and Ergonomics Society* 40 (1): 92–101.

Feng, Y., and W. Fan. 2014. "A System Dynamics-based Simulation Model of Production Line with Cross-trained Workers". *Journal of Statistical Computation and Simulation* 84 (6): 1190–1212.

Hopp, W. J., E. Tekin, and M. P. Van Oyen. 2004. "Benefits of Skill Chaining in Serial Production Lines with Cross-trained Workers". *Management Science* 50 (1): 83–98.

Inman, R. R., W. C. Jordan, and D. E. Blumenfeld. 2004. "Chained Cross-training of Assembly Line Workers". *International Journal of Production Research* 42 (10): 1899–1910.

Jahangirian, M., T. Eldabi, A. Naseer, L. K. Stergioulas, and T. Young. 2010. "Simulation in Manufacturing and Business: A Review". *European Journal of Operational Research* 203 (1): 1–13.

Jordan, W. C., R. R. Inman, and D. E. Blumenfeld. 2004. "Chained Cross-training of Workers for Robust Performance". *IIE Transactions* 36 (10): 953–967.

Kendall, K., C. Mangin, and E. Ortiz. 1998. "Discrete Event Simulation and Cost Analysis for Manufacturing Optimisation of an Automotive LCM Component". *Composites Part A: Applied Science and Manufacturing* 29 (7): 711–720.

Marks, M. A., M. J. Sabella, C. S. Burke, and S. J. Zaccaro. 2002. "The Impact of Cross-training on Team Effectiveness". *Journal of Applied Psychology* 87 (1): 3.

Mccreery, J. K., and L. J. Krajewski. 1999. "Improving Performance Using Workforce Flexibility in an Assembly Environment with Learning and Forgetting Effects". *International Journal of Production Research* 37 (9): 2031–2058.

Mjema, E. 2002. "An Analysis of Personnel Capacity Requirement in the Maintenance Department by Using a Simulation Method". *Journal of Quality in Maintenance Engineering* 8 (3): 253–273.

Monostori, L., J. Váncza, and S. R. Kumara. 2006. "Agent-based Systems for Manufacturing". *CIRP Annals-Manufacturing Technology* 55 (2): 697–720.

Nembhard, D. A., and M. V. Uzumeri. 2000. "Experiential Learning and Forgetting for Manual and Cognitive Tasks". *International Journal of Industrial Ergonomics* 25 (4): 315–326.

Shafer, S. M., D. A. Nembhard, and M. V. Uzumeri. 2001. "The Effects of Worker Learning, Forgetting, and Heterogeneity on Assembly Line Productivity". *Management Science* 47 (12): 1639–1653.

Volpe, C. E., J. A. Cannon-Bowers, E. Salas, and P. E. Spector. 1996. "The Impact of Cross-training on Team Functioning: An Empirical Investigation". *Human Factors: The Journal of the Human Factors and Ergonomics Society* 38 (1): 87–100.

Yelle, L. E. 1979. "The Learning Curve: Historical Review and Comprehensive Survey". *Decision Sciences* 10 (2): 302–328.

Zülch, G., S. Rottinger, and T. Vollstedt. 2004. "A Simulation Approach for Planning and Re-assigning of Personnel in Manufacturing". *International Journal of Production Economics* 90 (2): 265–277.

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