WILEY | Hindawi

Research Article

Visual Detection Application of Lightweight Convolution and Deep Residual Networks in Wood Production

Zhijie Chen,[1] **Zhihui He,**[2] **Bao Chao,**[3] **and Hongfei Guo** [1,4]

[1]*School of Artificial Intelligence, Jinan University, Zhuhai, China*
[2]*Zhuhai Hengqin Building & Construction Quality Inspection Centre Co., Ltd., Zhuhai, China*
[3]*School of Mechanical Science and Engineering, Huazhong University of Science and Technology, Wuhan, China*
[4]*Institute of Physical Internet, Jinan University, Zhuhai, China*

Correspondence should be addressed to Hongfei Guo; ghf-2005@163.com

In order to improve the production capacity of traditional wood manufacturing industry, efficient wood quality and thickness detection is a challenging issue. This paper firstly carries out digital twin modeling for a drawer side panel processing line of a wood company and explores the efficiency problems existing in the links of quality inspection and thickness inspection of wood by means of value stream mapping. Therefore, we adopted a lightweight convolution neural network MobileNetV2 for wood quality detection, which realized efficient wood quality identification. In contrast, traditional convolution neural network has many weighting parameters and large scale of generating detection model, which makes it difficult to apply in situations with limited computing power and memory. Secondly, due to the stronger robustness and generalization ability of the residual network, we used ResNet to detect the wood thickness and obtain reliable performance. Finally, we reasonably embedded them in the whole wood production process and established the simulation model of production line before and after improvement in FlexSim simulation software. The experimental results show that the improved plan can simplify the workshop production process, increase the production balance rate by 29.07%, increase the product value-added rate from 0.08% to 0.11%, and shorten the production cycle by 2 hours. Performance indicators such as product inventory, number of people, and equipment utilization also improve significantly. Based on the above results, the validity of the production process improvement model proposed by US based on lightweight convolution and deep residual network is demonstrated.

1. Introduction

Driven by national strategies such as "Made in China 2025" and "Industry 5.0," many discrete manufacturing enterprises in China have conducted in-depth research in important business fields such as technology manufacturing and information system. In order to make the transition of discrete manufacturing enterprises to digitalization smoothly, we need to construct a digital model for resources first and increase the production flexibility of enterprises [1]. The key to the solution is correctly using virtual simulation technology to achieve the goals of multiple experimental iterations at the virtual level and one successful experiment at the physical level. Digital twin technology uses a mathematical model, historical data reference, and real-time data feedback to construct the physi-

cal and virtual mapping relationship, and, through continuous iteration and feedback, make people, machine, material, ring, and method really merge together. To be exact, the digital twin model is a software-based, data-based drive to simulate and predict the physical entity's actual state and future behavior with relevant improved knowledge [2].

Value stream mapping is a tool for implementing lean manufacturing, one of which is designed for physical processes and is a process analysis tool that starts with suppliers supplying raw materials to warehouse, and then goes into warehouse manufacturing, finished goods to warehouse, products to warehouse, and until the product reaches the customer. First of all, we need to optimize the key parts. Drawing a "future state" of the value stream by pulling and smoothing the process as the goal of improvement is the main tool for value

stream analysis. Then, we return to the analysis of the status quo map with the problems found in the future value stream mapping (VSM) and cycle until a suitable VSM is identified. Finally, a value flow of the lean production line is designed by drawing the future value stream status map, and a working plan is set to eliminate the non-value-added activities in the production process as far as possible, so as to reduce costs, speed up the response to customer needs, and improve enterprise competitiveness, as shown in Figure 1.

In addition, the physical process also includes product inspection and parking. However, because the VSM can not describe the dynamic behavior of production system in detail, it has limitations in lean production application. The static limitation of VSM can be overcome by combining simulation technology. Figure 2 shows the FlexSim simulation model, which is an object-oriented simulation software, which can efficiently establish the process of discrete events and provide a highly simulated three-dimensional virtual reality environment for material handling and workflow of manufacturing industry, thus achieving virtual simulation and dynamic layout of production lines and avoiding the limitations of traditional equipment schemes.

In this study, from the point of view of production line transformation and in order to change the static defects of previous VSM, we combine VSM and simulation technology and apply VSM to identify the problems existing in the workshop production process. We use ECRS principles to improve standard operations and FlexSim to quickly and accurately build a three-dimensional model of the equipment layout for the drawer side panel production line. Production simulation was carried out under preset parameters, and improved simulation of production links was carried out according to lean criteria. Finally, the simulation test on the improvement plan of the production line has been completed to meet the increasing customer demand; at the same time, the operating cost and processing cycle of the production line have been reduced. Overall, our contributions are as follows:

(1) The digital twin model of the wood side panel production process was established by using VSM and FlexSim simulation model, which effectively simulated the real production environment

(2) We have simulated and improved the production links according to the lean principle, which effectively improves the production efficiency of wood side panels

(3) In addition, we have adopted the computer vision method to complete the tasks of wood quality inspection and wood thickness inspection, respectively, and realized the high automation of the process flow

The remaining sections of this paper are arranged as follows: Section 2 introduces the relevant work of this paper, Section 3 discusses the details of our model concretely, Section 4 is the experimental data and results, and the summary and discussion are arranged in Section 5.

2. Relevant Work

2.1. Value Stream Mapping. At present, the application of value stream mapping (VSM) mainly adopts VSM as a method to identify waste in production. It considers whether the production process can be rescheduled in a more efficient order and analyzes result to reach a better process pattern [3]. However, this does not take into account that the VSM can only reflect static information and can not present the problems occurring in workshop production in real time. And improvement plans based on the VSM can only be reflected on the future VSM, and we do not know whether these plans match actual production and can not show the complexity and dynamic behavior of the production process [4]. In the current research, Huang et al. [5] used BS-CONWIP (base stock CONWIP control strategy) as the production control strategy in combination with VSM and simulation experiment and used genetic algorithm to optimize buffer capacity to improve on-board panel workshop. Yanhong et al. [6] combined simulation technology to verify the effectiveness of BS-CONWIP in multiple manufacturing environments. VSM is mainly used to analyze value streams within an organization in industrial engineering. Ma et al. [7] combined VSM with the Lean Six Sigma method to reflect the impact of lean thinking on cost savings in manufacturing. FlexSim software is also used in the technical aspect. Punna Rao et al. [8] combined VSM through method and time study and also used FlexSim software to simulate the time study of current and future state. Aziz et al. [9] studied the integration of discrete event simulation (DES) and VSM. However, in order to facilitate the study, some variables are ignored, and more in-depth studies can be done. Besides, the hybrid DES-VSM method ensures that an integrated process optimization method is used. Guo et al. showed how the process of the service system in a pharmaceutical facility could achieve the minimum queue time [10] and listed four scenarios which were simulated with FlexSim software to reduce the time and increase the number of prescriptions provided. In their research [11], Jeong and Phillips developed and demonstrated a concept development process (CDP) as a framework to solve process layout optimization problems related to VSM. CDP and SCLI are very practice-oriented because they do not require any complex analytical knowledge. FlexSim software is also used for improvement through industrial engineering methods, mainly reducing production and environmental improvements.

2.2. Simulation Technology. Visualization simulation technology is a technical means to change the digital information in simulation into intuitive, graphic, and image representation, and to present the simulation process changing with time and space. With the development of system simulation and computer technology, it has become an important technical branch in the field of simulation, which attracts people's attention and develops rapidly [12]. Generally speaking, the current three-dimensional simulation modeling is a one-time realization of modeling, so in order to reduce the operation of redrawing and importing, half of
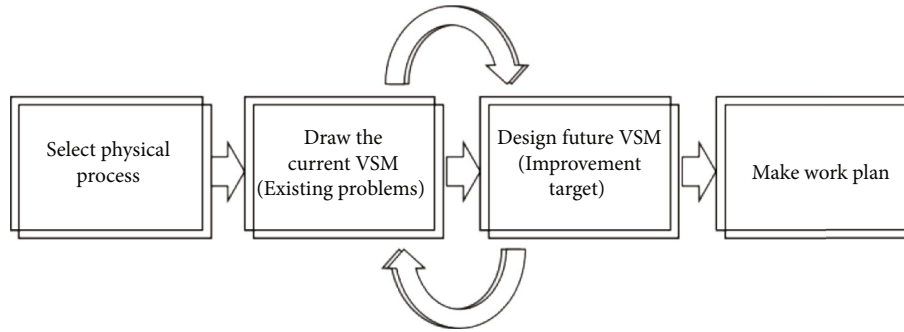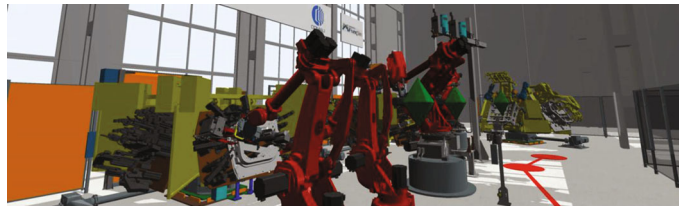
FIGURE 1: VSM design process.

FIGURE 2: FlexSim simulation model (propaganda map of FlexSim software official website).

the simulation software will be assembled using the model with component library. At the same time, in order to consider the real time and fidelity of simulation technology, a compromise between the two needs to be adopted in the design, seeking various help in software and hardware. Simulation software, in fact, has great guiding significance for the discrete system manufacturing industry. Schriber and others [13] discussed simulation software such as AutoMod, SLX, ExtendSim, Simio, Arena, ProModel, and GPSS/H to illustrate the entity, resources, control elements and operation, simulation operation, entity status, and list of entities, and their general management ideas are implemented in AutoMod, SLX, ExtendSim, and Simio.

2.3. Visual Inspection

(1) At present, there are three commonly used methods for single-board UV quality inspection, namely, manual inspection, sensor inspection, and machine vision inspection. For examples, Ryu et al. [14] put the geometric features of wood surface defects into multilayer perceptors, and the correct rate of defect classification and recognition reached 84%. Karsulovic et al. [15] used ultrasound to identify wood joints, growth rings, textures, etc. The recognition results are consistent with visual judgment results. Guo et al. [16] take local threshold segmentation and global visual significance as defect segmentation methods, extract texture features such as gray level cooccurrence matrix and local binary mode of defect image, and then classify and identify defects using a support vector machine based on manifold. The final experimental accuracy rate is 91.67%. Hu performs superpixel segmentation on the real wood floor image and uses the improved random forest model

to sort the real wood floor, and the average execution time of this sorting system is 0.4 s, which provides the technical basis for online detection of real wood floor [17]. Note that we have adopted the method of random sampling to improve the random forest model, which effectively improves the generalization ability of the model

(2) Traditional thickness detection methods are very backward. They usually relying on workers to use Vernier calipers or micrometers for off-line contact detection of thickness, but their efficiency is low and affected by production conditions. Therefore, manufacturers turn their eyes to noncontact detection devices one after another. At this time, y-ray, laser, optical, ultrasonic, microwave, infrared, and other methods are commonly used and mature in the artificial panel detection devices for thickness detection [18]. These devices enable continuous and noncontact thickness measurements with the advantages of high precision and fast speed. However, sensors for noncontact detection are expensive, and dust and wood chips and thickness greatly affect detection accuracy during the detection process. Li et al. [19] proposed a glass thickness detection algorithm based on the moment invariant algorithm. We refer to ResNet here to classify the qualified and unqualified board thicknesses. ResNet uses the residual module to realize the deep network

3. Model Framework

As shown in Figure 3, in view of the problems existing in the improvement of the side panel production line for drawers, we first draw a current VSM and analyze the production process of the side panel. Through the VSM analysis, we found
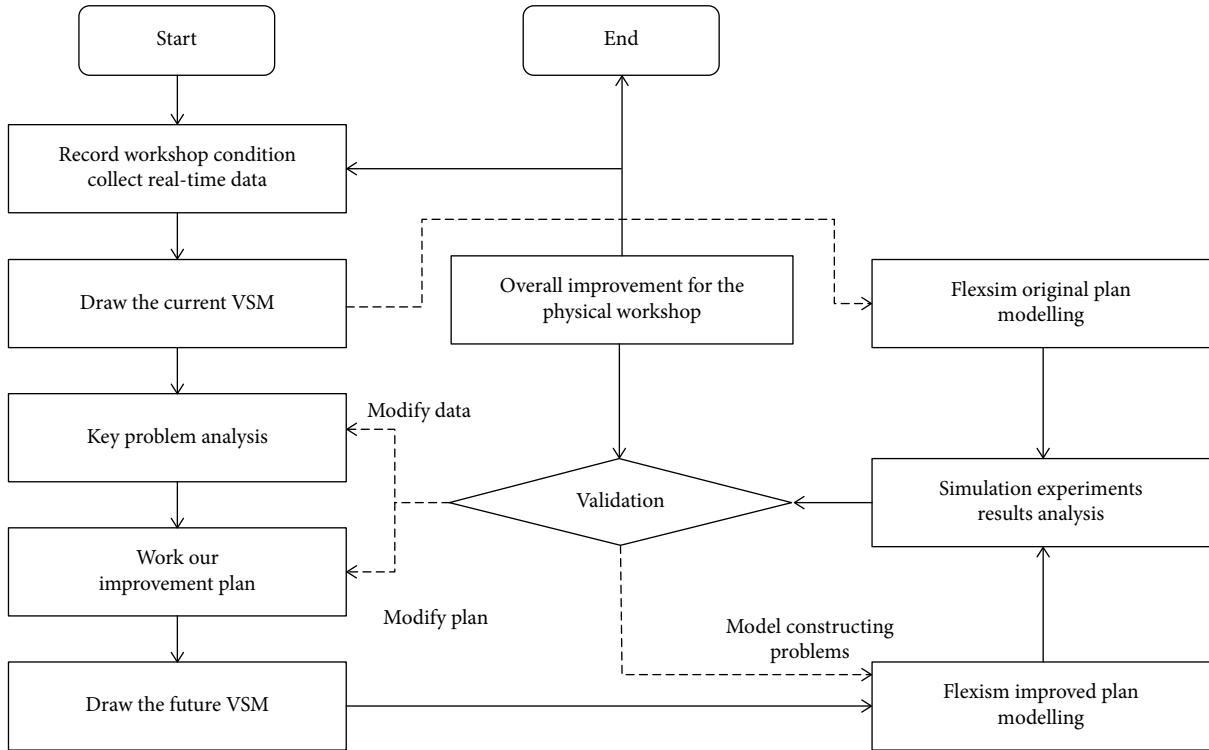
FIGURE 3: Lean improvement model for wood drawer side panel processing line optimized by simulation.
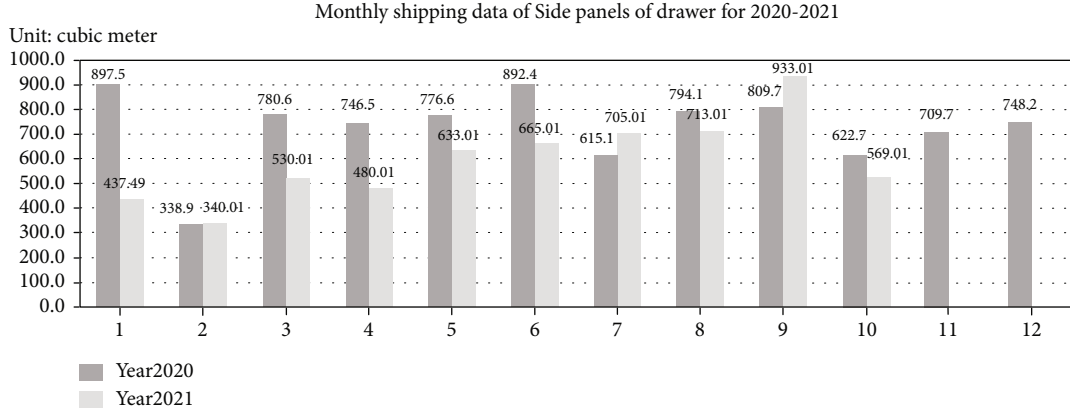

FIGURE 4: Monthly customer demand of drawer panel statistical table for 2020-2021.

out the root causes of the existing production line problems and formulated improvement measures. Then, we optimize and restructure the production process and draw the future state map of the value stream to achieve lean improvement and reduce waste. At the same time, we established FlexSim models of foundry workshops before and after improvement according to the current and future state maps of VSM. Next, we will make a comparison between the before and after validation to see if the optimization goal we set at the beginning has been achieved. If not, we will check the process in which the validation found the problem. If required, the workshop model can be exported. Finally, process optimization can be carried out on the actual workshop according to the virtual workshop. Through the continuous circulation of such process, we can finally iterate out a satisfactory optimized workshop.

3.1. Pilot Selection. Through on-site inspection of the production line and according to the process analysis value stream, the improvement of the production line is mainly based on pull-type. The suitable work-in-process capacity and supermarket system are determined, and the unreasonable equipment and personnel on the production line are laid out to solve the problems of large material handling volume, improper staffing of key processes, and unbalanced production.

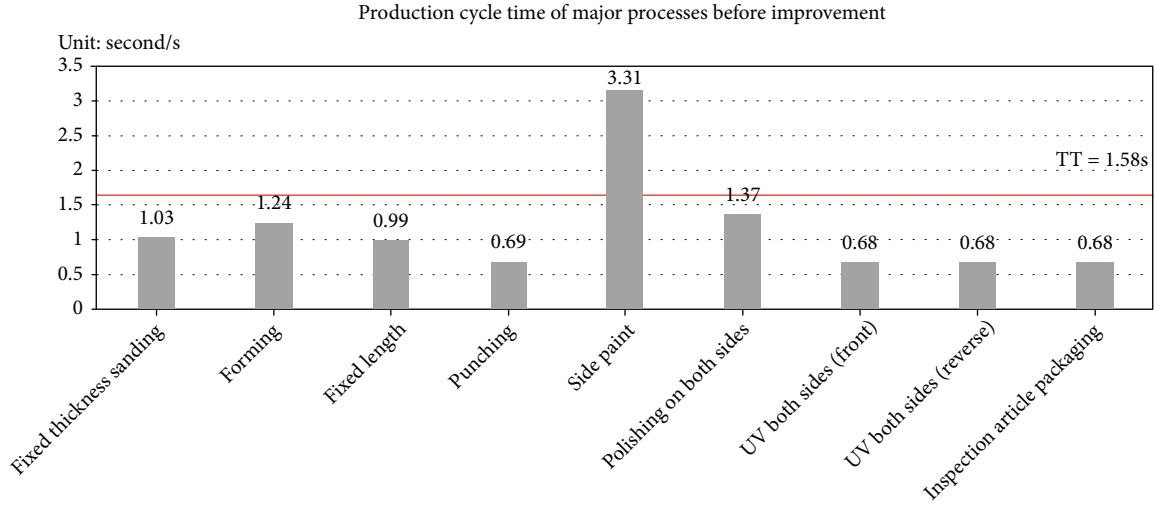Production cycle time of major processes before improvement

FIGURE 5: Production cycle time of major processes before improvement (TT = 1.58 is the industry standard, a value below that indicates a premium level of production speed).

Through field investigation on the production situation of the whole wood processing workshop, it is found that there are a lot of production problems in the drawer side panel production line, which affects the processing and manufacturing of the whole enterprise. With the increase of customer demand, it is difficult to fulfill the order demand gradually. Therefore, we selected the side panel processing line for drawers as the main target for lean improvement.

3.2. Mapping the Current Value Stream

3.2.1. Analysis of Production Status. Key data are acquired based on customer order information. To ensure data reliability, interviews are conducted and validated by department managers to obtain production plan control and information flow data. These data mainly include customer demand of products and relevant information of production processes. Considering the Sino-US trade war in 2019 and the impact of the pandemic from 2020 to the present, this paper only takes into account the customer order requirements of the company in 2021, as shown in Figure 4.

Shipments from January to June, 2020 are 4432 cubic meters and 3085 cubic meters from January to June, 2021, with a 30.39% drop in shipments; 4299.5 cubic meters from July to December, 2020, 2920 cubic meters from July to October, 2021, with lost orders from U.S. customers, and there were no orders from November to December 2021. The formulas for average demand and demand production takt are shown below:

$$MD = \frac{YD}{12}, \tag{1}$$

$$DD = \frac{MD}{22}, \tag{2}$$

$$TT = \frac{Daily\,Working\,Time}{DD}. \tag{3}$$

MD is the monthly average customer demand, DD is the daily average customer demand, and TT is the production task according to customer demand.

According to the formula, the monthly average customer demand (MD) reached 614.06 cubic meters, and the average daily demand (DD) reached 27.9 cubic meters. According to the customer's daily demand (DD), the production takt time was calculated to be 1.58 seconds.

3.2.2. Overview of Drawer Side Panel Production Workshop. The drawer production workshop works 22 days a month, using a double shift system with one shift being 8 hours. The actual production capacity of the current workshop without overtime is 292.60 cubic meters per month and 13.30 cubic meters per day. According to the customer's order demand, without considering customization and according to the customer demand volume from 2020 to 2021, combined with the average demand calculation formula, the customer's monthly average demand (MD) for drawer boards has greatly increased, reaching 614.06 cubic meters monthly; the daily demand (DD) reached 27.91 cubic meters; therefore, the original production is unable to meet customer demand. Other information requested by the client is as follows: the order task is shipped once a month, and each transportation is transported in a 40-foot container, with 54 cubic meters per box. The conventional product specification is 520 length * 92 width * 16 thickness (mm), that is, the volume of 1306 products is 1 cubic meter.

3.2.3. Collect Each Process Information. Figure 5 shows the production cycle of the main processes of the workshop that needs to be improved before improvement. The production line of drawer side panels mainly includes 9 main processes such as thickness-setting sanding and molding. According to the definition of value stream, the production activities of the entire workshop are divided into value-added and non-value-added activities. It can be divided into the following: personnel allocation of each process, single-shift output, equipment working time, equipment quantity, and other primary data. In order to draw the VSM, it is necessary to
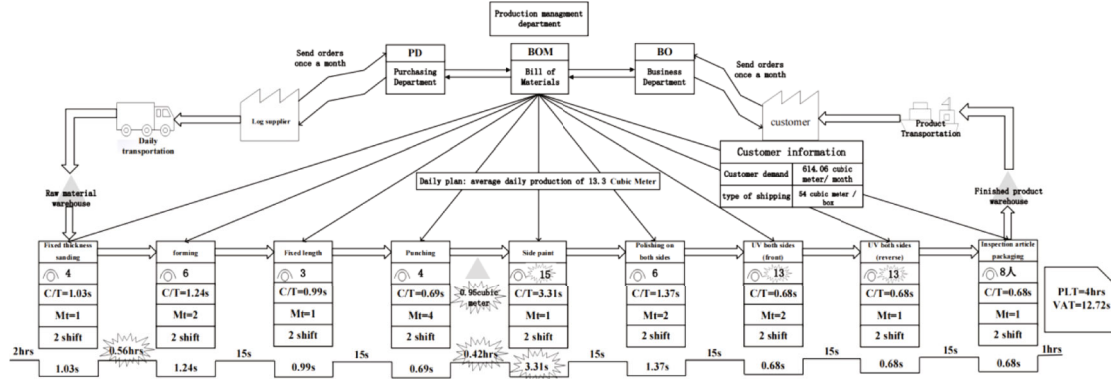
FIGURE 6: Current VSM before improvement (the figure shows the specific details of each step and the time they take, and the arrows indicate the sequence of each step).

use the collected primary data to calculate the secondary data through formulas (4)–(6). The secondary data represents the mapping parameters required by the model.

The mapping parameters required to draw a VSM mainly include the equipment utilization rate, value-added time, and non-value-added time. The specific calculation formula is as follows:

$$U_t = \frac{\text{Actual Production Time}}{\text{Total available Time}}, \tag{4}$$

$$\text{VAT} = \sum_{i=1}^{n} \text{CT}_i, \tag{5}$$

$$\text{PLT} = \sum_{i=1}^{n} \left(\text{CT}_i + \bar{\text{CT}}_i \right). \tag{6}$$

Among them, CT_i refers to the production time of the i process, $\bar{\text{CT}}_i$ refers to the interval time between the i and $i + 1$ processes. After data collection, it can be concluded that the value-added time of the production line is 12.72 seconds, and the sum of the value-added time and non-value-added time of the product is 4 hours.

3.2.4. Drawing the Current VSM. According to the information of each process, the VSM is drawn as shown in Figure 6. Considering that the purpose of status map is to fully visualize the waste in the current production situation by drawing and calculating and the supply of transport lines and filler lines is sufficient, we selected 8 processes in the production line that have a greater impact on the value-added time and carried out VSM analysis. According to the above VSM, it can be seen that the equipment of the entire production line is backward and the production efficiency is low.

3.3. Improvement of ECRS Principles. Based on the analysis of the key data above, we utilize the principle of ECRS (cancel, merge, adjust, and simplify) and analyze the following schemes to improve the production line: process improvement of production line, elimination of bottleneck process (check wood quality), updating equipment, improving tool quality to meet customer personalized customization (adopting wood

thickness), improving employee operation posture, and reducing bending motion. By analyzing the value of the whole production line, the link of benefit waste is analyzed, and the following improvement scheme is put forward in detail.

3.3.1. Bottleneck Process Improvement. For the two processes of forming and lengthening, the equipment used for forming is four-sided planing, which is mainly used for widening and grooving of sanded wood with fixed thickness. The equipment used for fixing the length is double-end milling, with the main purpose being setting the length at both ends. Four and six people are needed for the original two processes, respectively, and only one person in each process is responsible for production, i.e., value-added activities and the non-value-added activities for intermediate feeding need 0.56 hrs. According to the principle of merging improvement in ECRS principle, we merge two processes, two four-sided planers plus feeding device, and adopt double-end milling connection in the end feeding. Through this improvement, only three people are needed in the two processes.

For the drilling procedure, we have improved the original single-row drilling equipment. Single-row drilling equipment is responsible for perforating 3 rows of holes in the product. Half of the 20 cubic meters of single shift output need to be perforated repeatedly, which will lead to inventory accumulation and low equipment utilization. According to the principle of simplified equipment improvement in the ECRS principle, we adopted automatic multirow drilling, which changed the original equipment that had to repeat perforation many times into automatic feeding and one-step forming and adjusted the staffing from 4 to 2.

For the side painting process, the original equipment was the paint line, requiring 15 employees to perform the following processes: spray primer-air dry-grind-spray primer-air dry-grind-spray finish-air dry-shelf. These complex procedures result in inconsistency between the upstream and downstream procedures. According to the eliminate and compile principles of ECRS, the vacuum UV line is used to improve the original multipass painting process to one-step forming after vacuum UV process, which is not only environmentally friendly but also cost-effective. Because of the reduced process, the original 15 people were also reduced to 3.
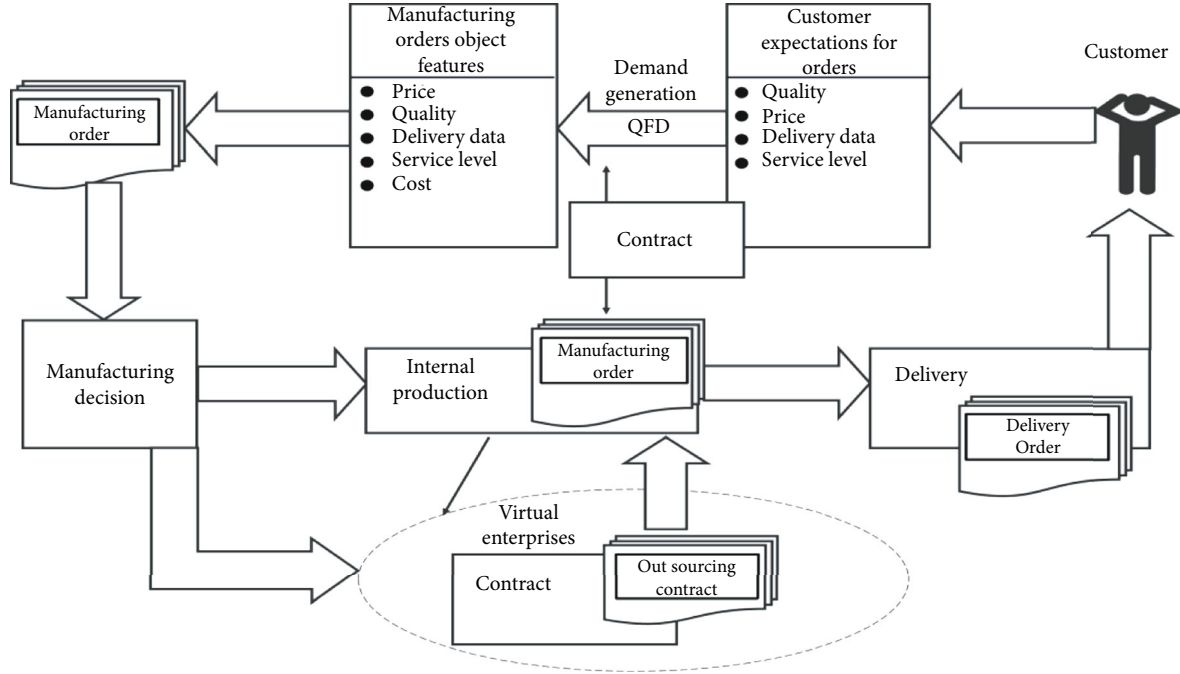
FIGURE 7: Production planning and order operation system model based on supply chain management.

TABLE 1: Description of network structure parameters for MobileNetv2.

Input	Operator	T	C	N	S
224 * 224 * 3	Conv2d		32	1	2
112 * 112 * 32	Bottleneck	1	16	1	1
112 * 112 * 16	Bottleneck	6	24	2	2
56 * 56 * 24	Bottleneck	6	32	3	2
28 * 28 * 32	Bottleneck	6	64	4	2
14 * 14 * 64	Bottleneck	6	96	3	1
14 * 14 * 96	Bottleneck	6	160	3	2
7 * 7 * 160	Bottleneck	6	320	1	1
7 * 7 * 320	Conv2d 1 * 1	—	1280	1	1
7 * 7 * 1280	Avgpool 1 * 7	—	—	1	—
1 * 1 * 1280	Conv2d 1 * 1	—	k	—	—

For two-sided polishing, two sets of sanders were originally used for fine polishing on both sides of the product to facilitate the next UV process. Replacing one-sided sanders with two-sided sanders, according to the compile principle in ECRS principle, saves one sander and supporting operators.

3.3.2. Non-Value-Added Time Improvement. We analyzed the temporary storage area of the production line according to the current VSM and found that the temporary storage area was set from fixed thickness sander, four-sided planing, and double-end milling. However, in practice, there is the possibility of realizing process linkage in these three processes. Our goal is to ensure that the number of semifinished

products produced per minute is the same, i.e., the synchronization of production lines. At the same time, the inspection of raw materials before the first procedure, without relevant equipment in the workshop, requires manual inspection. Through a comprehensive and innovative planning of the supply process, this part of the treatment is passed on to the supplier. With the supplier processing, the production activities can, therefore, be quickly organized based on the actual dynamic demand of the current market [20].

Considering that the processing speed of punching in the later process is still slower than that of the first three processes, after these three processes, tray code package is carried out to establish a semifinished supermarket. Priority is given to the storage of some semifinished products. After start-up, the UV line can be started as long as the preheating is completed without waiting for the upstream process to pack and deliver the semifinished products, thus shortening the inventory level of the upstream process and improving the order cycle [21]. At the same time, the production plan and order operation system model associated with the supplier, customer, and order is established, forming pull-type production oriented to customer demand and realizing flexible restriction of production, production schedule adjustment, and production capacity restriction. From user order input to order completion, all departments revolve around order operation, demonstrating the integrated enterprise thought of vertical and horizontal integration: horizontal order-driven pull-type production and vertical resource-constrained production control. The specific model is shown in Figure 7.

3.4. Quality and Thickness Detection Model of Board. Wood quality inspections are two important link in side panel

(a)   (b)

FIGURE 8: Unqualified (a) and qualified (b) UV surfaces.

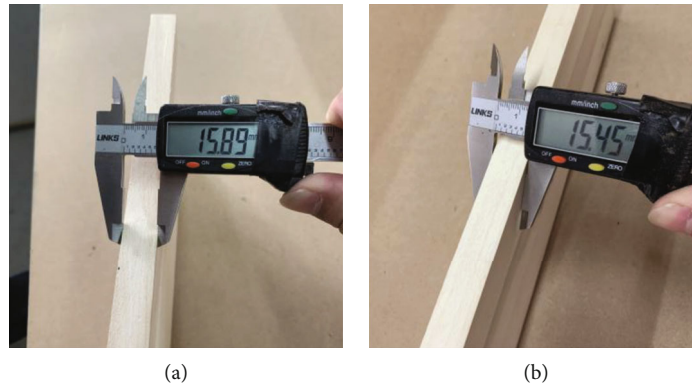(a)   (b)

FIGURE 9: Qualified thickness (a). Unqualified thickness (b).

production, but manual screening is easy to misjudge and time-consuming. In order to realize automatic inspection of wood surface quality and wood thickness, we established in-depth learning models for both.

(1) In order to detect wood surface quality, we introduced convolution neural network for identification processing. Here, we use MobileNetv2, which has the advantage of highly movable model and high performance. Table 1 illustrates the network structure settings of our model. Input refers to the characteristic input scale of the layer, operator refers to the operation of the layer, T refers to the expansion index, C refers to the output dimension, N refers to the number of repetitions, and S refers to the step

We randomly divided 1000 datasets collected from the factory into training, test, and validation sets at 8 : 1 : 1. First, we used image enhancement on the dataset, as shown in Figure 8. Then, we use MobileNetv2 to capture the picture features. Finally, we use the Softmax classifier to process the acquired features to get the probability of image classification. After cross-validation, the current accuracy rate is 96.875%, which can meet the requirements of the task.

(2) In order to detect the thickness of wood and achieve automatic tool selection, we refer to ResNet here to classify the qualified and unqualified wood board thickness, as shown in Figure 9. ResNet implements

a deep network using the residual module, which is more robust than traditional deep networks. As the neural network gets deeper, the correlation between the returned gradients gets worse and worse and finally approaches the white noise, making the depth of the neural network meaningless. Since images are locally correlated, it can be assumed that gradients should have similar correlations, so updating gradients with residual modules makes sense. ResNet learns from residuals and passes features prior to the previous activation function through an identical connection to the output of this calculation, with their sum as the output of the cost layer. Then, the whole network is followed by a Softmax classifier, which classifies it into normal thickness and abnormal thickness, completing an effective classification. Specifically, our ResNet structure settings are shown in Table 2

4. Experiment

4.1. Data Sources. In this study, the quality control in wood processing is mainly the quality detection of wood thickness and brightness. We take pictures on the spot according to the workshop and select more shooting angles to ensure more accurate results of training detection. It is divided into self-made CNN datasets made after evaluation, mainly wood thickness datasets, including 500 eligible thickness picture

TABLE 2: Description of ResNet's structure parameters.

Layer name	Outputs size	34-layers
Conv1	112 ∗ 112	7 ∗ 7, 64 stride 2
		3 ∗ 3 max pool, stride 2
Conv2.x	56 ∗ 56	$3 \times \begin{cases} 3*3, 64 \\ 3*3, 64 \end{cases}$
Conv3.x	14 ∗ 14	$4 \times \begin{cases} 3*3, 128 \\ 3*3, 128 \end{cases}$
Conv4.x	7 ∗ 7	$6 \times \begin{cases} 3*3, 256 \\ 3*3, 256 \end{cases}$
Conv5.x	1 ∗ 1	$3 \times \begin{cases} 3*3, 512 \\ 3*3, 512 \end{cases}$

TABLE 3: Testing results of wood quality.

	Ours	Model A	Model B
AUC	97.78%	84%	91.67%
Recall	99.62%	—	—
F1-score	98.2%	—	—
Precision	96.875%	—	—

TABLE 4: Testing results of wood quality.

	Ours	Model A	Model B
AUC	99.61%	74%	98%
Recall	99.24%	—	—
F1-score	99.61%	—	—
Precision	100%	—	—

TABLE 5: Model performance after improving training strategy.

Parameters	Accuracy rate
Baseline	99.61%
+cosine decay	99.77%
+label smoothing	98.79%
+mixup	98.76%

datasets and 500 unqualified thickness picture datasets. Label is also used for image labeling of thickness datasets, which can be used as additional data to detect the position of the board in the training of a neural network. Another dataset is the wood paint surface dataset, which includes 500 qualified picture datasets and 500 unqualified picture datasets. Both datasets were acquired by the participants during field shooting in the workshop. Of the two datasets, 80% were used for training and 20% for testing. The number of experiments was the same and was performed under the same experimental conditions. Personal PC (Intel(R) Core(TM) i5-8300H CPU @ 2.30 GHz) repeats the experiment 30 times and takes the average value.

4.2. Evaluation Index

4.2.1. Product Value-Added Rate.
Product value-added rate is an important indicator to measure the processing efficiency of production line. By comparing product value-added time with non-value-added time, we can find relevant data to reflect the production mode and time utilization rate of production line; map the value generated for the layout of production line, the configuration of personnel, and the storage of material filling temporary storage area; and identify the waste problem. The formula for calculating the product value-added rate is as follows:

$$PCE = \frac{VAT}{PLT} \times 100\%. \tag{7}$$

According to the current VSM, the product value-added rate is 0.08%, which indicates that the actual value-added time used in the production line is very short. Due to the long preparation time in wood side panel processing, improper material filling and handling arrangements lead to long waiting time of equipment and large storage of line materials. Although UV line production needs to be warmed up for more than one hour in advance, the processing speed is far ahead of the first 6 procedures, which will cause inconsistency between downstream production and downstream production. At the same time, most personnel arrange non-value-added links such as feeding, discharging, and handling materials. This will result in many downstream processes being on standby when the material does not arrive, leading to a lot of waste.

4.2.2. Balance Rate of Production Line.
As an index to measure the leanness and performance of production line, the production balance rate reflects whether the time load of each process is uniform in the whole process. The higher the balance rate of production line is, the waiting time between processes is less and the non-value-added time in the process is less. The formula for calculating the balance ratio of the production line is as follows:

$$LOB = \frac{\sum_{i=1}^{n} CT_i}{n \times CT_{max} n}. \tag{8}$$

The total value-added time of the product is 12.72 seconds, and there are 9 processes in total. Among them, two process exceeds the takt, and the bottleneck process is the side paint. Not only the production cycle is long but also 15 employees are required to carry out the following processes in this process: primer spraying-drying-polishing-primer spraying-drying-polishing-topcoat spraying-drying-shelf, and the weather factor should also be considered.

According to the formula, the balance rate of the production line is only 42.76%. The production cycle of each process is too different, and the imbalance problem is obvious. At the same time, due to the problems of the equipment itself, it takes 1-2 hours to adjust the machine for production when the customer needs to develop new samples. In addition, the bottleneck process needs to be improved urgently due to the long waiting time of materials and a serious waste of personnel.
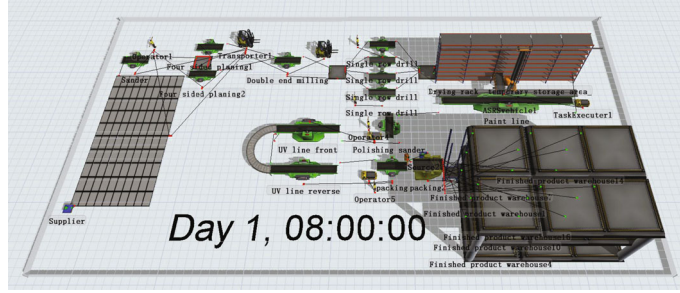
FIGURE 10: FlexSim model of the production process of drawer side panel workshop before improvement.

4.2.3. Image Classification Error Rate.
The AUC calculation is shown in

$$\text{AUC} = \frac{\sum_{\text{ins}_i \in P\text{class}} \text{rank}_{\text{ins}_i} - (M * (M + 1))/2}{M * N}, \quad (9)$$

where the serial number representing the i sample is the $\text{rank}_{\text{ins}_i}$; M, N are number of positive samples and negative samples, respectively; $\sum \text{ins}_i \in P\text{class}$ indicates that only the serial numbers positive sample are added together.

4.3. Experimental Results.
Model A is a laser-based method to calibrate the distance between upper and lower laser sensors by static and dynamic noncontact measurements of the thickness of manmade panel using two laser sensors. Model B is a thickness detection method based on machine vision. Through image gray level processing, perspective correction, sliding plate image filtering, and sliding plate image enhancement processing, image preprocessing is completed for sliding plate images taken in laboratory environment. An image tracking method is proposed for edge detection and morphological open-close operation of sliding plate image to extract and locate the edge of sliding plate and calculate the minimum thickness of sliding plate.

Model A is a thickness detection method based on laser with two laser sensors being used to carry out static and dynamic noncontact measurement experiments on an artificial panel thickness. A calibration method for distance between the upper and lower laser sensors is proposed.

Model B is a thickness detection method based on machine vision. Through gray processing, perspective correction, skateboard image filtering, and skateboard image enhancement processing of skateboard pictures taken in the laboratory environment, image preprocessing is completed. It is proposed that after edge detection and morphological on-off operation of skateboard image, image tracking is used to extract and locate skateboard edges, and the minimum skateboard thickness is calculated. Tables 3 and 4 shows the testing results of wood quality.

Through the experimental results, we can find that our model achieves more than 90% performance on multiple indicators and has higher accuracy than Model A and Model B, which indicates the validity of our experimental model. In addition, to verify the validity of our model parameters, we also explored the effect of different training strategies on the convergence speed of the wood thickness detection model.

(1) The learning rate decay strategy uses cosine function. The diagram of learning rate change with epoch is similar to cos, as shown in

$$\text{new}_{\text{lr}} = \text{eta}_{\text{min}} + 0.5 * (\text{initial}_{\text{lr}} - \text{eta}_{\text{min}}) * \left(1 + \cos\left(\frac{\text{epoch}}{T_{\text{max}}} * \pi\right)\right)$$

$$(10)$$

(2) Label smoothing softens the label of one-hot type that was commonly used in the past, so that it can reduce overfitting to some extent when calculating the loss value

(3) Mixup is a data enhancement method. If mixup training is used, then two input images are read at a time; assuming that they are represented by (x_i, y_i) and (x_j, y_j), then a new image can be synthesized by the following two formulas, and this new image can be used for training as follows:

(i) $x = \lambda x_i + (1 - \lambda)x_j$ where x_i, x_j are the raw input vectors,

(ii) $y = \lambda y_i + (1 - \lambda)y_j$ where y_i, y_j are one-hot label encodings

Note that all the experiments, except the above improvements, remain the same settings and are trained on NVIDIA V100. Table 5 shows the model performance after improving training strategy.

5. Summary and Discussion

5.1. Modeling Simulation Lean Model.
According to the improvement scheme, the FlexSim simulation model of the side panel workshop of the drawer before improvement which is shown in Figure 10 (unit time in seconds) should be improved. In the process of modeling, the required modules are selected first, and the raw materials are supplied to the required feeding process with the generator. Key processes in the production line are completed with a processor. Considering the production bottleneck in the original process, the temporary storage area is set before length fixing,
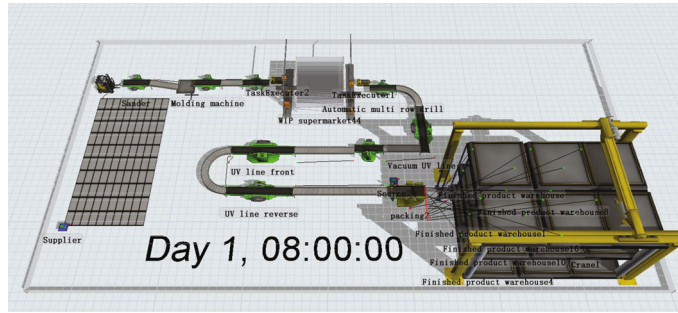
Figure 11: Improved FlexSim model of the production process of drawer side panel workshop.
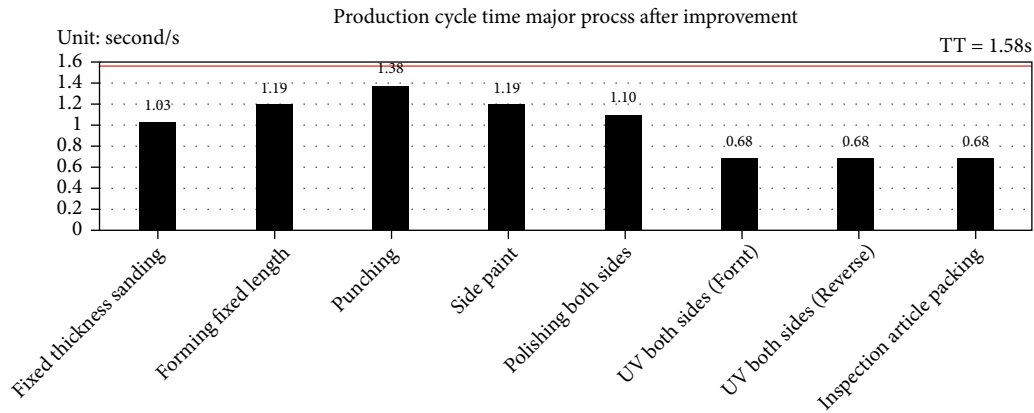

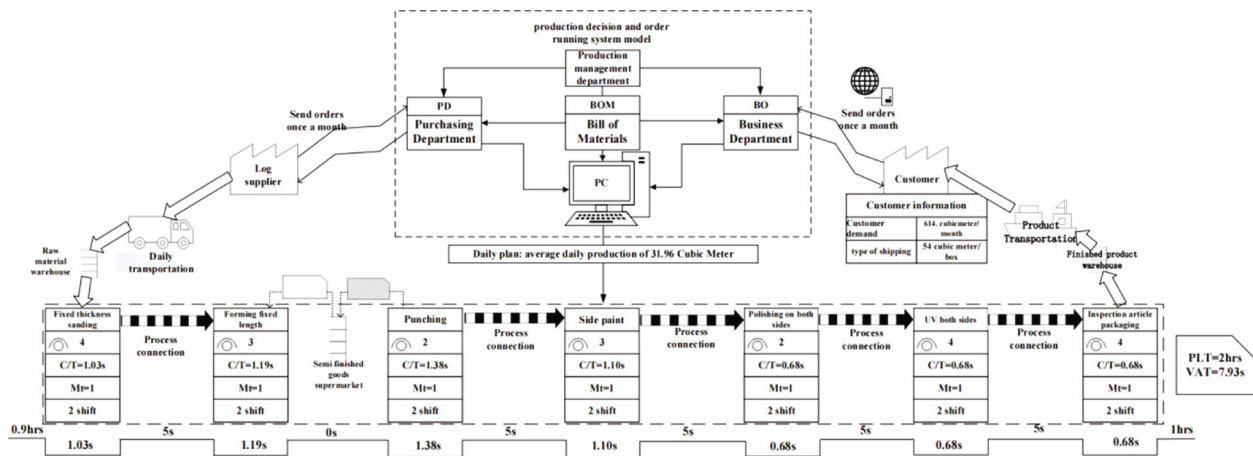Figure 12: Production cycle time of main process after improvement.

Figure 13: Future VSM with improvement.

punching, and side painting process. Finally, the corresponding means of transport is selected, or connecting each process directly. To simplify the model and reduce runtime, operators are not allocated in the model.

The FlexSim simulation model of the production process of the drawer side panel workshop, which is built according to the improved scheme, is shown in Figure 11 (unit time in seconds).

5.2. Drawing the Future VSM. According to the improvement plan and FlexSim simulation model made by specific analysis, the future VSM is shown in Figure 12.

According to the above simulation model and improvement plan, we draw the future of VSM. After improvement, 37 employees were reduced, 4 single-row drills are changed to 1 automatic multirow drills, and 2 single-sided sanders to 1 double-sided sander. For the improvement of the
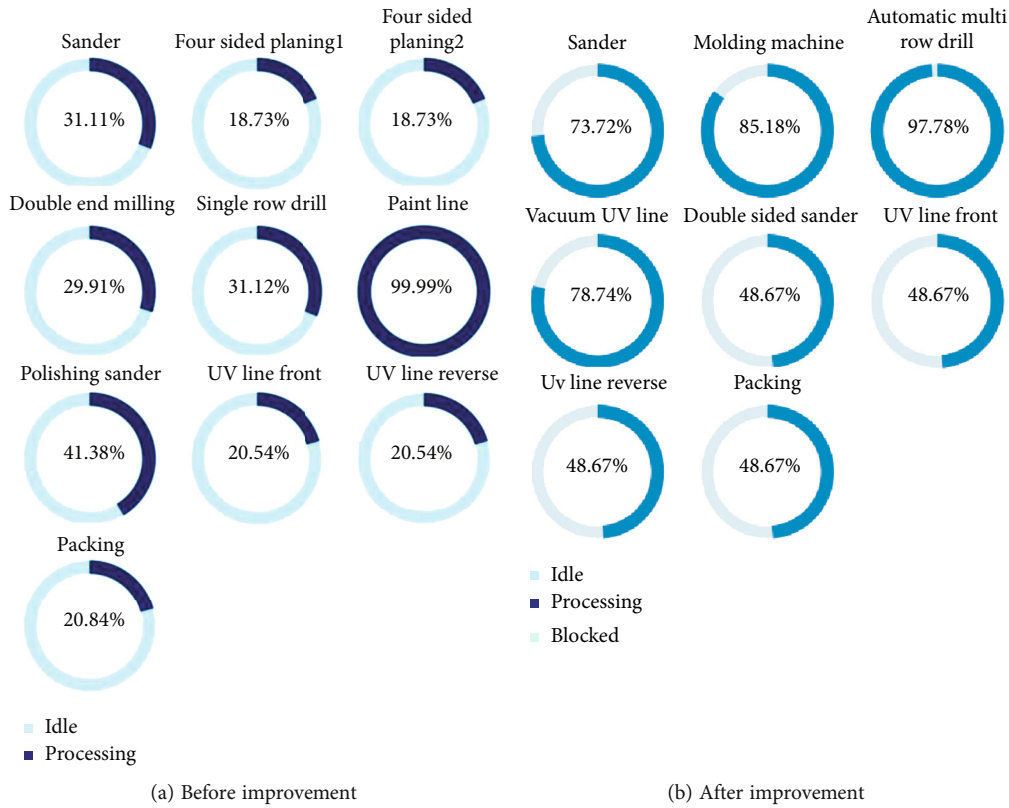
Figure 14: Pie chart of utilization ratio of main process equipment in drawer side panel production.

bottleneck process, the production time of each process is made less than the takt time, and the balance rate of production line changes from 42.76% to 71.83%. The product value-added rate has been increased from 0.08% to 0.11%. The monthly production volume of products has changed from 292.60 cubic meters/month to 703.10 square/month. The production cycle of the improved main processes is shown in Figure 13.

5.3. Simulation Lean Model Analysis. The FlexSim model is run to compare the equipment utilization rate of production line before improvement. The results are shown in the figure. It can be seen from Figure 14(a) that before improvement, the overall workshop production balance is low and the main reasons are the bottleneck process and equipment failure. The highest utilization of paint line equipment as a bottleneck process also means that equipment burden is high and are prone to equipment failures. Secondly, although the processing cycle of single-disc drilling exceeds the production takt, four single-row drills are running due to the production process considerations in the workshop, which leads to the low utilization of the overall equipment, and one equipment is basically idle. Other processes are affected by bottleneck processes and equipment utilization is low for a long time. In addition, the equipment is idle due to the low product value-added rate caused by manual transportation and packing as well as preheating of the equipment. As shown in Figure 14(b), the overall utilization of the improved equipment has been increased, with the highest utilization being achieved in the perforation process

that is closest to the production pace. After forming and length synthesis, the utilization ratio of overall equipment has been improved a lot, and after two Sanders are combined into one double-sided sander, the utilization ratio of equipment has also been improved. Besides, after replacing the vacuum UV line of equipment, the overall equipment utilization of the original high-load paint line is eased down. The utilization ratio of adjacent production equipment is similar, which improves the stability and continuity of the whole production process, reduces blockage, and smoothens interval of the whole production line.

5.4. Summary and Discussion. In this paper, the drawer side panel processing workshop is selected, and the digital twin technology is introduced to carry out the lean improvement and simulation analysis research of this production line. Firstly, the basic product information of the workshop is collected and the current VSM is drawn. Through the value flow chart and the ECRS principle, the existing waste problems are analyzed, and the improvement plan is put forward in light of the key problems. In order to verify the objectivity and reliability of the improvement plan, a simulation model of the drawer side panel processing workshop based on Flex-Sim software is established. Finally, the improvement plan is determined according to the operation results of the simulation model and the future VSM was drawn. The research shows that the combination of VSM and simulation model technology based on digital twin technology boasts certain guiding significance and reference value for improvement of the manufacturing industry.

However, this paper only uses the concept of digital twin for reference, and the establishment of the model does not fully meet the requirements and level of digital twin technology. At the same time, there is still room for research on the optimization of workshop logistics handling route and on-site customization improvement. Relevant intelligent algorithms can be considered to verify the simulation optimization, which is also the optional direction in the future.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

References

[1] L. Tian, G. Liu, and S. C. Liu, "Digital twin and production line simulation technology," *Journal of Graphics*, vol. 42, no. 3, pp. 349–358, 2021.

[2] Siemes, "Digital twin - driving business value throughout the building life cycle," [2020-12-28].https://new.siemens.com /global/en/products/buildings/contact/digital-twin. html.

[3] H. Guo, X. Lian, Y. Zhang et al., "Analysis of environmental policy's impact on remanufacturing decision under the effect of green network using differential game model," *IEEE Access*, vol. 8, pp. 115251–115262, 2020.

[4] Y. H. Lian and H. V. Landeghem, "Analysing the effects of lean manufacturing using a value stream mapping-based simulation generator," *International Journal of Production Research*, vol. 45, no. 13, pp. 3037–3058, 2007.

[5] X. B. Huang, L. Y. Gong, and L. X. Yang, "Study on automotive back door panel injection molding process simulation and process parameter optimization," *Manufacturing Engineering*, vol. 2021, article 9996423, pp. 1–15, 2021.

[6] W. Yanhong, H. Junxia, T. Yuanyuan, T. Zhongda, and Z. Jun, "A modified CONWIP production control strategy for lamp production line," in *2018Chinese Control And Decision Conference (CCDC)*, pp. 3916–3921, Shenyang, China, 2018.

[7] J. Ma, H. Chen, Y. Zhang et al., "A digital twin-driven production management system for production workshop," *International journal of Advanced manufacturing technology*, vol. 110, no. 5-6, pp. 1385–1397, 2020.

[8] G. V. Punna Rao, S. Nallusamy, and P. Raman, "Enhancement of production in subassembly line of a medium scale industry using different lean tools and FlexSim simulation software," *International Journal of Engineering Research in Africa*, vol. 44, pp. 229–239, 2019.

[9] Z. Aziz, R. M. Qasim, and S. Wajdi, "Improving productivity of road surfacing operations using value stream mapping and discrete event simulation," *Construction Innovation*, vol. 17, no. 3, pp. 294–323, 2016.

[10] H. Guo, L. Zhang, Y. Zhang et al., "A differential game-based approach for school-enterprise collaborative R&D strategy on digital twin technology," *IEEE Access*, vol. 8, pp. 188688–188698, 2020.

[11] K. Y. Jeong and D. T. Phillips, "Application of a concept development process to evaluate process layout designs using value stream mapping and simulation," *Journal of Industrial Engineering and Management (JIEM)*, vol. 4, no. 2, pp. 206–230, 2011.

[12] F. J. Kang, X. Hua, H. H. Li, B. Zhang, and M. Su, "Overview of development of visualization simulation technology," *Journal of System Simulation*, vol. 21, no. 17, pp. 5310–5313, 2009.

[13] T. J. Schriber, D. T. Brunner, and J. S. Smith, "Inside discrete-event simulation software: how it works and why it matters," in *2013 Winter Simulations Conference (WSC)*, pp. 424–438, Washington, DC, USA, 2013.

[14] C. Ryu, S. G. Kong, and H. Kim, "Enhancement of feature extraction for low-quality fingerprint images using stochastic resonance," *Pattern Recognition Letters*, vol. 32, no. 2, pp. 107–113, 2011.

[15] J. T. Karsulovic, L. A. León, and L. Gaete, "Ultrasonic detection of knots and annual ring orientation in Pinusradiata Iumber," *Wood and Fiber Science*, vol. 32, no. 3, pp. 278–286, 2020.

[16] H. Guo, Y. Zhu, Y. Zhang, Y. Ren, M. Chen, and R. Zhang, "A digital twin-based layout optimization method for discrete manufacturing workshop," *The International Journal of Advanced Manufacturing Technology*, vol. 112, no. 5-6, pp. 1307–1318, 2021.

[17] J. F. Hu, *Research on Technology of Solid Wood Floor Sorting Based on Machine Vision*, Northeast Forestry University, 2015.

[18] G. Wang and D. Li, "Development of automatic detection technology for artificial wood panel thickness," *Forestry Machinery &Woodworking Equipment*, vol. 4, pp. 4–6, 1999.

[19] J. X. Li, H. L. Lin, B. Yu, W. Chen, C. H. Lin, and S. T. Huang, "Machine vision-based non-congeneric product detection algorithm for vehicle quarter glass," *Journal of Fujian University of Technology*, vol. 19, no. 3, pp. 223–229, 2021.

[20] H. Guo, M. Chen, K. Mohamed, T. Qu, S. Wang, and J. Li, "A digital twin-based flexible cellular manufacturing for optimization of air conditioner line," *Journal of Manufacturing Systems*, vol. 58, pp. 65–78, 2021.

[21] H. Guo, M. Chen, R. Zhang et al., "Research on improvement of truck vibration based on systematic G8D method," *Shock and Vibration*, vol. 2019, Article ID 1416340, 11 pages, 2019.