An OLE Centred Production Line Maintenance Prioritisation: Guided by the criticalities of the specific characteristics of equipment operational reliability

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Abstract

Maintenance task prioritisation is essential for production system, especially when available resources are limited. Related studies take either system safety or productivity as the objective of system maintenance prioritisation. While since improper system maintenance can make bad equipment cooperation thus induce unstable manufacturing process and big equipment operation time loss, system process ability is also necessary to be improved in production line maintenance. Therefore, the overall line efficiency (OLE) which comprehensively evaluates production line productivity and process ability is adopted as the objective to develop maintenance prioritisation in this study. Specifically, an OLE centred maintenance prioritisation policy which assigns priorities according to the influences of the specific characteristics of equipment operational reliability on OLE is proposed: To correctly allocate limited maintenance resources to truly critical equipment and achieve good maintenance effect, equipment influences on OLE are analysed from the level of the specific performances of their operational reliability: equipment mean time between stops (MTBS), mean time to resume from stops (MTTR) and buffer size \( N \). Considering the interactions between these parameters, a surrogate model-extended Fourier amplitude sensitivity test (SM-EFAST) process is integrated to accurately and rapidly analyse the total effects of them on OLE. In the end, an application case adopting the proposed OLE centred maintenance prioritisation method achieved higher OLE and lower total maintenance cost than two current popular maintenance prioritisation methods.

Keywords Production line, Maintenance prioritisation, Overall line efficiency, Operational reliability, EFAST, SM

List of abbreviations and Symbols

Nouns and phrases:

\begin{tabular}{ll}
\textbf{QN} & Total number of the qualified products \\
\textbf{CYT} & Cycle time \\
\textbf{CYT}_i & CYT of a whole production line \\
\textbf{CYT}_i & CYT of equipment \( i \) \\
\textbf{CNBD} & Cumulated number of workpieces in a buffer when its previous station stops \\
\textbf{PM} & Preventive maintenance \\
\textbf{OLESEM} & Production line OLE simulation evaluation model \\
\textbf{SM} & Surrogate model \\
\textbf{EFAST} & Extended Fourier amplitude sensitivity test \\
\textbf{SM-EFAST} & Surrogate model-Extended Fourier amplitude sensitivity test, the process
\end{tabular
OLE range  The range where OLE may reach when system equipment are operated under different maintenance policies.

RBF  Radial Basis Function

RSM  Response Surface Method

**Production line parameters**

\[ M_i \]  Equipment at the \( i \)-th workstation

\[ N_j \]  Capacity of the \( j \)-th buffer

\[ mtbs_{ij} \]  Mean time between stops for \( M_i \).

\[ mtr_{ij} \]  Mean time to resume from stops for \( M_i \).

\[ tbs_{ij} \]  The time period between the \( (j-1) \)-th and the \( j \)-th stop occurred on \( M_i \).

\[ ttr_{ij} \]  The time period for \( M_i \) to resume from its \( j \)-th stop.

\[ ST_k \]  The total effect of parameter \( k \) on OLE.

\[ S_k \]  The main effect of \( k \) on OLE.

\[ I_k \]  The total interaction of \( k \) with all other parameters.

**EFAST parameters**

\( x_k \)  An array generated by EFAST consisting of all experimental sample points for parameter \( k \).

\( G_k \)  Transformation function required for generating experimental sample points for parameter \( k \).

\( \omega_k \)  The integer frequency assigned to parameter \( k \).

\( s \)  Real numbers that vary uniformly between \(-\pi\) and \( \pi \), required by EFAST.

\( \omega_{\text{max}} \)  Maximum of the frequencies assigned to all parameters.

\( \omega_{\text{-x}} \)  An array of frequencies assigned to all parameters except the \( \omega_{\text{max}} \).

\( f(s) \)  Experimental output corresponding to each \( s \), which is also the OLE at each experimental sample point \( x_k \).

\( M \)  Essential parameter in EFAST, usually takes 4.

\( l \)  The number of OLE influencing parameters.

\( N_r \)  The number of adopted transformation functions.

\( N \)  The number of sampling points designed for parameter \( k \).

1. **Introduction**

System maintenance is of great significance for production lines. Appropriate maintenance can improve system productivity and reduce production cost [1–3]. Therefore, rational maintenance should be arranged timely when maintenance opportunity arises, whether caused by equipment failure or production planning [4]. However, since available maintenance resources such as time, technologist and spare parts, are limited, they should be allocated orderly and scientifically in accordance with equipment criticalities to achieve good maintenance effect. For this reason, developing maintenance prioritisation for production systems is essential.

Gopalakrishnan [5] revealed the gaps in maintenance prioritisation between academic and industrial fields in his research: (i) criticality analysis methods widely adopted in practices usually lack a clear goal; (ii) most enterprises prioritise their maintenance activities according to subjective impression or experience given the unreliable results of present criticality analysis methods.

In terms of a clear goal, current studies on production line maintenance prioritisation can be classified into system risk centred [6, 7] and productivity centred [8–10]. Since system safety and continuous production are basic principle of industrial production, risk centred prioritisations are usually adopted to establish basic rules for system operation and maintenance. In cases when system safety and continuous production has been guaranteed through these rules, its maintenance usually aims at system productivity improvement. However, the effects of risk centred maintenance prioritisations are usually limited in meeting the demand of system productivity.

Compared to risk centred prioritisations, although higher productivities were achieved in productivity
centred maintenance prioritisation studies [8, 10–13], another important task of system maintenance: the improvement of system process ability, representing the cooperation of all devices and buffers in a production line, was ignored in these studies. As is known to all, improper system maintenance will make the state of each equipment greatly affected by others thus induce unstable manufacturing process, big equipment operation time loss, and low system efficiency. Therefore, the ultimate goal of production system maintenance should be its comprehensive improvement of system process ability and productivity.

From the perspective of criticality analysis methods, fuzzy interference system (FIS) [6], failure mode effect analysis (FMEA) [7], bottleneck analysis [8–10, 14–16], a system efficiency influence diagram [11], and sensitivity analysis [12] were adopted to evaluate equipment criticality. Besides, Gopalakrishnan and Skoogh [17] surveyed 71 factories in Sweden and summarised that maintenance prioritisation in practices is mostly based on ABC classification, operator influence and bottleneck analysis. Chong et al. [18] reviewed production system maintenance prioritisation studies and pointed out that analytic hierarchy process (AHP), priority criterion, priority matrix and failure mode effect and criticality analysis (FMECA) are the most commonly used methods at present.

However, further analysis shows some defects of these methods in guiding production line maintenance prioritisation: ABC classification, FIS, AHP, priority criterion, and priority matrix only qualitatively classify all equipment into several priority levels, which makes it difficult to determine the specific maintenance priorities of the equipment in the same level when available resources are limited.

In comparison, bottleneck analysis, the system efficiency influence diagram and the sensitivity analysis can quantitatively analyse equipment specific maintenance priorities. But the influence of equipment on system performance were only analysed from the overall machine level, which is insufficiently specific: Even though the equipment whose reliabilities significantly affect production line efficiency are identified, whether their failure rate or repair rate is more critical to system efficiency is still unclear. This ambiguous result usually makes maintenance actions prone to bias.

Although FMEA and FMECA can provide maintenance prioritisation guidance from equipment specific critical failure modes [7, 19], they are only risk centred suggestions which may be not effective enough for system comprehensive performance improvement.

Therefore, to guide specific maintenance prioritisation for production line comprehensive performance improvement, the OLE which can evaluate the overall performance of a production line integrating its productivity and process ability is adopted for the first time as the objective to make maintenance prioritisation in this paper, namely an OLE centred system maintenance prioritisation policy is proposed. Specifically, considering OLE is mainly affected by buffer capacities $Ns$ and equipment operational reliability which is specifically shown as equipment $mtbs$ and $mtr$, their total effects on OLE are accurately and efficiently analysed through an integrated SM-EFAST process, to make it clear which equipment performance should be assigned maintenance priority to get better system OLE.

The remainder of this paper is organised as follows: Section 2 introduces OLE, analyses its influencing parameters, and provides the procedure for developing OLE centred maintenance prioritisation. Section 3 integrates a SM-EFAST process to accurately and efficiently analyse parameter influences on OLE. Lastly, an application case is studied in Section 4, where the efficiency of the SM-EFAST process and the effectiveness of the OLE centred maintenance prioritisation are verified.

2. OLE centred maintenance prioritisation

2.1 OLE introduction
Due to the comprehensive evaluation of system overall efficiency, OLE is fully recognized and
applied in industry [20, 21]. It was proposed by Nachiappan and Anantharaman [22], and defined as:

\[ OLE = \text{line availability} \times \text{line production quality} \]
\[ = \frac{OT}{LT} \times \frac{QN \times CYT}{OT} \]  

(1)

where \( LT \) is the actual loading time of the whole production line. \( QN \) represents the number of the qualified products and \( CYT \) is the cycle time of the system. \( OT_i \) and \( OT_n \) represents the actual operating time of the first and the last equipment in the system, which can be calculated recursively by:

\[ OT_i = OT_{i-1} \times PD_i \times DT_i \quad (i = 1, 2 \ldots n, OT_0 = LT) \]  

(2)

where \( PD_i \) is the independent planned downtime of equipment \( i \) except for the system overall planned downtime, and \( DT_i \) represents the total failed down time of equipment \( i \).

Although system throughput (TH) and production rate (PR) (defined as Eq. (3) and (4), provided by Kang et al. [23]) are more common system maintenance effect evaluation indexes, there are shortcomings of them compared to OLE:

\[ \text{TH} = \frac{\text{system good quality} + \text{system rework quality}}{\text{system actual order execution time}} \]
\[ = \frac{\text{system qualified products}}{\text{system loading time}} \]  

(3)

\[ \text{PR} = \frac{\text{actual production time}}{\text{system actual order execution time}} \times \frac{\text{system cycle time}}{\text{system loading time}} \]
\[ = \frac{QN \times CYT}{LT} \]  

(4)

It is clear in Eq. (3) that TH expresses the number of output products per unit time thus is suitable for making production plans. While PR analyses system production efficiency which seems more suitable than TH for system maintenance effect evaluation.

However, further comparing Eq. (4) with (1), OLE covers one more factor than PR: \( OT_n/OT_i \) (production line process ability). This factor represents the system operation time loss accumulated by the operation time loss of all equipment in the production process, reflecting the connection and cooperation of all equipment and buffers in the system. Considering that improper system maintenance always makes the operation of each equipment in the system greatly affected by others thus induce big system operation time loss (low \( OT_n/OT_i \)) and decrease system process stability and productivity, system process ability improvement is also an important task of system maintenance. This mean that OLE is more suitable than system PR to evaluate the comprehensive effect of system maintenance. Therefore, it is taken as the evaluation index and objective of system maintenance in this paper.

2.2 Improvement of OLE

For production systems without buffers, there is no doubt \( OT_i \) is the theoretical available operation time for equipment \( i \), as is expressed in Eq. (2). While for production lines with buffers, part of \( PD_i \) and \( DT_i \) can be made up by the downstream buffer of equipment \( i-1 \), thus longer actual available operation time than \( OT_i \) are provided to equipment \( i \).

Although this compensation is limited, it is nonignorable for short-term equipment failures and the cases when \( CNBD_{i-I} \) can last for a long time, where \( CNBD_{i-I} \) is the cumulated number of workpieces in buffer \( i-I \) (the buffer before equipment \( i \)) when equipment \( i-I \) stops, and \( CYT_i \) represents the cycle time of equipment \( i \). Therefore, for production lines with buffers, the important role that buffers play in maintaining the continuous production of downstream stations should be fully considered in \( OT_i \) calculation:

\[ OT_i = (OT_{i-1} + CNBD_{i-I} \times CYT_i) - PD_i - DT_i \]  

(5)

After recursive calculation, \( OT_n \) and the system process ability \( OT_n/OT_i \) can be expressed as follows:

\[ OT_n = LT + \sum_{i=1}^{n} (CNBD_{i-I} \times CYT_i) - \sum_{i=1}^{n} (PD_i + DT_i) \]  

(6)
Accordingly, when system maintenances are properly organised, \( \sum_{i=1}^{n} (CNBD_{i} \times CYT_{i}) \) can make up for \( \sum_{i=1}^{n} (PD_{i} + DT_{i}) \) as much as possible thus improve system internal cooperation, achieve good system process ability, and finally result in good OLE. Therefore, to accomplish proper system maintenance, an OLE centred maintenance prioritisation policy is proposed in the next section.

2.3 Prioritisation based on OLE influencing parameters

In practice, allocating limited resources to really critical objects according to the criticality of OLE influencing factors is very important for system maintenance. For this purpose, production line OLE influencing factors are analysed in Fig. 1 on the basis of Eq. (1) and (7).

The green blocks in Fig. 1 are system maintenance related factors while the grey ones are out of the responsibility of system maintenance. For the reason that equipment degradations are always shown as reactive maintenance (RM) and preventive maintenance (PM) in practice, only equipment PM, RM, as well as buffer size adjustment are recognised as system maintenance related OLE influencing factors in this paper.

Furthermore, since equipment PM and RM are specifically shown as equipment stop and maintenance, their characteristics can be uniformly expressed as \( mtbs_{i} \) and \( mttr_{i} \):

\[
mtbs_{i} = \frac{\sum_{j=1}^{n} tbs_{ij}}{n} \quad (8)
\]

\[
mttr_{i} = \frac{\sum_{j=1}^{n} tr_{ij}}{n} \quad (9)
\]

where \( tbs_{ij} \) is the time period between the \((j-1)^{th}\) and \(j^{th}\) stop of equipment \(i\), \( tr_{ij} \) represents the time period of equipment \(i\) to resume from its \(j^{th}\) stop, and \( n \) is the total stop times of equipment \(i\).

To be noted, different from \( mtbf \) (mean time between failures) in equipment inherent reliability, \( mtbs \) is a characteristic of equipment operational reliability: the former stipulates that only equipment relevant failures can be considered, while the latter includes non-relevant failures and PM caused equipment stops besides that, which are also meaningful in equipment practical stage thus should be contained in equipment operational reliability evaluation.

In conclusion, equipment \( mtbs_{i}, mttr_{i} \), and buffer size \( N_{i} \) are system maintenance related OLE influen-
ing parameters to be studied in this research to make maintenance prioritisations. The specific procedure of the OLE centred maintenance prioritisation policy is shown in Fig. 2. The main procedure of this method: parameter influence analysis is detailed in the following section.

![Flowchart](image)

**Fig. 2** The procedure of the OLE centred maintenance prioritisation policy

### 3. Analysis of parameter influence on OLE

#### 3.1 Parameter total effect on OLE

Considering the status of each equipment in the system can affect the production of upstream and downstream equipment, the impact of any equipment on OLE is not independent, but affected by the performance of other equipment [24]. Therefore, interactions among all equipment mtbs, mttr, and buffer capacities Ns should be considered: the actual influence of a parameter on OLE should be its total effect. Taking a system with three factors \((k, l\) and \(h\)) as an example, the total effect of \(k\) on OLE should be:

\[
ST_k = S_k + I_k = S_k + (I_{lk} + I_{lk} + I_{lk})
\]  

(10)

where \(S_k\) represents the main effect of \(k\) on OLE, and \(I_k\) is the total interaction of \(k\) with all other parameters, including the interactions between \(k\) and \(h\), \(k\) and \(l\), and \(k\), \(h\) and \(l\).

Apparent, it is the total effects of each \(mtbs, mttr\), and \(N\) on production line OLE that should be recognised as their actual influences on OLE.

#### 3.2 The SM-EFAST process

As a typical global sensitivity analysis method available for systems with a great number of influencing factors [25–28], the extended Fourier amplitude sensitivity test (EFAST) is adopted to analyse the total effect of each parameter \(k (mtbs, mttr,\) and \(N\) on production line OLE. The conventional process of parameter total effect analysis with EFAST is shown in Fig. 3 (a).

Specifically, EFAST experiments should first be designed for each parameter \(k\) with Eq. (11): Assign an integer frequency \(\omega_k\) to each parameter \(k\) and select a transformation function \(G_k\) for it (Details please refer to [27]). Subsequently, the experimental sample points \(x_i\) for parameter \(k\) can be calculated by:

\[
x_i(s) = G_k(\sin(\omega_k s)) \quad k = 1,2...l
\]  

(11)

As \(s\) varies uniformly between \(-\pi\) and \(\pi\), the experimental sample points \(x_i\) for each parameter \(k\) can be generated.

After performing the designed EFAST experiments on the simulation model of the target production line, outputs (OLEs) at the experimental sample points can be calculated with Eq. (1). Then the total effect of parameter \(k\) on OLE can be approximately calculated with the generated outputs by:

\[
ST_k = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(s) \cos(js)ds
\]  

(12)

\[
A_j = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(s) \cos(js)ds
\]  

(13)

\[
B_j = \frac{1}{2\pi} \int_{-\pi}^{\pi} f(s) \sin(js)ds
\]  

(14)

where \(f(s)\) represents the experimental output corresponding to each \(s\), namely, the OLE at each experimental sample point \(x_i(s)\); \(M\) usually takes 4 [27]; \(\max(\omega_k)\) is the largest \(\omega\) assigned to other parameters (the complementary \(\omega\) assigned to other parameters) except for \(k\); \(N\) is the number of sampling points required to analyse the
total effect of $k$:

$$N = 2M \omega_{\max} + 1$$  \hspace{1cm} (15)

where $\omega_{\max}$ should satisfy:

$$\omega_{\max} = \omega_k = 2M \max(\omega_{\max})$$  \hspace{1cm} (16)

According to [27], the EFAST experimental sample size required for a complete EFAST to analyse the total effects of all parameters of a system is as follows:

$$C = l N_c, N$$  \hspace{1cm} (17)

where $l$ is the number of OLE influencing parameters, and $N_c$ is the total number of transformation functions adopted for all parameters.

It is required in [27] that: 1) the step between the frequencies of the complementary set ($\omega_{\omega_i}$) must be as large as possible and 2) the number of factors to which the same frequency is assigned must be as low as possible. These rules make the EFAST experimental sample size for systems with a large number of parameters enormous.

However, the number of OLE influencing parameters in a production line is unfortunately large, which may inevitably cause great EFAST experiment time if the experiments are performed on a production line OLE simulation evaluation model (OLESEM), making the parameter influence analysis process inefficient. Therefore, an SM-EFAST process is integrated in Fig. 3 (b) to analyse parameter influences on OLE more efficiently.

The highlighted processes and the red words are the differences of the SM-EFAST process compared with the conventional process: For the quick response characteristic of surrogate models (SM) [29, 30], EFAST experiment time can be greatly reduced by conducting the experiments on the SM of the OLESEM instead of the OLESEM itself.

However, from the view of the whole parameter influence analysis process, although EFAST experiment time can be greatly reduced by conducting experiments on the SM, the SM-EFAST process adds a SM training step to the conventional process. To effectively improve the efficiency of the whole process, it is necessary to minimise the time required for this additional step.

In the process of SM training, two essential elements are required [31]: sample size and model algorithm. To avoid blind exploration time wasted on these two elements, next section analyses clear SM-training rules to efficiently and quickly train an accurate SM for an OLESEM.

![Fig. 3 Analysis of parameter influences on OLE with the conventional process and the SM-EFAST process](image-url)
3.3 SM-training rules

The difficulty of training an accurate SM is related to four factors: the complexity, dimension and breadth of the original model, as well as the algorithm adopted to train the SM. For an OLESEM, the first three factors respectively refer to the structure of the production line, the number of OLE influencing parameters and the range where OLE may reach when system equipment are operated under different maintenance policies (hereafter called OLE range).

To study how these factors affect SM training and explore the rules to quickly train an accurate SM for an OLESEM, six experimental production lines are designed and analysed (detailed in Appendix). The SM-training rules are summarised as follows:

1) For algorithm selection, preference should be provided to the radial basis function (RBF) or the response surface method (RSM);
2) Compared with production lines without buffers, those with buffers require less samples to train accurate SMs, because buffers can maintain more stable production process;
3) In terms of the sample size for accurate SM training, it should be set according to production line OLE range, specific suggestions are shown in Table 1.

Table 1. Recommended SM-training sample sizes for production lines (with buffers) with different OLE ranges

| OLE range | SM-Training Required Sample size * |
|-----------|-----------------------------------|
| 2%        | 300                               |
| 2%~4%     | 500                               |
| 4%~6%     | 1000                              |
| 6%~8%     | 1300                              |
| 8%~10%    | 1800                              |

* The provided sample size recommendations are applicable to RBF and RSM.

With the SM-EFAST process provided in Fig. 3 (b) and the SM training rules explored above, it is easier to efficiently and accurately analyse the total effects of mtbs, mttr; and N on OLE.

4. Case analysis

4.1 Case introduction

The proposed OLE centred maintenance prioritization policy is applied on a real auto spare part processing line in simulation. Basic information for this processing line is shown in Table 2.

Equipment mtbs, mttr and buffer N ranges shown in Table 2 are statistically analysed with the tbs and ttr data recorded in the PLCs of the CNC machine tools, production line computerized maintenance management system, as well as worker experience. Since each parallel workstation is equipped with the same machine model, and the processing task and working environment of each machine at a parallel station are the same, their performances are basically the same. Therefore, the range of the same parameter of each machine tool at a parallel station is the same, for example, mtbs1 = mtbs2 = mtbs1 and mttr1 = mttr2 = mttr1.

4.2 Results and corresponding strategy

Influences of equipment mtbs, mttr and buffer size N on the OLE of this line are analysed with the SM-EFAST process: With the parameter ranges in Table 2, the OLE range of this processing line is evaluated to be 4.54%. According to the SM-Training rules, an accurate SM of this processing line is trained with RBF by 1000 samples. After conducting the EFAST experiments (designed by Eq. (11)) on the obtained SM, the OLEs at the experimental points are obtained and finally used to analyse the total effect of each parameter on the OLE of this processing line (by Eq. (12)-(16)). Results are shown in Fig. 4.

It is obvious from Fig. 4(a) that the SM-EFAST process can greatly reduce the EFAST experiment time compared with the conventional process and efficiently analyse the total effects of mtbs, mttr; and N on the OLE of the case line. This improvement not only owes to the replacement of the OLESEM by the SM, but also strongly supported by the SM training rules, which clearly guided the SM training process without blindness thus guaranteed the efficiency and accuracy of the whole SM training process.
Table 2. Basic information of the auto spare part processing line

| Items | $M_{11}/M_{12}$ | $M_2$ | $M_3$ | $M_{41}/M_{42}/M_{43}$ | $M_5$ | Available capacity of each buffer | OLE Range |
|-------|-----------------|-------|-------|-------------------------|-------|---------------------------------|-----------|
| mtbs range (h) | [320,450] | [250,420] | [200,350] | [420,520] | [100,180] | [15,30] | 4.54% |
| mttr range (h) | [0.8,2.5] | [1.2,2.8] | [1.2,3] | [2.4,5] | [0.8,1.5] |

Fig. 4 Parameter influence analysis results of the case production line

Besides, the analysis results displayed in Fig. 4(b) show that $mttr_2$ has the most significant total effect on OLE, followed by $N_3$ and $mttr_4$. The impact of $N_4$, $mttr_2$ and $mttr_5$ can be classified to the third echelon. As to the other parameters, the impact of $mtbs_1$, $mtbs_5$, $N_2$, $mtbs_2$, $mtbs_4$ on OLE decreases in turn. While $M_1$ and $N_1$ have little impact within their available ranges.

Accordingly, guided by the generated parameter total effects, the maintenance prioritisation strategy for this processing line is formulated as follows:

1) Reduce the maintenance time of equipment whose $mttr$ is more critical to OLE (mttr critical equipment): a) In cases when multiple equipment fail at the same time, maintenance priority (technologists, accessories etc.) should be set to $mttr$ critical equipment; b) Quickly respond to the failures of $mttr$ critical equipment thus reduce their maintenance response time; c) Strengthen the maintenance skill training of the $mttr$ critical equipment.

2) Since $N_3$ and $N_4$ have the second and the fourth significant influence on OLE, their capacities are adjusted to 30 and 25 respectively, comprehensively considering their significances, cost of roller setting, and the space adequacy for online workers to operate and place tools.

3) Fig. 4(b) apparently showed that equipment $mtbs$ generally does not have significant effect on system OLE. Besides, although more intensive PM (the most common way to improve equipment $mtbs$) can decrease $DT_i$ by reducing failure numbers and improve OLE, it requires more $PD_i$ thus decreases $OT_i$ and decreases OLE conversely,
which may not only end up with marginal effect (negligible OLE improvement but higher maintenance cost) but also disrupt the original production plan. Therefore, maintaining the original PM plan is enough. While considering equipment \( mtbs \) contribute to OLE, it is still beneficial to strengthen equipment PM without adding extra production burden to system. Based on this, making full use of the passive maintenance opportunities caused by other equipment (equipment idle caused by other equipment failure or maintenance, etc.) to strengthen equipment PM is a better choice: Conduct supplementary PM on equipment within the available time of passive maintenance opportunities according to their \( mtbs \) significance shown in Fig.4 (b).

4.3 Comparison analysis with other strategies

The strategy provided above is simulated on the simulation model of this processing line. The resulted OLE, system PR, and maintenance total cost are compared with those resulted from the original first-come-first-served without prioritisation policy (FCFS), a risk centred policy, and a productivity centred policy (Table 3). To be specific, the most popular methods of the latter two policies: FMECA and active period-based bottleneck analysis [9] are adopted.

It is obvious that from both the perspective of system performance and maintenance total cost, the application results generated from the three prioritisation strategies are significantly better than those from the original FCFS strategy. It is also apparent that the OLE centred prioritisation results better than the risk centred and the productivity centred ones. This is due to its reasonable resource allocation:

FMECA analysed critical failure modes to system safety and continuous production, which have already been given full attention and strict regulations to in the original PM plan and operation specification. Under such circumstances, only system safety and reliability rather than system efficiency will be further improved when resources are further tilted to these aspects, because the equipment performances that have important contribution to system efficiency are ignored and did not get timely maintenance.

As for bottleneck analysis, it only detects system critical equipment thus suggests to improve both the \( mttr \) and \( mtbs \) of the critical equipment as much as possible. While in cases when either \( mtbs \) or \( mttr \) of some critical equipment are less important than some parameters of lower critical equipment, these actions may lead not only to waste of resources but also worse effect, for allocating limited resources to less important equipment performance whilst ignoring the actual critical equipment performance.

In comparison, the SM-EFAST process analyses equipment influences on OLE from the level of the specific characteristics of their operational reliability, thus provide clear and specific prioritisation suggestions to system maintenance and correctly allocate the limited resources to really important equipment, avoiding the waste of resources and

| Prioritization policies | OLE (%) | \( \frac{OT_n}{OT_I} \) | System PR (%) | Cost (unit)\(^c\) |
|------------------------|---------|----------------|-------------|-----------------|
|                        |         |                | Maintenance | Production Loss | Total      |
| FCFS                   | 78.54   | 0.90           | 87.21       | 3733.50        | --         | 3733.50    |
| SM-EFAST               | 83.64   | 0.93           | 90.07       | 3107.90        | -2608.45   | 499.45     |
| FMECA\(^a\)           | 81.21   | 0.91           | 89.01       | 3478.20        | -1575.60   | 1902.60    |
| Bottleneck analysis\(^b\) | 81.69   | 0.92           | 89.01       | 3441.80        | -1577.45   | 1864.35    |

\(^a\) The prioritisation is set according to equipment critical failure modes: tool changing failure and oil blockage of \( M_s \) – oil and gas instability of \( M_1 \) – numerical control system failure of \( M_3 \) – switch failure of \( M_3 \) – switch failure of \( M_2 \).

\(^b\) The maintenance priorities are: \( M_i \) (bottleneck machine) – \( N_b \) (bottleneck buffer) – \( M_s \) – \( M_2 \) – \( M_1 \) – \( M_1 \).

\(^c\) Total cost=Maintenance cost + Production Loss cost; besides, the unit of cost is the cost of a single part blank.
getting better maintenance effect meanwhile. This is the most fundamental reason why the system maintenance prioritisation strategy guided by the SM-EFAST process can result better from both the aspects of system performance and total cost.

In addition, comparing the values of OLE and system PR shown in Table 3, the former is significantly lower. This is resulted from the system process ability $OT_2/OT_1$ covered by OLE: It is impossible to perfectly make up for all equipment PD and DT losses no matter how perfect a maintenance strategy is, thus $OT_2/OT_1 < 1$. In terms of $OT_2/OT_1$ under different strategies, it is obvious the one under the OLE centred strategy is the best, indicating this strategy can guide better system maintenance, improve system internal cooperation and achieve good OLE.

5. Conclusions

An OLE centred maintenance prioritisation policy is proposed in this research, where OLE is adopted as the objective of system maintenance to improve system comprehensive performance. Moreover, with an integrated SM-EFAST process which can accurately and efficiently analyse the total effects of equipment $mtbs$, $mtr$ and buffer size $N$ on OLE, this policy can provide clear and specific suggestions to system maintenance task prioritisation from the level of the specific characteristics of equipment operational reliability: $mtbs$ and $mtr$. With these two novelties introduced to the OLE centred maintenance prioritisation policy, limited maintenance resources can be rationally allocated to truly critical equipment, so as to achieve good maintenance effect and low maintenance cost.

Advantages of this OLE centred maintenance prioritisation policy is verified through its application on a real auto spare part processing line: Analysis results show that OLE is more appropriate for production line maintenance effect evaluation than system PR, for its comprehensive and objective. Besides, thanks to the replacement of OLESEM with SM in EFAST experiments and the explored SM-training rules, the efficiency of the SM-EFAST process is evidently better than that of the conventional EFAST process. More importantly, with the prioritisation guidance provided from the level of the specific characteristics of equipment operational reliability, maintenance resources can be correctly allocated to the truly critical equipment performance, thus result in higher OLE and lower total maintenance cost than the popular and widely used bottleneck analysis and FMECA maintenance prioritisation methods.

For future direction, with the development of equipment prognostic and health management, equipment online and prognostic performance will be further considered in equipment maintenance task prioritisation and decision making.

**Ethical Approval**

Not applicable.

**Consent to Participate**

Not applicable.

**Consent to Publish**

Not applicable.

**Availability of data and materials**

Not applicable.

**Authors Contributions**

Zhaojun Yang: Supervision, Project administration, Funding acquisition.

Jieli Li: Background research, Methodology, Data curation, Software, Validation Writing -original draft, Editing.

Chuanhai Chen: Review & editing, Supervision.

Jialong He: Modification suggestion.

Hailong Tian & Lijuan Li: Review & suggestion.

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Competing Interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix
Basic information of the six experimental production lines is displayed in Table A1. To explore the influence of the number of parameters on SM training, Line 1 is designed with 10 OLE influencing parameters, Lines 2–5 are designed with 14 OLE influencing parameters, and Line 6 with 17 parameters.

Meanwhile, Lines 2–5 are designed with gradually complex structures to study the influence of structure complexity:
• Line 2: a seven-workstation serial line without buffers, increasing two single-machine workstations on the basis of Line 1;
• Line 3: a five-workstation serial line with buffers, increasing four buffers on the basis of Line 1;
• Line 4: a five-workstation mixed line with buffers, changing a single-machine workstation to a parallel workstation on the basis of Line 3;
• Line 5: an assembly line with five workstations and buffers, changing a workstation from the trunk into a branch on the basis of Line 3.

To study the influence of OLE range on SM training, the OLE ranges of the experimental production lines are set differently, which are displayed in Table A1.

Lastly, five SM algorithms (RSM, RBF, Kriging, artificial neural networks (ANN) and support vector machine (SVM)) and five sample sizes (100, 150, 300, 500 and 800) are adopted to train SMs (details refer to [31]) for the OLESEMs of the six experimental production lines. Comparing the accuracies of the SMs trained with different algorithms and different sample sizes, the applicability of the five algorithms and the recommended SM training sample size to OLESEM can be analysed.

The accuracies of the SMs of the OLESEMs are examined with root mean square error (RMSE) and goodness of fit ($R^2$), as shown in Fig. A1.

It is clear from Fig. A1 (a) and (b) that with the same sample size, the accuracies of the SMs trained with RBF and RSM are significantly higher than those trained with ANN and SVM. Besides, the parameter number has no significant influence on SM accuracy: With the same sample size, as the number of parameters increases from 10 (Line 1) to 14 (Lines 2–5) and to 17 (Line 6), the accuracies of the SMs trained by the same algorithm do not show evident increase or decrease. Similarly, with the same parameter number (Line 2–5), sample size, and algorithm, the accuracies of the generated SMs display no evident growth or decline when the system structure complexity increases, indicating the production line structure has no influence on SM accuracy either. At last, comparing the accuracies of the SMs trained by RBF and RSM under the same sample size and SM algorithm, the order of the SM accuracies (Line 5 > Line 2 > Line 3 > Line 4 > Line 6 > Line 1) is exactly the reverse of corresponding system OLE ranges. This indicates that the accuracy of an SM is related to the OLE range of the production line: Larger system OLE range requires larger sample size to train accurate SM.

In conclusion, the following suggestions can be summarised to efficiently train accurate SMs for OLESEMs:
1) Preference should be provided to RBF and RSM in algorithm selection;
2) Compared with the production line without buffers, that with buffers requires less samples to train accurate SM, for the reason that buffers can cause more stable production process;
3) The SM-training sample size for OLESEMs (with buffers) should be set according to the OLE range of the production line: If RBF and RSM are selected, only 300 sample points are sufficient to train a well-fitted SM when the OLE range is under 2%, 500 sample points are required when 2% < OLE range < 4%, and approximately 800 sample points are adequate to train an accurate SM when 4% < OLE range < 5%.

Table A1. Basic information of the experimental production lines

| Experimental Lines | Influencing parameter Number | Line Structure | OLE range (%) |
|-------------------|-----------------------------|---------------|---------------|
| Line 1            | 10                          |               | 4.83          |
| Line 2            |                             | M₁ → M₂ → M₃ → M₄ → M₅ → M₆ → M₇ | 1.86          |
| Line 3            | 14                          | M₁ → B₁ → M₂ → B₂ → M₃ → B₃ → M₄ → B₄ → M₅ → M₆ → M₇ | 3.2           |
| Line 4            |                             | M₁₀ → B₀₁ → M₁₂ → B₂ → M₁₄ → B₃ → M₁₆ | 3.6           |
| Line 5            |                             | M₁₈ → B₀₂ → M₂₀ → B₃ → M₂₂ | 1.81          |
| Line 6            |                             | M₁₄ → B₀₁ → M₁₆ → B₂ → M₁₈ | 4.41          |

Fig. A1 Accuracies of the experimental production line SMs obtained with different SM algorithms and sample sizes
On the basis of these findings, the sample sizes needed to train SMs for production lines (with buffers) with larger OLE ranges are further explored: 4%–6%:1000; 6%–8%:1300; 8%–10%:1800.

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