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Research Article

A Textile Manufacturing Information System with Exponential Smoothing Method

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Abstract: The traditional textile industry is characterized by a discrete production pattern, because the manufacturing workshop and equipment are quite old, and the level of information construction is low. To assist textile enterprises in improving the construction of informatization, the utilization of production data, and production management efficiency, the textile manufacturing information system must strengthen data integration. In this paper, a textile manufacturing information system with the exponential smoothing method is proposed. The proposed textile manufacturing information system is to assist managers in making decisions, analyzing data, and providing a convenient platform for sharing information. It uses MySQL and MongoDB dual databases as data storage and uses Apache servers as web services. The front end uses Echarts technology to complete the data visualization. According to the shortcomings in its production management process, the following modules are designed around the needs of the enterprise: production management, equipment management, employee management, statistical information, and basic information maintenance. It also connects with the front-end data acquisition system and presents the data in a visual form to achieve real-time data monitoring of production. Furthermore, the proposed information system uses a single exponential smoothing method to predict production. From the experimental results, the single exponential smoothing method can well predict the trend of textile production output in a short term, and the results are more accurate than other approaches.

***Keywords*:** textile manufacturing information system, textile enterprise, information system, exponential smoothing method

1. Introduction

The textile industry mainly originated in the United Kingdom, and then transferred to Europe and the United States, so the research on textile informatization systems is quite in-depth. With the rapid development of Internet information technology, the traditional textile industry has continuously improved in the level of informatization [1]. Under the continuous promotion of a new generation of information technology such as the Internet of Things, big data, and artificial intelligence, the traditional textile industry is transforming into a new direction of intelligent manufacturing [2-4]. Farooq et al. [5] studied the optimization problem of the multi-automatic guided vehicle (MAGV) algorithm for path planning and decision-making problems in multi-stage industries such as textile spinning. Lee et al. [6] of South Korea

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studied the application of cyber-physical systems (CPS) in the intelligence of production plants. Tayyab et al. [7] studied how textile production processes and process management systems can be improved to achieve sustainability in textile production. Wang et al. [8] proposed a dual-band planar inverted-F antenna (PIFA) for wearable applications. Chen [9] proposed a periodic maintenance scheduling problem in a textile company. Chen et al. [10] studied how to use integrated production information to develop a monitoring system to achieve intelligent management of spinning production. Doran et al. [11] used artificial neural network (ANN) and support vector machine (SVM) models to predict the quality characteristics of cotton/elastane core yarn, using fiber quality and spinning parameters. Kusuma et al. [12] evaluated the accuracy of forecasting demand for Batik Fendy using MAPE techniques. The textile manufacturing informatization system started earlier and had a broad foundation, but the development was unbalanced. There are currently more small and medium-sized textile enterprises with difficulties in information intelligence especially in China, such as the overall low level of information technology applications and the manual production management methods [13].

Textile enterprises can collect production process data by using punch-card machines, bracelets, communication gateways, and other equipment. Integrating the information through the textile manufacturing information system can realize the utilization and sharing of internal resources, standardize the production process and production quantity, effectively predict the required output information, and can make the reasonable allocation of resources between the workshop and the workshop. It still needs to improve the level of information construction and work efficiency for textile enterprises. To solve the above problems, a textile manufacturing information system is proposed in this paper. In the proposed system, the FastAdmin framework is used to develop the textile manufacturing information system. It can predict production capacity to optimize production solutions and improve the level of informatization to enhance the competitiveness of enterprises. Moreover, it can receive and process the information from the production workshop. It can provide real-time feedback information of the equipment status, automatic maintenance management of orders and inventory, and early warning of orders. To timely find or trace the problems in production, it can provide data visualization. Finally, it can provide an exponential smoothing method intuitively to predict production and then improve production efficiency.

This paper is organized as follows. Section 2 introduces system architecture. Section 3 presents the data process and visualization. Section 4 deals with the results of the application of the exponential smoothing method. Finally, Section 5 draws conclusions.

2. System architecture

The data mainly comes from the textile equipment of a manufacturing company in China. To collect equipment data through the communication gateway installed on textile equipment, EMQX is installed as the messaging middleware on the system to support the MQTT message transmission protocol. MQTT is used to subscribe to the subject number of the machine and the data of the receiver station. The original data is stored in MongoDB and then sent to the data interface layer of the textile manufacturing information system. The data interface layer receives the data and processes the data with Python script, and the processed data is stored in the MySQL database. The diagram of system architecture is shown in Figure 1.

The Entity-Relationship (ER) diagram carefully depicts the internal relations between entity types and is used to describe the conceptual model of the database [14-16]. Through ER diagram, it is very intuitive to establish the relationship among the entity in the textile manufacturing information system. Thus, it obtains the relationship for all tables in the MySQL database. Figure 2 shows the ER diagram in this system.

The textile manufacturing information system includes two modules, the front-end and the back-end, as shown in Figure 3 below. The front end of the system is a visualized large-screen display module. The main functions include a line graph of total output statistics in the past seven days, a histogram of semi-finished products statistics, a histogram of real-time output statistics, a dashboard chart of average production progress, a pie chart of workshop operation status, the statistical line graph of the number of failures in the past seven days, real-time equipment monitoring, interactive panels, rolling early warning, etc. The background modules mainly include console, production management, equipment management, employee management, statistical information, information maintenance, routine management, and authority management.

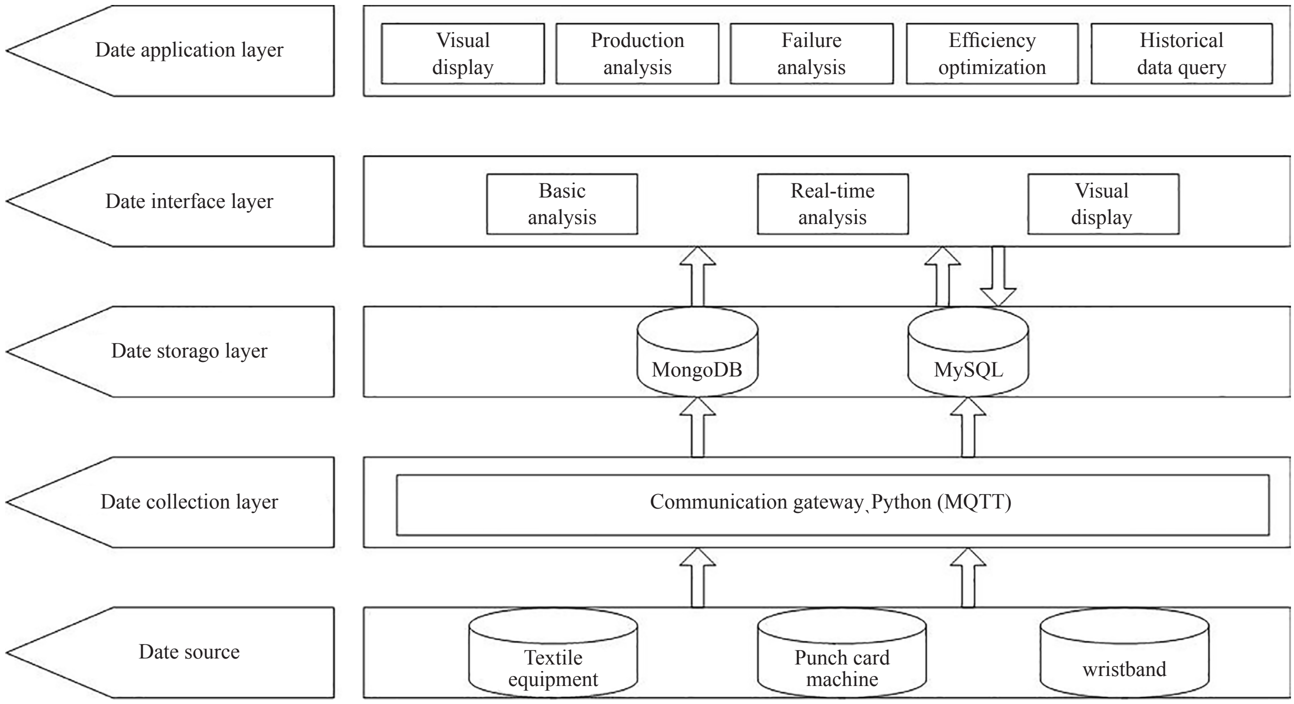

Figure 1. The diagram of system architecture

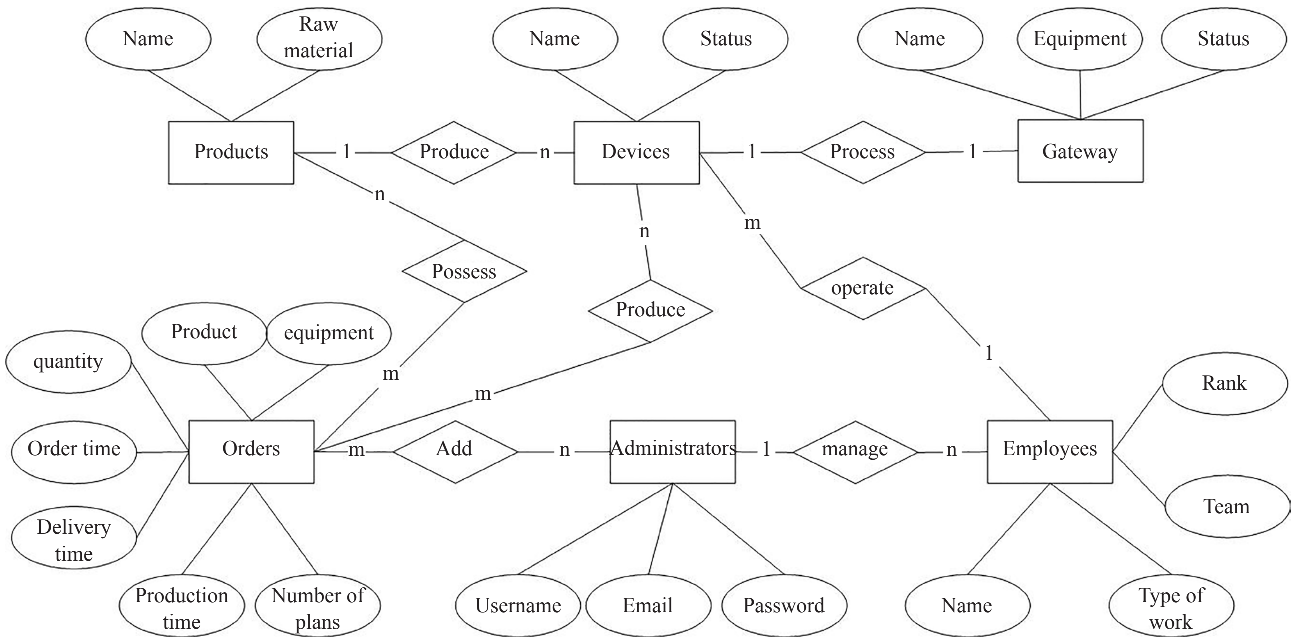

Figure 2. The ER diagram

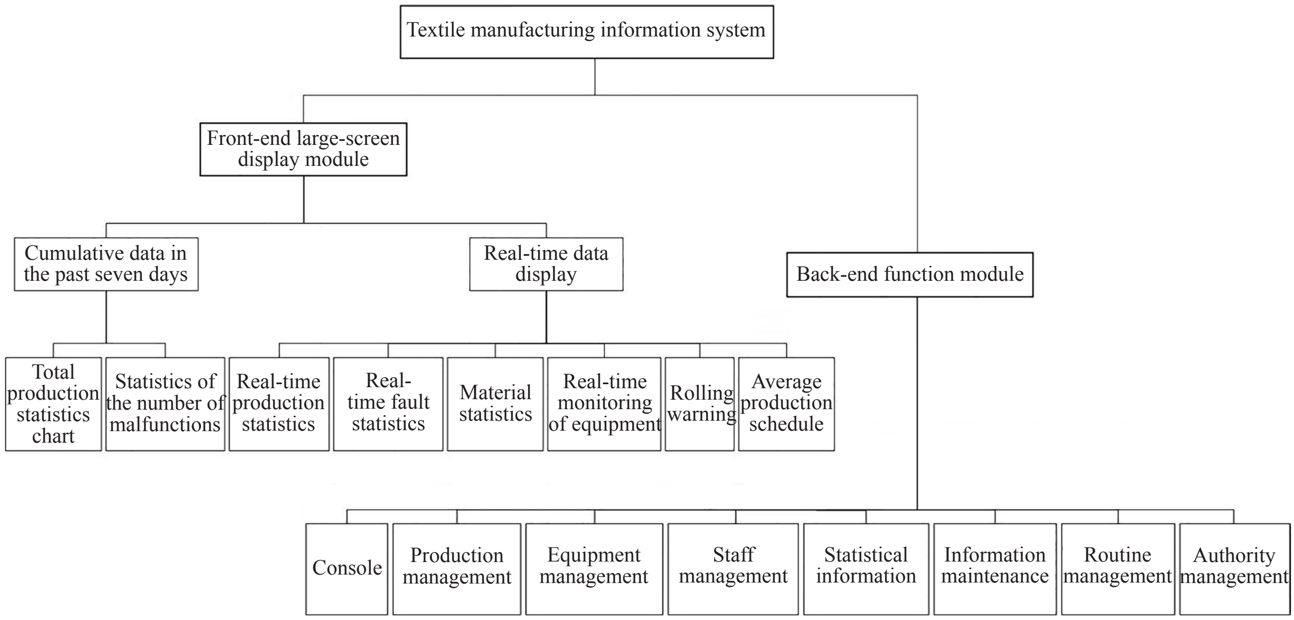

Figure 3. The diagram of the system function

Data analysis through the textile manufacturing information system can provide functions such as data visualization, production analysis, failure analysis, and historical data query. This system is mainly based on the exponential smoothing method to forecast the output, realize the functions of early warning of order, material management, and equipment management, and make the system more intelligent. The system realizes the linkage between production equipment and the system. After adding an order, it can automatically maintain the production progress of the order according to the production data. An early warning message will be sent to the administrator when the order is due or overdue. The system monitors the running data of equipment in real time and warns the change of equipment status in time. If manual intervention is needed, an early warning message can be sent directly to the machine operator. It can deal with the abnormal situation of equipment in time, and then improve the production efficiency to make decision-making references for production scheduling.

Production management includes order management and gateway management. For order management, it can monitor the changes in the current data of cloth length of the production equipment in real time. According to the equipment bound to the order, it uses the exponential smoothing algorithm to calculate the expected output and thereby maintain orders and inventory. If the textile production equipment does not have an order task, the produced products will be automatically included in the inventory for subsequent orders. When adding an order, you can use the inventory to deduct the production progress. As the production task is approaching the delivery date and the production equipment cannot complete the production task before the delivery date, the system will send an order warning email to the enterprise manager. It will remind the manager to add production equipment for the production task to ensure that the order task is completed in time. In gateway management, it realizes real-time monitoring and storage of data of gateway production equipment. It only displays the generated data at the current time. The historical data will be stored in the MongoDB database and can be retrieved when needed. It is possible to draw a monitoring panel of the equipment operation status to view the production data changes, status changes, and status duration of the production equipment in real time.

Equipment management includes call management, maintenance management, and repair management. For call management, it can perform early warning of material exhaustion, call for product order completion, and call for equipment failure. Due to factors such as accumulation of raw materials and equipment failure, it is to ensure the smooth production of equipment and improve production efficiency to avoid waste of time and energy. For maintenance management, it uses Python scripts to compare actual output data with predicted output data through the collected gateway data. If the actual output data differs greatly from the predicted output and the forecasted output, the maintenance management will send a call to the equipment manager to remind the managers to maintain the equipment in time. It avoids the problem of equipment aging, which affects production efficiency and overdue orders.

Staff management includes staff information management and attendance management. For staff information management, managers can view the distribution of employees of various types of textile workshops. Through the system, it can make timely adjustments when a certain type of employee is saturated or lacking to ensure the normal operation of the textile workshop. Attendance management is mainly a check-in/check-out function. It needs to input ID and name or face recognition to complete the check-in/check-out. This function can record staff's daily check-in/check-out information, which is used to manage staff's attendance. Statistical information includes inventory information, production statistics, and failure statistics. For inventory information, it is the equipment inventory status. For production statistics, it counts the daily output of each piece of equipment and the daily cumulative output of each piece of equipment with different order numbers. The output statistical information provides effective data analysis and predicts the average output for the next week. The system uses tables, graphs, and other intuitive illustrations to draw production information statistics charts. It can benchmark and analyze the data of daily output and daily equipment cumulative output. For failure statistics, it counts the number of equipment failures. Managers can pay more attention to the equipment that frequently fails, and then repair the failed equipment in time.

3. Data process and visualization

To install MQTT on openEule and subscribe to the subject number of the machine, it receives the data through the written python script by using the MQTT protocol. It stores the original data in MongoDB, and then sends the data to the open API interface of the textile manufacturing information system. The received data is processed by this interface and stored in MySQL after processing, as shown in Figure 4.

```
[root@host-192-168-0-148 temp]#nohup python3 -u MachinedataReceive.py > log.log 2>&1 &
[1] 20718
[root@host-192-168-0-148 temp]#ps -ef |grep python
root        660      1  0 18:09 ?        00:00:00 /usr/bin/python3 -Es /usr/sbin/firewalld --nofork --nopid
root        879      1  0 18:09 ?        00:00:00 /www/server/panel/pyenv/bin/python/www/server/panel/BT-Task
root        943      1  0 18:09 ?        00:00:00 //wwn/server/panel/pyenv/bin/python/www/server/panel/BT-Panel
root      20718   2482  7 18:11 pts/1     python3 -u MachinedataReceive.py
root      20989   2482  0 18:11 pts/1    00:00:00 grep --color=auto python
[root@host-192-168-0-148 temp]#cat log.log
nobup:Ignore the input
2022 -04-23 14:27:40 Connection successful
broker 218.5.16.51
port 10209
topic yd_self_to_self_vS
client_id: 20220423142740
41 data lines inserted[root@host-192-168-0-148 temp]#
```

Figure 4. The diagram of the data process

For the textile manufacturing information system, it will request data from the background API interface every 2 seconds. The API interface will query the corresponding data from the database and return it to the large screen. For screen display, textile enterprises can view production data and statistical data on the screen. The data source mainly comes from textile equipment. The production equipment data is collected through the gateway installed in the workshop, and then the production data is transmitted using the MQTT protocol and the Python script at the back end. The original data is first stored in MongoDB, and then it is forwarded to the system's open API interface to process the data clean. After the data clean, it is stored in MySQL for subsequent programs.

The design concept of data visualization must meet the requirements of the enterprise while reducing development time. This work uses the bootstrap front-end development toolkit, which is essentially a CSS/HTML framework. It is simple and flexible to make front-end development easier. The frame design of the large-screen uses jQuery. It encapsulates JavaScript commonly used function codes. It also optimizes HTML document operation, event handling, animation design, and Ajax interaction. The large-screen visualization uses Ajax to request back-end data, and mainly uses ECharts to visualize the data. ECharts has the characteristics of strong compatibility, simple use, rapid development, and rich icon components. The data visualization is shown in Figure 5.

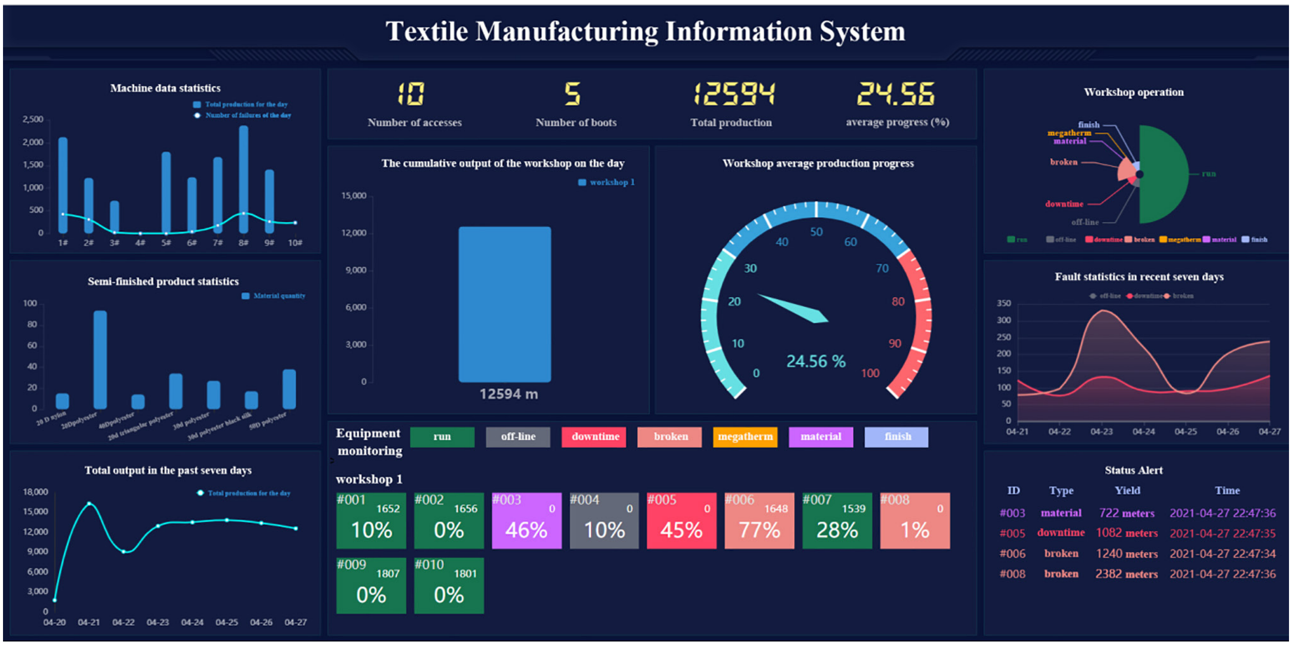

Figure 5. The diagram of data visualization

4. The results of the application of the exponential smoothing method

4.1 *The introduction to the exponential smoothing method*

The exponential smoothing method is a prediction method in time series, and it is among one of the best forecasting methods for many applications. The data predicted by the algorithm refers to a group of predicted values of the same data variable arranged according to the sequence of events [17]. Exponential smoothing forecasting is a common time series analysis method. It is a special weighted average method in production forecasting [18-20]. Different weights are assigned to the observed values in different periods, and larger weights are assigned to the new data. Exponential smoothing is performed again for the sliding values, and the changes are shown as a slanting straight line, which retains the trend information. Then a prediction model is established, and the prediction method is carried out according to the mathematical model.

Combined with the characteristics of output nonlinear changes, the average errors of the first, second and third exponential smoothing models and the actual values are compared, and the smoothing model with the smallest average error is used to track the changes in the time series.

The single exponential smoothing formula is expressed as Equation (1).

$$S_t^{(1)} = \alpha F_t + (1-\alpha) S_{t-1}^{(1)} \tag{1}$$

In Equation (1), S represents the exponential smoothing value, and the first single exponential smoothing value at t is recorded as $S_t^{(1)}$. For α, it represents the exponential smoothing coefficient and its value range is [0,1]. F_t represents the actual value of period t.

The double exponential smoothing formula is expressed as Equation (2).

$$\begin{cases} S_t^{(2)} = \alpha S_t^{(1)} + (1-\alpha) S_{t-1}^{(2)} \\ a_t = 2S_t^{(1)} - S_t^{(2)} \\ b_t = \dfrac{\alpha}{1-\alpha}(S_t^{(1)} - S_t^{(2)}) \\ \hat{y}_{t+T}^{(2)} = a_t + b_t T \end{cases} \tag{2}$$

In Equation (2), $S_t^{(2)}$ represents the secondary exponential smoothing value of the *t*-period, $S_t^{(1)}$ is the primary exponential smoothing value of the *t*-period in Equation (1), α represents the exponential smoothing coefficient, a_t and b_t are the secondary smoothing indices, and $\hat{y}_{t+T}^{(2)}$ represents the secondary exponential smoothing the predicted value of the model.

The triple exponential smoothing formula is expressed as Equation (3).

$$\begin{cases} S_t^{(3)} = \alpha S_t^{(2)} + (1-\alpha) S_{t-1}^{(3)} \\ A_t = 3S_t^{(1)} - 3S_t^{(2)} + S_t^{(3)} \\ B_t = \dfrac{\alpha}{2(1-\alpha)^2}[(6-5\alpha)S_t^{(1)} - (10-8\alpha)S_t^{(2)} + (4-3\alpha)S_t^{(3)}] \\ C_t = \dfrac{\alpha^2}{2(1-\alpha)^2}[S_t^{(1)} - 2S_t^{(2)} + S_t^{(3)}] \\ \hat{y}_{t+T}^{(3)} = A_t + B_t T + C_t T^2 \end{cases} \tag{3}$$

In Equation (3), $S_t^{(3)}$ represents the triple exponential smoothing value of the t-period, $S_t^{(2)}$ is the second exponential smoothing value of the *t*-period in Equation (2), $S_t^{(1)}$ is the single exponential smoothing value of the *t*-period in Equation (1), and α represents the exponential smoothing coefficient. Where A_t, B_t, and C_t are smoothing indices of the *t*-period, $\hat{y}_{t+T}^{(3)}$ represents the predicted value of the $t + T$ period, T is the predicted number of overruns [21].

To determine whether the smoothing coefficient α is accurate, the mean square deviation is introduced to judge it. The smaller the mean square deviation, the higher the accuracy. The formula of mean square deviation is as Equation (4).

$$\sigma = \sqrt{\sum_{t=1}^{n} (F_t - \hat{y}_t)^2 / n} \tag{4}$$

σ represents the mean square error value, which is used to test the prediction accuracy. The smaller σ is, the more accurate the prediction result is. Where $\hat{y}_t$ is the predicted value and F_t is the actual value.

When arbitrarily taking α as the result of 0.7, the predicted values of the single, double, and triple exponential smoothing are obtained, as shown in Table 1. Using Equation (4) to calculate the mean square error, it is calculated as: 35.4, 57.07, 71.32, respectively. The three exponential smoothing trends are shown in Figure 6. Compared with the second and third exponential smoothing, the average error of the single exponential smoothing is smaller, indicating that it is more suitable to use single exponential smoothing for production forecast in this system.

Table 1. Various exponential smoothing results

Time	Actual value	Single exponential smoothing	Double exponential smoothing	Triple exponential smoothing
2021-3-18	1313.70	1313.70	1313.70	1313.70
2021-3-19	1290.00	1297.11	1302.09	1305.57
2021-3-20	654.50	847.28	983.72	1080.28
2021-3-21	1009.00	960.48	967.46	1001.30
2021-3-22	1645.00	1439.65	1297.99	1208.98
2021-3-23	1783.00	1679.99	1565.39	1458.47
2021-3-24	1929.00	1854.30	1767.63	1674.88
2021-3-25	1844.00	1847.09	1823.25	1778.74
2021-3-26	956.00	1223.33	1403.30	1515.93
2021-3-27	821.00	941.70	1080.18	1210.91
2021-3-28	281.25	479.38	659.62	825.01
2021-3-29	965.00	819.32	771.41	787.49
2021-3-30	916.00	886.99	852.32	832.87
2021-3-31	1851.00	1561.80	1348.95	1194.13
2021-4-1	1185.00	1298.04	1313.31	1277.56
2021-4-2	1959.00	1760.71	1626.49	1521.81
2021-4-3	1465.00	1553.71	1575.55	1559.43
2021-4-4	1881.00	1782.81	1720.63	1672.27
2021-4-5	1110.00	1311.84	1434.48	1505.82
2021-4-6	1676.00	1566.75	1527.07	1520.70
2021-4-7	1491.00	1513.73	1517.73	1518.62
2021-4-8	1604.00	1576.92	1559.16	1547.00
2021-4-9	1813.00	1742.18	1687.27	1645.19
2021-4-10	1513.00	1581.75	1613.41	1622.94
2021-4-11	1932.00	1826.93	1762.87	1720.89
2021-4-12	1509.00	1604.38	1651.93	1672.62
2021-4-13	-	-	-	1795.00

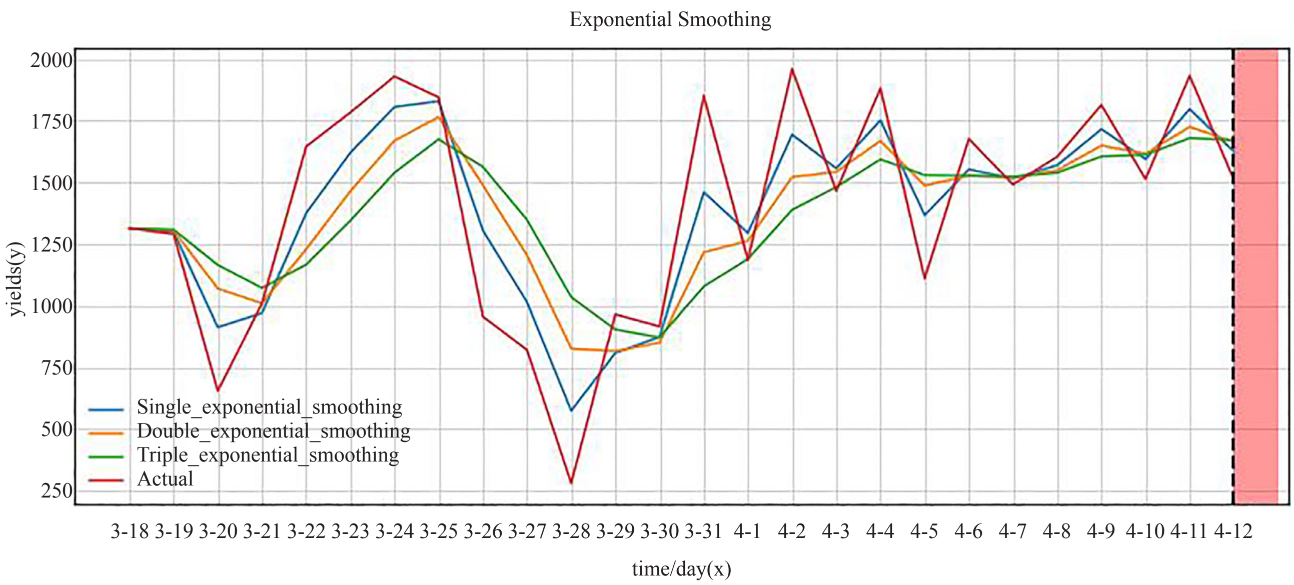

Figure 6. Trends of three types of exponential smoothing

4.2 *The simulation results*

Using the sliding window estimation, the sliding window is set to 3, and then calculate the error to find the data change trend. It is shown in Figure 7. The data are within the 95% confidence interval, indicating that the data has a high degree of confidence and can be used for prediction.

When using the exponential smoothing method, it is also necessary to reasonably determine the smoothing coefficient α. As the time series is relatively stable, choose a smaller α with a value from 0.05 to 0.20. If the time series fluctuates and the long-term trend does not change significantly, a slightly larger α could be selected with a value from 0.20 to 0.40. As the time series fluctuates greatly, the long-term trend changes greatly and there is an obvious upward or downward trend. Then, a larger α value could be selected with a value from 0.50 to 0.80. As the time series rises or falls and it satisfies the additive model, the larger α value is selected with a value from 0.80 to 1.0 [22]. From variant values of α in Figure 8, it can be seen that the long-term trend changes greatly. The smoothing coefficient α should take a larger value to track recent data changes, so the value of is selected from 0.50 to 0.80.

When α is closer to 1, it is closer to the real data in Figure 8. If α is too large, then over-fitting may occur, that is, the training value is accurate and the test value is inaccurate. To avoid over-fitting, the trial method is used to calculate the RMSE (Root Mean Square Error) for the result of each coefficient within the value range. RMSE is used to compare the accuracy and select the optimal prediction result, and the prediction result with a smaller value of RMSE is better. The period of the dataset is from March 18 to April 12, 2021. Four selected values from 0.5 to 0.8 were used empirically to compare the predicted value of output produced from April 11 to 12, 2021. The results are shown in Figure 9 and Figure 10. It can be seen from Figure 9 that when is set as 0.6, the RMSE is the smallest and the prediction result is the best among their compared values.

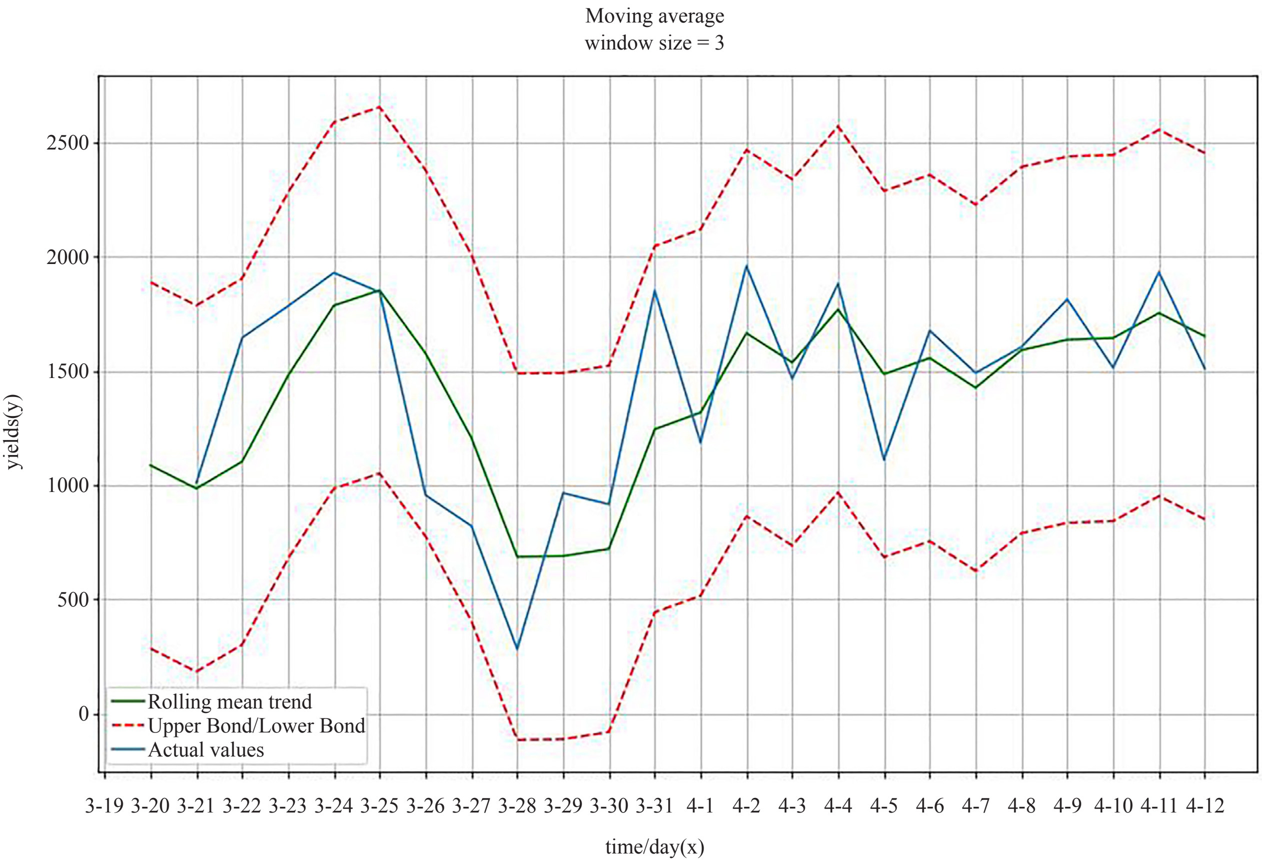

Figure 7. The figure of the confidence interval

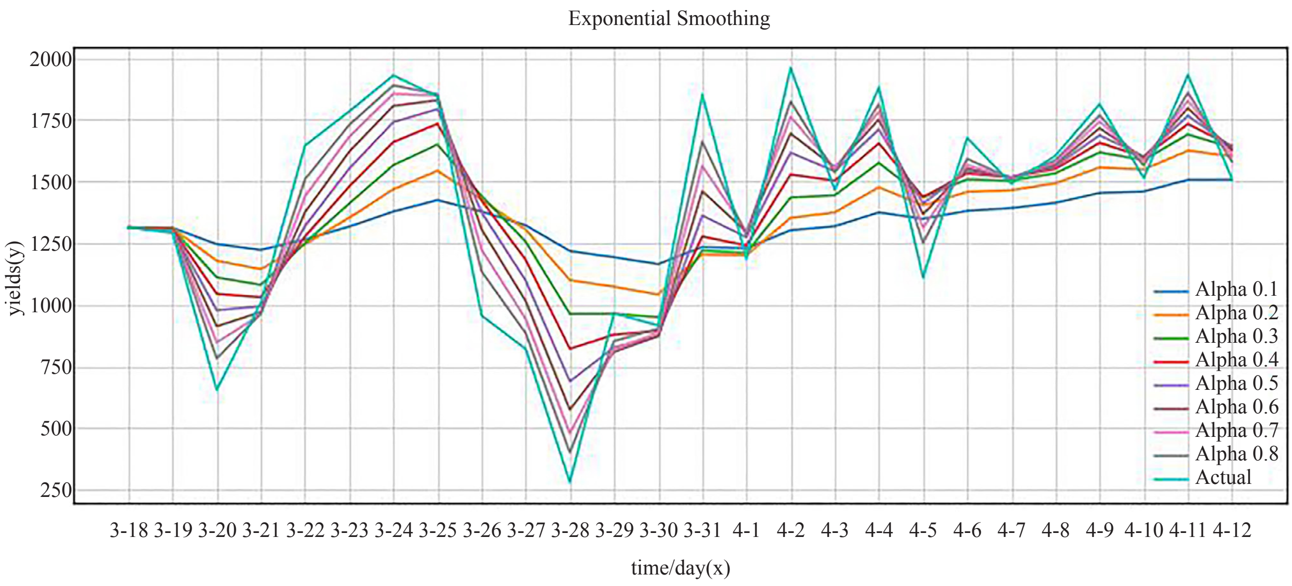

Figure 8. The results for different values of α

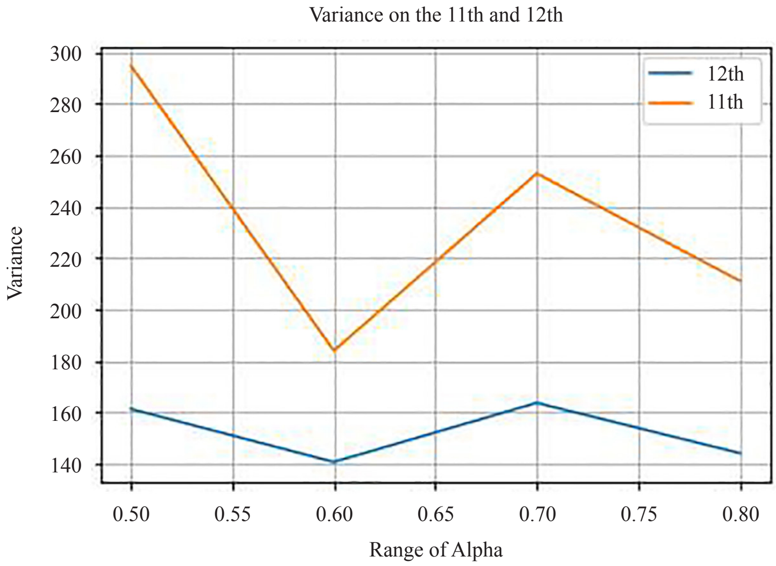

Figure 9. The difference between April 11 and 12, 2021

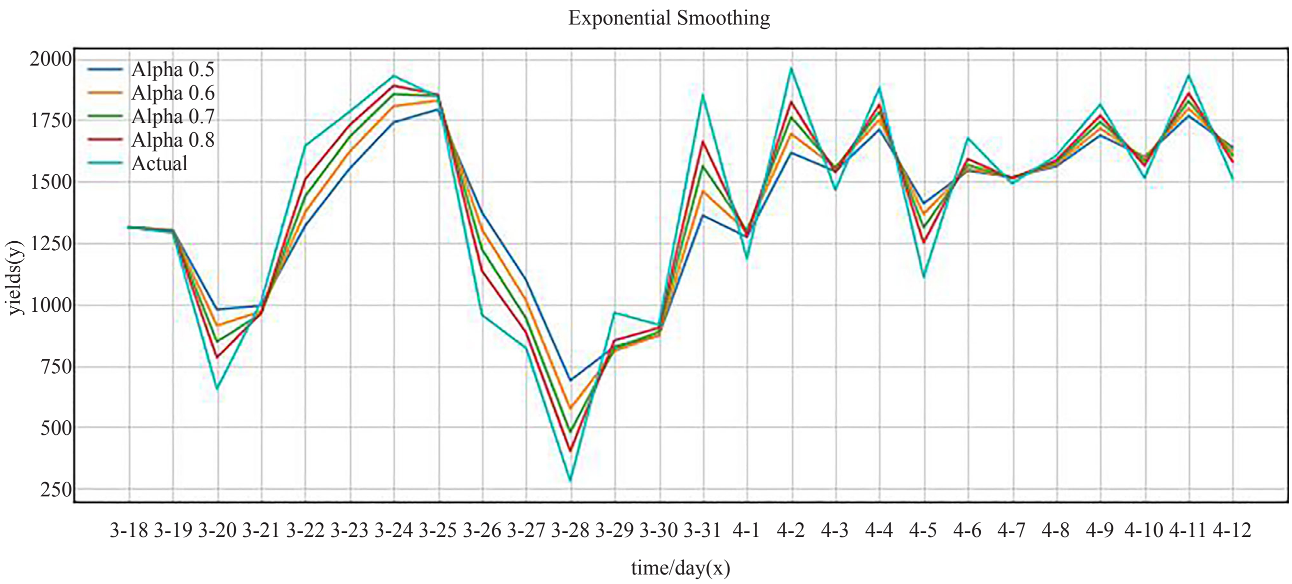

Figure 10. The error analysis of single exponential smoothing

5. Conclusions

The proposed system combines the production situation and takes into account the shortcomings in its management. It realizes automatic updating of output by information integration and sharing. It records the changes in equipment status to analyze and improve the efficiency of the production process. At the same time, the production process data is visualized and displayed by making a large visual screen. It simplifies the complex production data and enables managers to see the production and operation situation more intuitively. The system establishes an exponential smoothing model to predict the output. It intelligently reminds managers of the estimated completion time of the production task when adding new orders. Through the textile manufacturing information system, managers can avoid machines with low output and high failure rates when arranging emergency orders. It also ensures production efficiency and improves the competitiveness of products in the market. In addition, the single exponential smoothing method can predict the development trend of textile production in a short term, and the results are admirable. When arranging machines to produce products, managers can reduce the possibility of order delay and improve the production efficiency to avoid disputes. It is also an important issue to analyze regarding complexity in future work.

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Conflict of interest

The authors declare that there is no personal or organizational conflict of interest with this work.

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