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Optimized throughput improvement of assembly flow line with digital twin online analytics

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***Abstract* — This work studies a digital twin online analytics for throughput improvement of assembly flow line. As the representation of the physical assembly flow line, the proposed method includes two digital twin models to analyze the online data collected from the physical line and to calculate and apply optimal throughput improvement scheme to the physical line. With the proposed method, the online data could be fully utilized to serve the physical line, and the dependency on the experience of onsite engineers is greatly reduced. Two practical assembly lines are equipped with the proposed digital twin online analytics to demonstrate its effectiveness and efficiency.**

Keywords — optimized throughput improvement; throughput prediction; digitial twin; assembly flow line

I. Introduction

Nowadays, the assembly flow line is the primary mode of manufacturing in industry. Automobiles, food, toys, furniture, and many other items pass down the manufacturing flow line worldwide before landing in our home and on our table. Since Henry Ford developed the first manufacturing flow line in 1913, the researches on it keep moving forward in last one hundred years.

With the development of factory automation, many factories built their own digital pairings of the physical factories by SCADA (supervisory control and data acquisition) systems. However, most of the SCADA system only focus on data collection and visualization, and the history and online data is not fully utilized for analysis. In this way, engineers still cannot have an entire picture of assembly flow line status in real time to make a decision about how to tune and improve the line.

To support decision making of throughput improvement, the digital twin online analytics method for the assembly flow line is studied here, whose basic idea is shown in Fig. 1. With online data as input, the digital twin models are built to analyze the real-time status, to predict the future performance, and to optimize improvement scheme for the physical assembly flow line. After obtain the optimized improvement scheme, it will be applied to the physical line. In brief, online data is from the physical line, and will serve the physical line after the analysis by the digital twin online analytics.

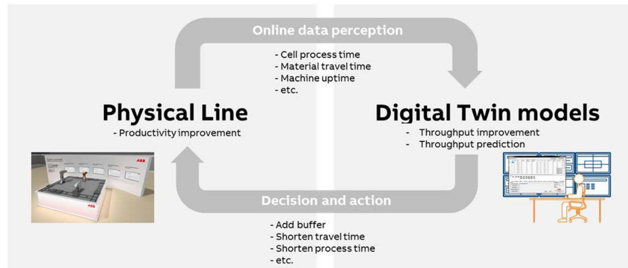

Fig. 1. Conceptual graph about relationship of physical line and its digital twin model

During the operation of the assembly flow line, the throughput might be unsatisfactory for tons of reasons, and there are lots of feasible solutions to smooth workloads at different stations towards a balanced line, such as adding parallel machines, process design change, layout change, buffer reallocation, higher speed of material transportation, and higher operational speed of workstation [1]. Within each feasible solutions, different parameter values will make a big different for the final result. Take buffer as an example, adding buffer before the bottleneck workstation might increase line throughput dramatically, but adding buffer before a workstation with low utilization rate may not lead to any difference [2]. Moreover, the costs, like labor cost and time cost, are also need to be taken into account for throughput improvement scheme selection. Therefore, facing so many factors to be considered, it is a tough task for onsite engineers to dig out an optimized throughput improvement scheme among tons of optional scheme, if the onsite engineer does not have too much experience on assembly flow line operation. To deal with abovementioned problem, a throughput improvement digital twin model is developed here to analyze the real time status of the line and provide the optimized scheme of line throughput improvement.

To support throughput improvement digital twin model to provide the optimized scheme, throughput of the potential improvement scheme need to be predicted accurately. Right now, lots of results about assembly flow line throughput estimation/prediction have been achieved by either analytical solution [2] or simulation solution [4] [5], but tradeoff between model simplicity and prediction accuracy is hard to made. In this work, a throughput prediction digital twin model is proposed to achieve low model simplicity and relative high prediction accuracy, which provides a solid foundation for throughput improvement digital twin model. The key idea behind the proposed throughput prediction digital win model is to calculate the throughput of the short assembly flow line including bottleneck, rather than calculate the whole assembly flow line, since the bottleneck is the limiting factor that slows down the whole operation chain and impedes a higher throughput in the strongest manner.

The remaining of the paper is organized as follows. The throughput improvement digital twin model is developed in Section II, and the throughput prediction digital twin model is studied in Section III. The proposed digital twin online analytics is further verified by two practical cases of assembly flow line in Section IV. Finally, conclusions are stated in Section V.

II. Throughput Improvement Digital Twin Model

By considering tunable parameters and customer-concerned factors of the assembly flow line, the workflow of the throughput improvement digital twin model to figure out the optimized solution is described as below, which is also shown as Fig. 2.

Step a. According to the limitation of the specific assembly flow line, build a feasible solution set first to involve all potential parameters to be redesigned. Assume the feasible solution set A is

$$\mathrm{A} = \{\mathrm{s_1(i_1), s_2(i_2), \cdots, s_J(i_J)}\} \quad (1)$$

where $s_j(i_j)$ is the *j*-th feasible solution, and i_j is the parameters to be optimized for the *j*-th feasible solution. Take adding buffer as an example, i_j could be the location and number to add buffer.

Step b. Based on online data from physical assembly flow line, the optimization will be made to for each solution in the feasible solution set A to obtain an optimized solution set B,

$$s_j^* = s_j(i_j^*) = \max_{i_j} \frac{\partial UPH}{\partial s_j(i_j)},\ j = 1,2,\cdots,J \quad (2)$$

$$\mathrm{B} = \{(s_1^*, \rho_1^*), (s_2^*, \rho_2^*),, \cdots, (s_J^*, \rho_J^*)\} \quad (3)$$

where s_j^* is the optimized choice for the *j*-th feasible solution with the optimal parameter i_j^*, and ρ_j^* is its corresponding predicted throughput, which is predicted by the throughput prediction digital twin model given in Section III.

Step c. Make a decision on the most suitable solution among different optimized solutions in the optimized solution set based on the customer-concerned factors, which will be different for each specific assembly flow line.

$$S^* = (s^*, \rho^*) = \max_{j} \frac{\partial F(s_j^*)}{\partial s_j^*} \quad (4)$$

where s^* is the most suitable solution, ρ^* is the corresponding predicted throughput, and $F(s_j^*)$ is the defined cost function of customer-concerned factors for the specific assembly flow line.

After analysis of throughput improvement digital twin model based on online data, the most suitable solution S^* will be applied to the physical line.

During the application of the throughput improvement digital twin model, the key part is to predict the line throughput for each feasible solution with certain line parameters in *Step b*. If the predicted throughput is not accurate enough, the optimization result will be questionable. And if the computational time of the prediction is not short enough, the proposed workflow is no longer suitable for online analytics. Therefore, a throughput prediction digital twin model with low computational complexity and relative high accuracy is critical here, and will be studied in the next section.

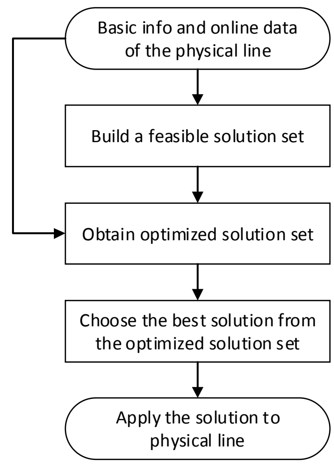

Fig. 2. Workflow of the bottleneck-based production line throughput calculation method

III. Throughput Prediction Digital Twin Model

As an enabler for line throughput improvement function, various throughput estimation methods of the assembly line have developed for decades. If the process time of the workstation on the line is constant, the line throughput estimation is quite straightforward. However, when there is variable process time and the machine breakdown is considered on the line, the line throughput estimation become complex and the simplified method will lead to great error. To solve this problem, some methods are studied to deal with short lines with less than 4-6 stations, and large-scale lines will cause computational complexity problems which will make the existing methods not applicable. Lots of commercial discrete-event simulation software could help build the model of the line and evaluate line throughput, like Quest from Dassault Systemes, FlexSim, Arena, etc. However, the model building is a time-consuming and effort-consuming process, and strong relies on the skilled engineers, let alone the extremely high license fee.

In this section, a throughput prediction digital twin model is developed. Assume that there are M workstations on the assembly flow line. The workflow of the proposed throughput prediction digital twin model is provided as below, which is also shown as Fig. 3,

Step 1. Obtain operational data of the assembly flow line, including

- Process time of each workstation ($T_{i,pro}$, unit: second),

- Travel time from the upstreaming workstation/buffer to the certain workstations ($T_{tr,i}$,unit: second)
- Buffer number between two neighboring workstations (N_i)

where $i = 1, \cdots, M$.

Step 2. Identify the bottleneck workstation(s) in the assembly flow line and compose the bottleneck subline, which includes bottleneck workstation, one neighboring upstream workstation and one neighboring downstream workstation of the bottleneck workstation. Assume that i-th workstation is the identified bottleneck workstation, and the bottleneck subline includes *(i-1)*-th workstation, i-th workstation, and *(i+1)*-th workstation, as shown in **Error! Reference source not found.**.

Step 3 Calculate the throughput of upstream subline of bottleneck workstation(s), ρ_{up} (unit: unit per hour), wherein the upstream subline comprises the neighboring upstream workstation (*(i-1)*-th workstation) and one further upstream workstation (*(i-2)*-th workstation) of the bottleneck workstation, as shown in **Error! Reference source not found.**.

Step 4. Calculate the throughput of downstream subline of bottleneck workstation(s), ρ_{down}(unit: unit per hour), wherein the downstream subline comprises the neighboring downstream workstation (*(i+1)*-th workstation) and one further downstream workstation (*(i+2)*-th workstation) of the bottleneck workstation, as shown in **Error! Reference source not found.**.

Step 5. Compensate for the process time of upstream workstation and downstream workstation of the bottleneck workstation,

$$T'_{i-1,pro} = \frac{3600}{\rho_{up}} \quad (5)$$

$$T'_{i+1,pro} = \frac{3600}{\rho_{down}} \quad (6)$$

where $T_{i-1,pro}$ and $T_{i+1,pro}$ are the process time of the neighboring upstream workstation and neighboring downstream workstation, respectively, and $T'_{i-1,pro}$ and $T'_{i+1,pro}$ are the compensated process time of neighboring upstream workstation and neighboring downstream workstation, respectively.

Step 6. Calculate the throughput of the bottleneck subline with the compensated process time of neighboring upstream workstation and neighboring downstream workstation ($T'_{i-1,pro}$ and $T'_{i+1,pro}$) as the throughput of the whole assembly flow line throughput.

The subline throughput calculation method in *Step 3*, *Step 4*, and *Step 6* can be any existing method [2]-[5] since these sublines only include a few number of workstations and computational complexity is not problem there.

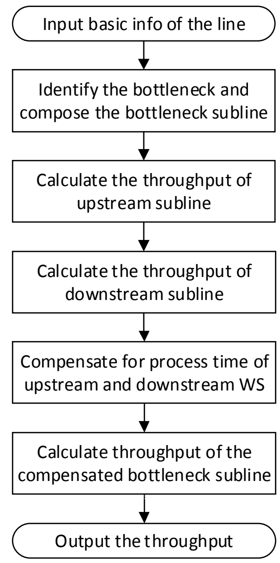

Fig. 3. Workflow of the bottleneck-based production line throughput calculation method

IV. DEMONSTRATION

In this section, the proposed digital twin online analytics are applied to two practical assembly flow lines for verification.

A. Throughput improvement digital twin model

The assembly flow line applied here is a loop assembly flow line with 4 workstations to assemble an U disk, where three are robotic cells and one is manual cell. The layout of this assembly flow line is shown in the Fig. 5, and the raw materials of the U disk are provided in Fig. 6. The basic information and online data of the demo assembly flow line is provided in TABLE I. . The task of each workstation is described as below:

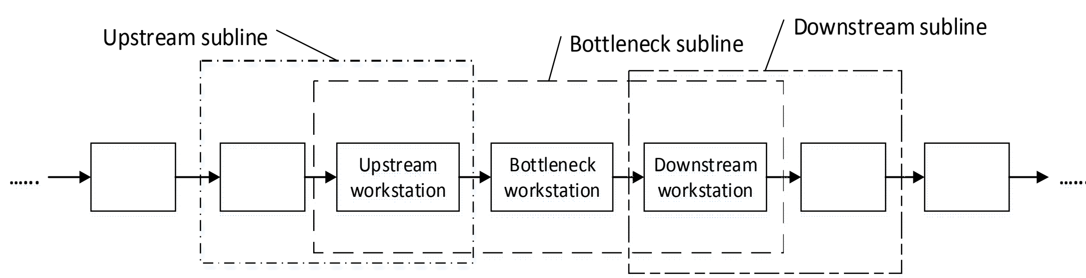

Fig. 4. Schematic diagram of bottleneck subline, upstream subline, and downstream subline

WS1 - load raw materials to pallet manually, including the lower cover, upper cover, and the PCB of the U disk.

WS2 - assemble the PCB and upper cover to the lower cover of the U disk

WS3 - paste a logo to the upper cover of the U disk

WS4 - test the quality and put the cap onto the U disk

With the existing line layout design and operational online data, the throughput of the line is $\rho = 81.73$ unit per hour. And the digital twin online analytics will be applied here to help assembly flow line to figure out the most suitable solution for throughput improvement.

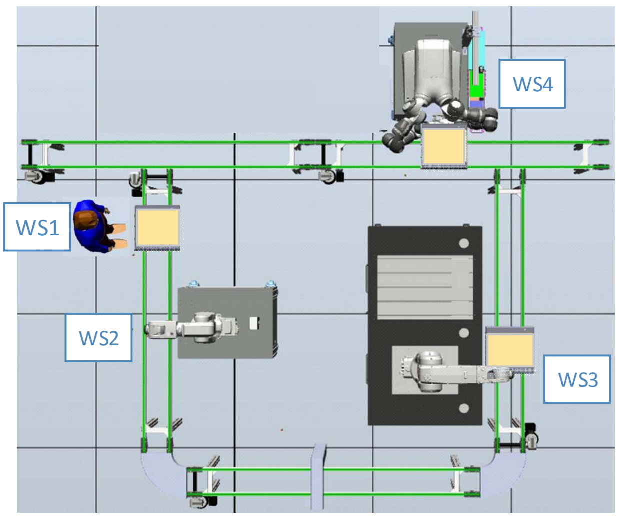

Fig. 5. Demo assembly flow line layout sketch

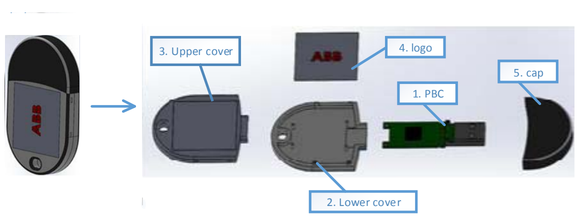

Fig. 6. Raw materials for U disk assembly

TABLE I. BASIC PARAMETERS AND ONLINE DATA OF DEMO ASSEMBLY FLOW LINE I

	Process Time (sec)		**Travel Time (sec)**		**Buffer number**
	Aver. [a]	***Dev.*** [b]	***Buffer-to-WS*** [c]	***WS-to-WS*** [d]	
WS1	10	0	2	2	0
WS2	17.79	0	4	4	0
WS3	29.06	3	2	21	1
WS4	25	0	2	19	0

a. Aver.: average value

b. Dev.: Deviation value

c. Buffer-to-WS: travel time from the buffer to its neighboring downstream workstation

d. WS-to-WS: travel time from the workstation to its neighboring downstream workstation

Step a. For the demo assembly flow line, the feasible solutions set is built as $\mathrm{A} = \{s_1(i_1), s_2(i_2), s_3(i_3)\}$,

- $s_1(i_1)$ is to add one more buffer before certain workstation, and its parameter i_1 is the buffer location, $i_1 = 2,3,4$.
- $s_2(i_2)$ is to shorten process time by 10% for certain workstation, and its parameter i_2 is the workstation index, $i_2 = 1,2,3,4$.
- $s_3(i_3)$ is to add another parallel machine for certain workstation, and its parameter i_3 is the workstation index, $i_3 = 1,2,3,4$.

Step b. Based on online data from TABLE I. , the optimized solution set is calculated as $\mathrm{B} = \{(s_1^*, \rho_1^*), (s_2^*, \rho_2^*), (s_3^*, \rho_3^*)\}$

- s_1^* is to add one more buffer before WS4, and its corresponding throughput is predicted as $\rho_1^* = 116.14$.
- s_2^* is to shorten process time of WS4 by 10%, and its corresponding throughput is predicted as $\rho_2^* = 87.74$.
- s_3^* is to parallel another machine for WS4, and its corresponding throughput is predicted as $\rho_3^* = 116.53$.

Step c. For the throughput achieved by each optimized solution, ρ_1^* and ρ_3^* are much higher than ρ_2^*. By comparing s_1^* and s_3^*, the cost of adding buffer is much lower than that of adding parallel machine. Therefore, with the tradeoff between cost and throughput value, s_1^* is chosen as the most suitable solution $S^* = (s_1^*, \rho_1^*)$.

Finally, the most suitable solution, which is to add one more buffer before WS4, is applied to the physical line, and its throughput is improved by 42.1%.

B. Throughput prediction digital twin model

To further verify the proposed throughput prediction digital twin model, an assembly flow line with 9 workstations are applied here. The actual throughput is $\rho_{actual} = 159.52$ unit per hour. To show the superiority of the proposed digital twin model, one popular throughput prediction algorithm is compared here.

Algorithm 1. For engineers to predict the line throughput, the most straightforward way is to only consider the bottleneck workstation, and it is quite useful for simple assembly flow line, where the process time of each workstation is not time-varying,

$$\rho = \frac{3600}{\max_i T_i} \tag{7}$$

$$T_i = T_{i,pro} + T_{i,tr} \tag{8}$$

where $T_{i,pro}$ is the process time of i-th workstation, and $T_{i,tr}$ is the material transportation time from upstream workstation or buffer to the i-th workstation.

For the case in this subsection, the throughput predicted by this algorithm is $\rho_{predict,1} = 195.76$ unit per hour.

TABLE II. BASIC PARAMETERS OF DEMO ASSEMBLY FLOW LINE II

	Process Time (sec)		Travel Time (sec)		Buffer number
	Aver. [a]	*Dev.* [b]	*Buffer-to-WS* [c]	*WS-to-WS* [d]	
WS1	11.02	5.61	1	1	-1
WS2	5.56	3.52	3	3	0
WS3	10.39	8.77	4	11	1
WS4	12.39	0.91	4	16	1
WS5	11.59	2.84	4	4	0
WS6	14.39	7.11	4	4	0
WS7	8.87	4.50	4	6	1
WS8	13.30	5.41	3	10	1
WS9	8.48	3.50	3	3	0

Algorithm 2. The detailed prediction process of proposed throughput prediction digital twin model is described here.

Step 1. Online data from the physical assembly flow line is provided in TABLE II. .

Step 2. Based on the calculation, the current bottleneck of the physical assembly flow line is identified as WS6, and the bottleneck subline is composed as WS5-WS6-WS7.

Step 3. The throughput of upstream subline (WS4-WS5) of bottleneck workstation WS6 is $\rho_{up} = 208.93$ unit per hour.

Step 4. The throughput of downstream subline (WS7-WS8) of bottleneck workstation WS6 is $\rho_{down} = 217.58$ unit per hour

Step 5. According to equation (5) and (6), the compensated process time of upstream workstation (WS5) and downstream workstation (WS7) is $T'_{i-1,pro} = 17.23$ second and $T'_{i+1,pro} = 16.55$ second.

Step 6. With the compensated process time $T'_{i-1,pro}$ and $T'_{i+1,pro}$, the throughput of the compensated bottleneck subline (WS5-WS6-WS7) is $\rho'_{BN} = 156.57$ unit per hour, and the throughput of the whole assembly line throughput is predicted as $\rho_{predict.2} = 156.57$ unit per hour.

The predicted throughput comparison of these two algorithms are provided in 0. It is observed that the simple algorithm is not suitable for the complex assembly flow line with time varying process time and buffer. However, the proposed digital twin model could achieve much more accurate line throughput prediction, and its prediction error is only 1.85%.

TABLE III. CALCULATION RESULT

	Throughput (unit per hour)	*Error (%)*
Physical line	153.73	0
Algorithm 1	195.76	27.34
Algorithm 2	156.57	1.85

V. CONCLUSION

In this paper, a digital twin online analytics is proposed to bridge the physical assembly flow line and its digital pairing, and makes the online data collected from physical line fully utilized to serve physical line back again. The key contribution of this work is to develop two digital twin models. By analyzing the online data, the proposed digital twin models could analyze real-time line status, predict throughput for future potential line, and optimize line parameters to provide most optimized line throughput improvement scheme. With the proposed digital twin online analytics, a whole picture of the current assembly flow line and future potential assembly flow line schemes, which reduce the dependency on the personal experience and knowledge about line operation of onsite engineers greatly.

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